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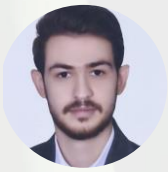
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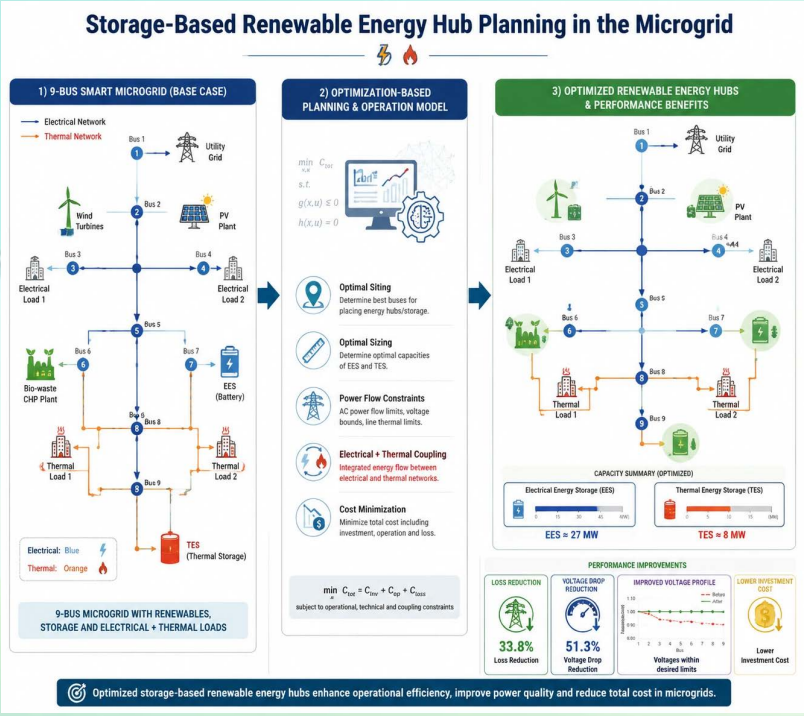
Storage-based Renewable Energy Hubs Sitting and Sizing in the Microgrid

Ehsan Akbari

Highlights

- **Identifying the most optimal locations for deploying EHs within electrical and heating networks,**
- **Determining the ideal sizing (capacity) for renewable sources and both electrical and thermal storage solutions within EHs,**
- **Designing a renewable hub model capable of managing both active and thermal power simultaneously, and**
- **Introducing a combined heat and power (CHP) based BU model for the simultaneous generation of electricity and heat within EHs.**

Graphical Abstract



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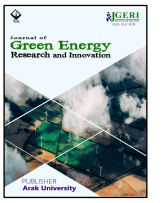
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Storage-based Renewable Energy Hubs Sitting and Sizing in the Microgrid

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A B S T R A C T

Renewable energy hubs have the potential to significantly improve the technical performance of microgrids while reducing environmental pollutants. This is achieved through efficient energy management within the hubs and determining their optimal capacities and placements in the energy network. This article focuses on the planning and operation of renewable energy hubs integrated with storage systems in microgrids. The objective is to minimize the overall costs related to building resources and storage facilities within these hubs. Key constraints addressed include power flow equations, operational limitations, and the planning-operational model of the hubs. The innovation of this approach lies in combining a comprehensive planning-operation model for renewable energy hubs with the implementation of a bio-waste unit model. The numerical results underscore the effectiveness of this strategy, demonstrating improvements in microgrid performance through efficient hub planning and operation. Specifically, the optimal planning process achieved the lowest construction costs for the hubs, while the optimal operation led to substantial reductions in energy losses and voltage drops within the microgrid by approximately 33.8% and 51.3%, respectively, in comparison with traditional power flow analysis. In this condition for the used case study, the planning cost of EHs is M$46.43.

1. Introduction

Extensive research has been carried out on the planning and operational management of energy hubs (EHs), reflecting their growing importance in integrated energy systems and modern microgrids. Energy hubs serve as key infrastructures capable of coordinating multiple energy carriers, like electricity, heating, and cooling, while improving overall system flexibility and efficiency. In this context, numerous studies have investigated different modeling approaches to enhance the performance, reliability, and economic viability of EHs. Reference [1] presents a stochastic two-stage optimization model developed to deal with the operational scheduling of EHs under uncertainty. In this framework, electricity and heat storage devices are incorporated to increase operational flexibility. The model explicitly considers uncertainties associated with electrical, heating, and cooling load demands, besides the variability of power generation from wind systems (WSs). Furthermore, demand response (DR) and integrated demand response (IDR) programs are integrated into the operational strategy, allowing the system to adjust consumption patterns in response to supply variations and market conditions. This integration enables a more adaptive and resilient operational structure for the EH. In reference [2], a sustainable long-term planning methodology is proposed for the design of EHs with high penetration of renewable energy sources (RESs). The proposed hubs are capable of simultaneously supplying electrical, heating, and cooling loads while incorporating dedicated storage units for electricity, thermal energy, and cooling energy. To improve planning accuracy, the study considers uncertainties related to load demands and photovoltaic (PV) generation output. The planning problem is formulated as a dynamic optimization model covering a 15-year horizon, allowing decision-makers to evaluate long-term investment strategies and operational performance under evolving system conditions.

Reference [3] investigates the role of stochastic optimization in facilitating the participation of EH-based systems in energy markets. In this work, demand response programs (DRPs) are incorporated into the optimization framework to provide additional operational flexibility. The results demonstrate that the implementation of DRPs can significantly reduce the operational costs of microgrids (MGs). Moreover, these programs contribute to shifting energy consumption from peak-demand periods to off-peak intervals, thereby smoothing the load curve and improving overall system efficiency and stability. A stochastic scheduling approach to multi-EH systems was proposed [4], where the coordinated operation of EHs and distribution networks is addressed. The proposed approach integrates renewable energy sources, uncertain operational parameters, DRPs, and environmental emission considerations into a unified optimization framework. By simultaneously considering these factors, the model enhances the operation of the integrated energy system while promoting more sustainable and environmentally conscious operation. Finally, reference [5] focuses on hydrogen-based micro-EHs, highlighting the growing role of hydrogen technologies in future energy infrastructures. The study emphasizes the integration of hydrogen storage systems alongside IDR mechanisms to improve operational flexibility and energy management. By incorporating hydrogen as an energy carrier and storage medium, the proposed framework supports cleaner energy utilization and provides additional pathways for balancing supply and demand within micro-scale energy systems.

In reference [6], the EH system consists of a WS, PV, and electric vehicles (EVs) that engage in energy exchange within energy and reserve markets. This system incorporates energy, thermal, and gas DRP. However, effectively managing the balance between energy demand and generation remains challenging due to the unpredictable nature of these units. Reference [7] introduces a double-step stochastic model that addresses EH operations in the context of day-ahead and real-time electricity markets. This model adeptly handles uncertainties related to demand fluctuations, RES outputs, and real-time electricity price variations. To minimize the risk of elevated operational costs under unfavorable conditions, the model integrates a value-at-risk (VaR) metric as a risk management tool. A hybrid linear programming-reinforcement learning approach for the optimal supervision of EHs is explored in [8]. Meanwhile, reference [9] focuses on managing energy flow within flexible EHs connected to the main grid. The proposed scheme integrates electricity and heating networks, combining RES, storage systems, and a centralized hub acting as a coordinator. The study decreases the operational costs of these interconnected grids by adopting an ideal power flow model and tailored formulations for flexible EHs. The problem formulation takes into account uncertainties in demand levels, electricity and heat costs, and renewable electricity availability. An unscented transformation method is employed to simplify the problem, enabling faster computation of optimal solutions. Reference [10] delves into energy management for electricity and heating networks, emphasizing the role of renewable EHs in enhancing network flexibility through dynamic pricing services. These EHs include RES, BUs, ESS, and responsive demand mechanisms. BUs provide combined electricity and heat generation. The primary objective is to narrow the gap between network energy costs and the revenue generated from the hub's flexibility. The analysis incorporates optimal power flow constraints, including equality and inequality conditions, as well as restrictions on network flexibility. Furthermore, it considers the operational models of energy generation units, storage systems, and responsive demand within EHs, alongside flexibility modeling for the hub itself. A novel energy hub management strategy is introduced in [11], which combines unified plug-in EV-based demand response with energy storage systems through a hybrid methodology. Meanwhile, [12] presents a two-layer optimization framework for managing energy between two energy hubs. These hubs are operated as a virtual energy hub (VEH) to supply heat, water, and power demands, while also participating in the thermal market and accommodating additional loads within the upstream distribution system's hosting capacity. In [13], a new approach is proposed to tackle complex challenges linked to energy hubs, with a particular focus on addressing issues related to energy transmission and generation within gas and power grids.

Previous research highlights notable gaps in the planning and operation of EHs. Most studies, as reflected in references [3-13], focus on investigating the integration of EHs within various energy networks. These studies primarily explore the selection of appropriate locations and dimensions for EHs. Subsequently, they analyze how the strategic management of energy resources impacts the operational performance of these networks. It is worth noting that the optimal placement and sizing of EHs significantly enhance network operation conditions. However, this subject was explored in few studies, such as [1-2]. Several studies, including [1-8], extensively incorporate renewable energy sources (RESs) like wind and solar. Additionally, bio-waste (BUs) were shown to generate gas from environmental waste, which is then converted into electrical energy, offering a promising solution for reducing environmental pollution. The incorporation of combined heat and power (CHP) within BU can further enable simultaneous production of electricity and heat. Consequently, integrating EHs into energy networks could accelerate the transition to RESs. Despite this potential, only a few researchers, as indicated in [9-10], have addressed this topic comprehensively.

This paper proposes a strategy to address existing research gaps by integrating renewable EHs into MGs utilizing storage solutions. Electric energy production within EHs is realized by integrating various systems, including WS, PV, and BU. Additionally, BU contributes to thermal energy production. EHs are equipped with EES and thermal energy storage (TES) functionalities. This method minimizes the cost of constructing resources and storage elements that constitute an EH. The constraints associated with this task include the planning and operational framework for renewable generation units and storage systems within the EH structure, along with the optimal power flow model of the MG. Upon analyzing prior research and the proposed solution, several innovations are highlighted: 1) Identifying the most optimal locations for deploying EHs within electrical network, 2) Determining the ideal sizing (capacity) for RESs and both electrical and thermal storage solutions within EHs, 3) Designing a renewable hub model capable of managing both active and thermal power simultaneously, and 4) Introducing a CHP based BU model for the simultaneous generation of electricity and heat within EHs.

This paper introduces a comprehensive strategy aimed at bridging the existing research gaps in the planning and operation of renewable-based EHs integrated into MGs. The proposed framework emphasizes the combined use of renewable generation, storage technologies, and bio-waste-based cogeneration to achieve a more efficient and sustainable energy ecosystem.

Within the proposed structure, electric energy generation inside each EH is realized through the integration of multiple renewable subsystems, including WSs, PV units, and a BU. In addition to electricity production, the BU plays a dual role by also contributing to thermal energy generation, thereby enhancing the energy conversion efficiency and supporting CHP operation.

Each EH is further equipped with two key storage components: EES and TES. The inclusion of these elements provides the flexibility required to manage temporal variations in renewable generation and energy demand, ensuring more stable and reliable microgrid performance.

This strategy minimizes the cost associated with constructing and installing the necessary RESs and storage facilities that constitute the EH. To achieve this, the optimization process incorporates both planning and operational constraints, encompassing the technical limits of renewable generation units, the dynamic behavior of storage systems, and the optimal power flow (OPF) model governing the MG's operation. This integrated approach ensures that economic efficiency is achieved without compromising system reliability or network stability.

A detailed comparison with previous research highlights several key innovations introduced by this study:

1. Optimal siting of energy hubs – developing an effective methodology for identifying the most appropriate installation locations of EHs within the microgrid to minimize network losses and improve voltage stability.
2. Optimal sizing of components – determining the ideal capacities of RESs and both electric and thermal energy storage units to balance cost and performance.
3. Dual-domain energy management – designing a renewable hub model capable of jointly managing electrical and thermal power flows, to boost coordination and efficiency of the energy conversion processes.
4. Bio-waste-based CHP modeling – introducing an innovative CHP model derived from a bio-waste unit (BU) to enable the simultaneous production of electricity and thermal energy within each EH, supporting cleaner and more sustainable system operation.

Through this integrated planning–operation approach, the paper provides a robust framework for the deployment of storage-based renewable EHs, contributing to the advancement of sustainable microgrid development and offering a realistic pathway toward optimized energy system design.

In Section 2, the planning and operation of EHs will be outlined. Section 3 will then present the details of the problem data. Section 4 discusses the numerical results obtained from various research scenarios, and finally, the conclusions are addressed in Section 5.

2. Formulation

Scheme of this paper is based on Figure 1.

A) Objective function: Equation (1) presents the objective function of minimizing the cost of constructing RESs and storage facilities within the EHs [14]. This objective reflects the planning-oriented nature of the model, in which optimal decisions regarding the installation and capacity of system components are determined to achieve an economically efficient EH structure.

More specifically, the first three terms in this function represent the investment costs of installing BU, WS, and PV systems. Each of these terms is calculated by multiplying the quantity of installed units and the investment cost of a single unit [14]. This formulation allows the optimization model to find the most appropriate combination and quantity of renewable generation resources within the EHs.

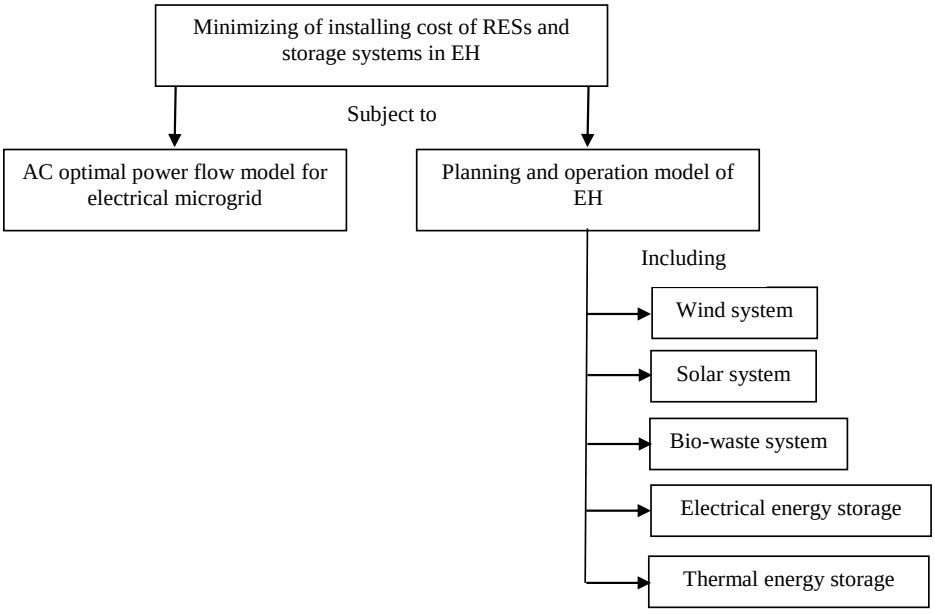


Figure 1. Planning of EH in the electrical MG.

The fourth and fifth terms of the objective function correspond to the installation costs of EES and TES, respectively. In these terms, the total cost is obtained by multiplying the storage capacity by the unit cost of storage with a capacity of 1 MWh. By incorporating these components into the objective function, the model simultaneously optimizes both renewable generation resources and storage capacities in the EHs, ensuring that the overall system configuration achieves the minimum possible investment cost while satisfying the operational and network constraints of the MG.

$$Cost = \sum_{e} c_B n_{Be} + c_W n_{We} + c_V n_{Ve} + c_E \bar{E}_{Ee} + c_T \bar{E}_{Te} \tag{1}$$

B) Planning and operational constraints of the EH: The subsequent Equations (2)-(20) outline the performance and planning model for RES and storage systems. Equations (2) and (3) address the active and heat power flow within the hub. Active power of the EH, from the MG's perspective, is achieved by summing the power generation of BU, WS, PV, and EES, while deducting the power consumed by passive loads and EES. In the thermal domain of the EH, BU and TES in discharge mode supply the required heat power for loads, while TES in charge mode absorbs energy. The planning-operational model for BUs is presented through Equations (4)-(6) [14]. Equation (4) provides the active power output calculation for BU farms, which involves factors such as the number of BUs, their efficiency, the methane content in production gas, low heating value (LHV), and output gas derived from eco-friendly waste. It is assumed that BUs utilize CHP technology, allowing simultaneous heat and electricity generation. Equation (5) involves the heat power generated by BUs as a component of their active power. Equation (6) defines the maximum number of BUs allowable in the EH system. The operational constraints for WS are defined in Equations (7)-(8) [15]. Equation (7) calculates the total active power of WSs within the EH system. This study identifies four operating zones based on wind output power and wind speed interactions: (1) below cut-in speed, where WS produces no active power; (2) between cut-in and nominal speeds, where power output increases linearly with wind speed; (3) between nominal and cut-out speeds, where power output is constant at nominal levels to avoid mechanical damage; and (4) above cut-out speed, where WS halts operations to prevent damage. Equation (8) addresses the maximum number of WS units that can be installed in the EH. The planning-operation model for PV systems is detailed in Equations (9)-(10) [15]. Equation (9) calculates PV active power output based on system count, efficiency, surface area, and received radiation. Equation (10) limits the number of PV installations permissible in the EH. The EES model is described through Equations (11)-(14) [16]. Equations (11)-(12) address charging and discharging rate limitations of EES. Equation (13) prevents simultaneous charging and discharging states. Equation (14) specifies how total energy stored in EES is computed by adding initial energy to the charging power while subtracting discharging power. Planning constraints for EES are defined in Equation (15), limiting its installed capacity within the EH. The TES operation-planning model is outlined in Equations (16)-(20). This model closely resembles that of EES but substitutes active power with heat power considerations.

$$P_{EH\,e,h,s} = P_{V\,e,h,s} + P_{W\,e,h,s} + P_{Be,h,s} + \left(P_{DCH\,e,h,s} - P_{CH\,e,h,s}\right) - P_{C\,e,h,s} \qquad \forall e,h,s \tag{2}$$

$$H_{Be,h,s} + \left(H_{DCH\,e,h,s} - H_{CH\,e,h,s}\right) - H_{C\,e,h,s} \qquad \forall e,h,s \tag{3}$$

$$P_{Be,h,s} = n_{Be}\eta_B \rho_{CH4} LHV_{CH4} G_{Be,h,s} \qquad \forall e,h,s \tag{4}$$

$$H_{Be,h,s} = \frac{\left(1-\eta_B\right)\eta_H}{\eta_B} P_{Be,h,s} \qquad \forall e,h,s \tag{5}$$

$$n_{Be} \in \left\{1,2,\ldots,\bar{n}_B\right\} \qquad \forall e \tag{6}$$

$$P_{We,h,s} = \begin{cases} 0 & v_{c-in} \le v_{e,h,s} \ge v_{c-out} \\ n_{We} P_R \dfrac{v_{e,h,s} - v_{c-in}}{v_r - v_{c-in}} & v_{c-in} \le v_{e,h,s} \le v_r \\ n_{We} P_R & v_r \le v_{e,h,s} \le v_{c-out} \end{cases} \qquad \forall e,h,s \tag{7}$$

$$n_{We} \in \left\{1,2,\ldots,\bar{n}_W\right\} \qquad \forall e \tag{8}$$

$$P_{Ve,h,s} = n_{Ve}\eta_V A_V I_{Ve,h,s} \qquad \forall e,h,s \tag{9}$$

$$n_{Ve} \in \left\{1,2,\ldots,\bar{n}_V\right\} \qquad \forall e \tag{10}$$

$$0 \le P_{CH\,e,h,s} \le \frac{\bar{E}_{Ee}}{\tau_{EC}} \qquad \forall e,h,s \tag{11}$$

$$0 \le P_{DCH\,e,h,s} \le \frac{\bar{E}_{Ee}}{\tau_{ED}} \qquad \forall e,h,s \tag{12}$$

$$P_{CH\,e,h,s} P_{DCH\,e,h,s} = 0 \qquad \forall e,h,s \tag{13}$$

$$\alpha_E \bar{E}_{Ee} \le \chi_E \bar{E}_{Ee} + \sum_{\tau=1}^{h} \left(\eta_{EC} P_{CH\,e,h,s} - \frac{1}{\eta_{ED}} P_{DCH\,e,h,s}\right) \le \bar{E}_{Ee} \qquad \forall e,h,s \tag{14}$$

$$0 \le \bar{E}_{Ee} \le E_{Ee}^{UP} \qquad \forall e \tag{15}$$

$$0 \le H_{CH\,e,h,s} \le \frac{\bar{E}_{T\,e}}{\tau_{HC}} \qquad \forall e,h,s \tag{16}$$

$$0 \le H_{DCH\,e,h,s} \le \frac{\bar{E}_{T\,e}}{\tau_{HD}} \qquad \forall e,h,s \tag{17}$$

$$H_{CH\,e,h,s} H_{DCH\,e,h,s} = 0 \qquad \forall e,h,s \tag{18}$$

$$\alpha_H \bar{E}_{T\,e} \le \chi_H \bar{E}_{T\,e} + \sum_{\tau=1}^{h} \left(\eta_{HC} H_{CH\,e,h,s} - \frac{1}{\eta_{HD}} H_{DCH\,e,h,s} \right) \le \bar{E}_{T\,e} \qquad \forall e,h,s \tag{19}$$

$$0 \le \bar{E}_{T\,e} \le E_{T\,e}^{UP} \qquad \forall e \tag{20}$$

C) Model of electrical MG: The optimal power flow constraints within an MG are represented in Equations (21) through (27) [17-18]. These equations describe the electrical network behavior and ensure that power flow within the MG operates in a technically feasible and secure manner. The AC power flow model for the MG is defined by Equations (21)-(24), which establish the balance between active and reactive power at the electrical buses of the network. These equations also determine the active and reactive power flows through the electrical distribution lines, ensuring that generation, demand, and network losses are properly balanced at each bus [17-18]. By modeling both active and reactive power interactions, this formulation provides an accurate representation of the electrical behavior of the MG. Equations (25)-(27) further represent the operational limitations of the MG. In particular, Equation (25) considers the allowable limits of voltage magnitude at each bus in order to maintain system stability and acceptable power quality levels. Equation (26) addresses the limits on the magnitude of apparent power transmitted through the distribution lines, preventing thermal overloading of the network conductors. Finally, Equation (27) specifies the permissible boundaries for the apparent power flowing through the distribution substation, ensuring that the substation operates within its rated capacity and maintains reliable interaction between the MG and the upstream grid [17,18].

$$P_{ES\,n,h} + \sum_{e} J_{E\,n,e} P_{EH\,e,h} + \sum_{l} I_{EL\,n,l} P_{EL\,n,l,h} = P_{C\,n,h} \qquad \forall n,h \tag{21}$$

$$Q_{ES\,n,h} + \sum_{l} I_{EL\,n,l} Q_{EL\,n,l,h} = Q_{C\,n,h} \qquad \forall n,h \tag{22}$$

$$P_{EL\,n,l,h} = G_{EL\,n,l} \left(V_{n,h}\right)^2 - V_{n,h} V_{l,h} \left\{ G_{EL\,n,l} \cos\left(\beta_{n,h} - \beta_{l,h}\right) + B_{EL\,n,l} \sin\left(\beta_{n,h} - \beta_{l,h}\right) \right\} \quad \forall n,l,h \tag{23}$$

$$Q_{EL\,n,l,h} = -B_{EL\,n,l} \left(V_{n,h}\right)^2 + V_{n,h} V_{l,h} \left\{ B_{EL\,n,l} \cos\left(\beta_{n,h} - \beta_{l,h}\right) - G_{EL\,n,l} \sin\left(\beta_{n,h} - \beta_{l,h}\right) \right\} \quad \forall n,l,h \tag{24}$$

$$V_{LO} \le V_{n,h} \le V_{UP} \quad \forall n,h \tag{25}$$

$$\sqrt{\left(P_{EL\,n,l,h}\right)^2 + \left(Q_{EL\,n,l,h}\right)^2} \le \bar{S}_{EL\,n,l} \quad \forall n,l,h \tag{26}$$

$$\sqrt{\left(P_{ES\,n,h}\right)^2 + \left(Q_{ES\,n,h}\right)^2} \le \bar{S}_{ES\,n} \quad \forall n,h \tag{27}$$

3. Problem Data

The method was assessed on a 9-bus MG depicted in Figure 2. The MG operates with a base power of 1 MVA and a base voltage of 1 kV, as reported in [9]. In this system, Bus 1 is considered the reference bus, where the voltage magnitude is fixed at 1 p.u. and the voltage angle is set to zero radians. The technical characteristics of the distribution lines, substations, active loads, and reactive peak loads are provided in [9] and are used as the basis for modeling the electrical network. The allowable range for voltage magnitudes in the system is considered between 0.9 and 1.1 p.u., ensuring acceptable operating conditions for the MG. The hourly electrical load values are determined by multiplying the maximum load by the corresponding hourly load factor, while the daily load factor profile used in this study is obtained from [19]. This approach enables the model to represent realistic daily variations in electricity demand. Data related to RESs, as well as specifications of electricity and thermal storage systems, are taken from [14-15]. These references also provide the daily profiles for wind speed rates, solar radiation rates, and BU gas rates [14-15,19]. The hourly values for wind speed, solar radiation, and BU gas are calculated by multiplying their respective maximum values by the corresponding hourly rate, allowing the model to capture the temporal variability of renewable resources. In this section, EHs are assigned to buses 2-9, enabling distributed integration of renewable resources and storage units across the MG. It is assumed that the load of each hub represents 50% of the total hub load. Additionally, each EH is designed to supply a thermal load with a peak value of 0.2 MW. The daily heat load profile is obtained from [14-15,19], while the combined thermal demand of all EHs is limited to a maximum of 0.8 MW, ensuring that the thermal energy supply remains within the operational capacity of the system.

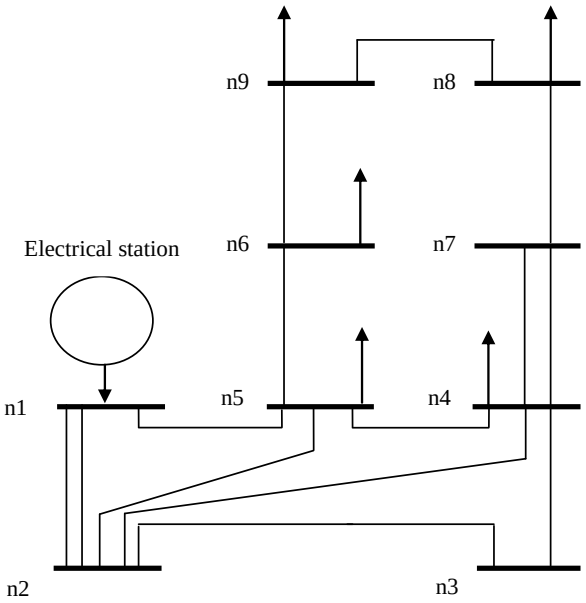


Figure 2. Test MG [9].

4. Results

The approach was implemented according to the problem formulation of Sections 2 and 3 using the GAMS optimization platform. The developed mathematical model, including the objective function and all planning and operational constraints, was coded and executed within this environment. Subsequently, the BONMIN solver was adopted to find the solution of the optimization problem [20]. BONMIN is particularly suitable for handling mixed-integer nonlinear programming problems, which arise due to the presence of nonlinear power flow equations and integer decision variables related to the installation of system components.

After solving the model, the obtained numerical results were analyzed under several different scenarios to assess the performance of the proposed scheme. The main findings and outcomes obtained from these scenarios can be summarized as follows.

A) Planning Status of EHs in Electricity and Heating Grids

The optimal placement of the selected EHs within the MG is illustrated in Figure 3. According to the obtained planning results, three hubs that are solely responsible for electricity generation are installed at buses 2, 5, and 9. These hubs operate as distributed electrical generation units and contribute to meeting the electrical demand of the network without providing thermal energy. In addition, four hybrid hubs that are capable of producing both electrical and thermal energy simultaneously are deployed at buses 4, 6, 7, and 8. The hybrid configuration enables these hubs to support the MG not only through electricity generation but also by supplying the thermal energy required by the system.

As discussed in Section 3, the total thermal power demand of the system is 0.8 MW. Since each EH with thermal capability can provide up to 0.2 MW of heat power, a minimum of four such hubs is necessary to fully satisfy the overall heat requirement. Consequently, the installation of four hybrid EHs ensures that the aggregated thermal production capacity reaches the required 0.8 MW level. This arrangement enables the system to reliably meet the thermal load while maintaining a distributed structure for heat supply, which improves flexibility and reduces dependence on a single thermal source.

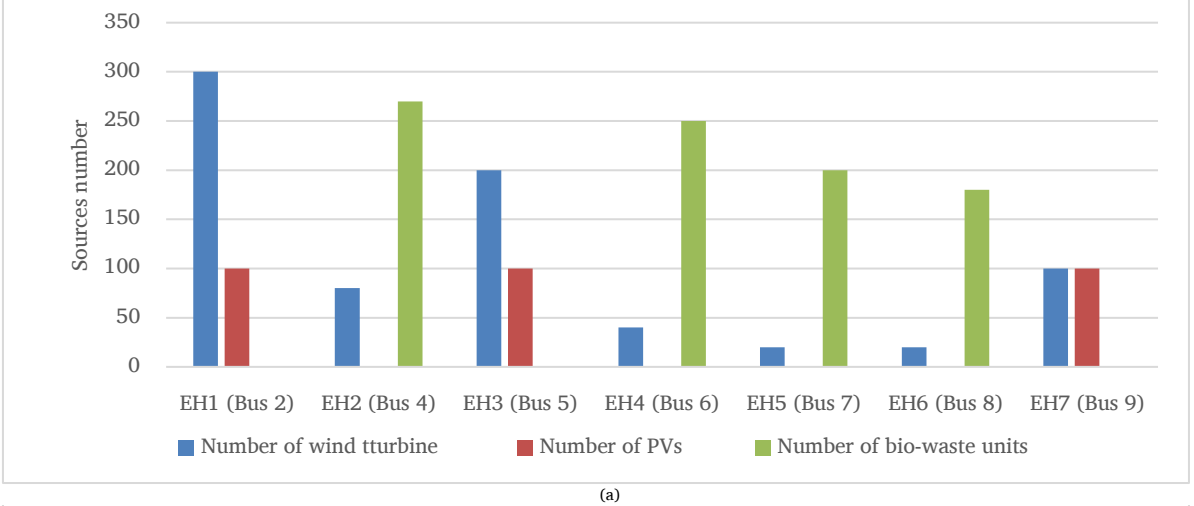
From the spatial distribution of the hubs, it can be observed that EH6 and EH7 are located at buses that are electrically farther from the reference bus (bus 1). This placement is deliberate and follows common principles in distribution network planning. In most MG power flow analyses, buses that are located at larger electrical distances from the reference bus are more susceptible to voltage drops due to line impedances and load concentration. Installing generation units at these remote buses introduces local power support, which reduces the amount of power that must be transmitted from the upstream network. As a result, the voltage magnitude at these buses can be improved and the overall voltage profile of the MG becomes more uniform. This local generation support also contributes to enhancing voltage stability and mitigating the risk of excessive voltage deviations during system operation.

The remaining hubs are installed at buses where the connecting distribution lines have relatively higher transmission capacities. Selecting such locations ensures that the electrical power injected by the hubs can be effectively transferred through the network without overloading the lines or violating their thermal limits. This consideration is particularly important when multiple distributed generation units operate simultaneously, as improper placement could lead to congestion in certain branches of the MG. By positioning the hubs in areas with adequate line capacity, the network is able to absorb the generated power more efficiently, thereby maintaining secure operation conditions.

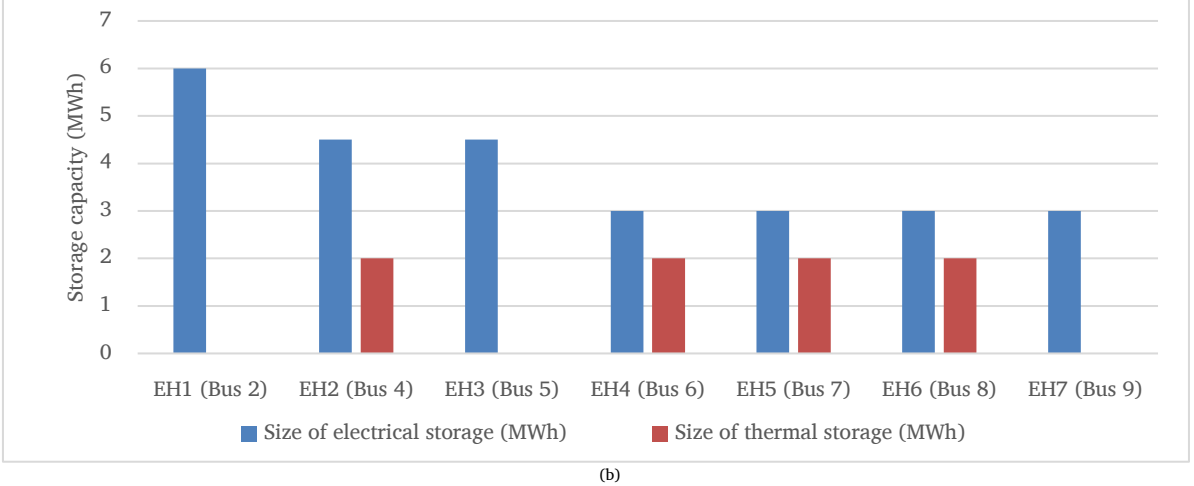
Overall, the obtained placement strategy reflects a balanced approach that simultaneously considers thermal demand satisfaction, electrical network constraints, and voltage support requirements. Through the coordinated installation of purely electrical hubs and hybrid hubs across different buses of the MG, the system benefits from improved operational flexibility, enhanced voltage regulation, and more efficient utilization of the distribution infrastructure. This strategic configuration ultimately contributes to strengthening the overall operational performance and reliability of the MG.

Figure 3 illustrates the size of RES installations and electricity and heat storage components within selected EHs, specifically hubs EH1 through EH7. BU and TES are absent in hubs 1, 3, and 7, as these hubs primarily serve to provide electrical energy. This is because BU and TES are important factors in thermal energy management. These hubs rely on WS and PVs as renewable sources, in addition to EES. In hubs EH1, EH3, and EH7, the number of WSs exceeds that of PVs because, based on findings [14-15], a WS with the same capacity as a PV can generate more energy. Additionally, the installation cost of a 1 MW WS is lower than that of a PV of equal size. Among these three hubs, hub EH1 features the highest number of renewable installations since it is connected to bus 2 (as noted in Figure 3), where the distribution line capacity is substantial. Conversely, hub EH7, connected to bus 9, has fewer renewable resources due to the comparatively lower distribution line capacity associated with bus 9. The size of EES in a hub correlates directly with the number of installed RES. If the number of renewables in a hub is high, the EES capacity is significant; otherwise, it remains smaller. Essentially, EES capacities are designed so that their charging rates align closely with the peak power output of the renewables, enabling them to store an amount of energy equivalent to the maximum output of the renewable systems. BU and WS are installed in hubs EH2, EH4, EH5, and EH6. As BUs also contribute to thermal energy provision, their numbers in these hubs surpass those of WSs. Hubs EH2 and EH4 have more renewable resources compared to hubs EH5 and EH6 due to the higher distribution line capacities connected to hubs EH2 and EH4. Meanwhile, the TES size remains consistent across hubs EH2, EH4, EH5, and EH6.

Table 1 presents a detailed breakdown of the installation costs for renewable and storage components at each hub, along with the total installation cost, as defined by the cost function in Equation (1). The data clearly shows that the installation costs of BUs significantly surpass those of WSs, while WSs have higher construction costs compared to PVs. This is explained by Figure 3, which indicates that the number of installed BUs is highest, while PV installations are the lowest. Additionally, BU units are priced higher than WS and PV units on a per-unit basis.



(a)



(b)

Figure 3. Size of, a) sources, and b) storages in the optimal location of EHs.

Figure 3 further reveals that the installed capacity for EES is approximately 27 MW, whereas TES capacity stands at about 8 MW. Based on references [14-15], the unit cost of EES is greater than that of TES, meaning EES incurs higher installation costs among storage systems. Ultimately, the total installation cost for the proposed scheme amounts to approximately M$46.43.

B) Analysis of the operational status of the electric and heating networks reveals the performance indicators presented in Table 2. These indicators include energy loss (EL), maximum voltage drop (MVD), and maximum overvoltage (MOV), which are evaluated for two different conditions: load flow analysis (Case I) and the proposed design (Case II). In Case I, a conventional load flow study is performed for the MG without the installation of EHs. In contrast, Case II considers the complete optimization framework represented by model (1)-(27), where EH planning and operational constraints are incorporated into the system. The comparison between these two cases allows the effectiveness of the proposed scheme to be clearly evaluated. According to the results, Case I exhibits the highest values of energy loss and voltage drop within the network. However, when the proposed design is applied in Case II, both EL and MVD are significantly reduced, while only a small amount of overvoltage is introduced, equal to 0.011 p.u. Under this improved configuration, the energy loss in the electrical network decreases by approximately 33.8% ($(3.673-2.432)/3.673$). In addition, the maximum voltage drop is reduced by about 51.3% compared with the results obtained from the basic power flow analysis. Furthermore, the overvoltage observed in Case II remains well within the acceptable operational limit of 0.1 p.u. ($1.1-1$). This confirms that the proposed planning and operational strategy not only improves the efficiency of the MG by reducing network losses and voltage drops, but also maintains the voltage profile within safe and reliable operating boundaries.

5. Conclusion

The research focused on identifying the most suitable locations and capacities for renewable EHs that are integrated with both electrical and thermal energy storage systems within an MG. The primary aim was to reduce the overall expenditure related to the installation of renewable generation units as well as the associated storage infrastructures in these energy hubs. In this context, the minimization of the total investment and deployment cost was defined as the main objective function of the optimization problem. To properly represent the interactions between the distribution network and the energy hubs, the objective function was developed in conjunction with the optimal power flow equations of the MG. In addition, the planning and operational characteristics of the EHs were incorporated into the formulation. By combining these elements, a comprehensive modeling framework was established that simultaneously captures the operational behavior of the MG and the strategic planning aspects of the EHs, enabling coordinated decision-making for both network operation and hub deployment. The numerical results demonstrated that the optimal strategy involved installing EHs at buses located farther from the reference bus in order to reduce the risk of significant voltage drops in the network. At the same time, some EHs were connected to buses closer to the reference bus, where a higher number of power transmission lines are available. This configuration helps reduce energy losses in the MG by taking advantage of stronger network connectivity at those buses. Therefore, the placement of EHs was performed in a balanced manner to improve both voltage profile and energy efficiency in the system. Among the renewable sources considered in the study, the BU had the highest installation rate because it is the only unit responsible for providing thermal energy within the network. In contrast, the number of WS units installed was higher than that of PV units. This difference is mainly due to the lower unit cost of WS compared with PV, which makes WS more economically attractive in the optimization process. The sizing of storage systems was also closely related to the number of renewable generation units installed in the EHs. In fact, an increase in the number of renewable power sources led to a proportional increase in the required storage capacity. Consequently, the capacities of EES and TES expanded as the renewable generation capacity increased, ensuring proper energy balancing and operational flexibility in the hubs. The proposed planning and energy management approach for EHs significantly improved the operational performance of the MG. In comparison with conventional load flow studies, the proposed design reduced energy losses by approximately 33.8% and decreased maximum voltage drops by about 51.3%. These results confirm the effectiveness of integrating renewable EH planning with MG operational constraints. The scheme enables the selection of the most suitable locations for integrating EHs into electrical networks. Second, it optimizes the sizing and capacity of RES as well as electrical and thermal storage systems within EHs. Third, it develops a renewable EH model capable of efficiently managing both active and thermal power simultaneously. Fourth, it implements a CHP to BU model that allows the simultaneous production of electricity and heat within EHs. In the proposed design, renewable resources and load demand inherently involve uncertainties. Therefore, stochastic, probabilistic, or robust modeling approaches should be considered in order to accurately represent these uncertainties. In the present paper, deterministic models were used for renewable generation and load demand. However, incorporating uncertainty modeling is considered as an important direction for future work in the proposed design.

Table 1. Installing cost (10^3 $) of sources and storages in the selected EHs.

Energy hub	Location	WS	PV	BU	EES	TES	Total cost (103 $)
EH1	Bus 2	4500	2000	0	360	0	6860
EH2	Bus 4	1200	0	8100	270	100	9670
EH3	Bus 5	3000	2000	0	270	0	5270
EH4	Bus 6	600	0	7500	180	100	8380
EH5	Bus 7	300	0	6000	180	100	6580
EH6	Bus 8	300	0	5400	180	100	5980
EH7	Bus 9	1500	2000	0	180	0	3680
Total cost ($)		11400	6000	27000	1630	400	46430

Table 2. Value of operation indices of network.

Variable	EL (MW)	MVD (p.u.)	MOV (p.u.)
Case I	3.673	0.111	0
Case II	2.432	0.054	0.011

Nomenclature

Indices

e	Energy Hub (EH)
h	Operation hours
l	Auxiliary index corresponding to bus
n	Bus

Variables

$\overline{E}_{E}$	The installed capacity of electric energy storage (EES) in EH (MWh)
$\overline{E}_{T}$	The installed capacity of thermal energy storage (TES) in EH (MWh)
H_B	Heat power of bio-waste unit (BU) (MW)
H_{CH}	Heat power of TES in charge mode (MW)
H_{DCH}	Heat power of TES in discharge mode (MW)
n_B	Installed number of BUs in EH
n_V	Installed number of photovoltaics (PV) in EH
n_W	Installed number of wind systems (WS) in EH
P_B	Active power of BU (MW)
P_{CH}	Active power of EES in charging mode (MW)
P_{DCH}	Active power of EES in discharge mode (MW)
P_{EH}	Active power of EH from the microgrid's viewpoint (MW)
P_{EL}	Active power flow in the electric distribution line (MW)
P_{ES}	Active power flow in the electrical distribution substation (MW)
P_V	Active power of PVs (MW)
P_W	Active power of WS (MW)
Q_{EL}	Reactive power flow in the electric distribution line (MVAr)
Q_{ES}	Reactive power flow in the electrical distribution substation (MVAr)
V	Voltage magnitude (p.u.)
β	Voltage angle (rad)

Parameters

A_V	Area of PV (m^2)
B_{EL}	Susceptance of electric distribution line (p.u.)
c_B	The cost of installing a BU in EH ($)
c_E	Installation cost of EES with a capacity of 1 MWh ($/MWh)
c_T	Installation cost of TES with a capacity of 1 MWh ($/MWh)
c_V	The cost of installing a PV in EH ($)
c_W	The cost of installing a WS in EH ($)
E_{E}^{UP}	Maximum installable size of EES in EH (MWh)
E_{T}^{UP}	Maximum installable size of TES in EH (MWh)
G_B	Gas emission from environmental waste (m^3)
G_{EL}	Conductivity of electrical distribution line (p.u.)
H_C	Heat load (MW)
I_{EL}	Incidence matrix of distribution lines and buses
J_E	Incidence matrix of EH and bus
I_V	Solar radiation (kW/m^2)
LHV_{CH4}	Low heat volume (kW/m^3)
$\overline{n}_{B}$	Maximum installable number of BUs in EH
$\overline{n}_{V}$	Maximum installable number of PVs in EH
$\overline{n}_{W}$	Maximum installable number of WSs in EH
P_C	Active load (MW)
P_R	Nominal active power of WS (MW)
Q_C	Reactive load (MVAr)
$\overline{S}_{EL}$	Maximum apparent power flow in the electrical distribution line (MVA)
$\overline{S}_{ES}$	Maximum apparent power flow in the electrical distribution substation (MVA)
v	Wind speed (m/s)
$v_{c\text{-}in}$	Cut-in wind speed (m/s)
$v_{c\text{-}out}$	Cut-out wind speed (m/s)
V_{LO}	Minimum voltage magnitude (p.u.)
v_r	Nominal wind speed (m/s)
V_{UP}	Maximum voltage magnitude (p.u.)
α_E	The ratio between the least and highest energy storage of EES
α_H	The ratio between the least and highest energy storage of TES
χ_E	The ratio between the initial energy and the highest energy storage of EES
χ_H	The ratio between the initial energy and the highest energy storage of TES
η_B	The efficiency of the electrical sector of BU
η_{EC}	EES efficiency in charging mode
η_{ED}	EES efficiency in discharge mode
η_H	Efficiency of the thermal sector of BU
η_{HC}	TES efficiency in charging mode
η_{HD}	TES efficiency in discharge mode
η_V	PV efficiency
ρ_{CH4}	Percentage of methane in BU gas
τ_{EC}	Charging period in EES
τ_{ED}	Discharge period in EES
τ_{HC}	Charge period in TES
τ_{HD}	Discharge period in TES

References

[1] S. Mansouri, A. Ahmarinejad, et al., "A Multi-Stage Joint Planning and Operation Model for Energy Hubs Considering Integrated Demand Response Programs," *International Journal of Electrical Power & Energy Systems*, vol. 140, 108103, 2022.

[2] H. A. Honarmand, and S. M. Rashid, "A Sustainable Framework for Long-Term Planning of the Smart Energy Hub in the Presence of Renewable Energy Sources, Energy Storage Systems and Demand Response Program," *Journal of Energy Storage*, vol. 52, 105009, 2022.

[3] W. Jiang, X. Wang, H. Huang, D. Zhang, and N. Ghadimi, "Optimal Economic Scheduling of Microgrids Considering Renewable Energy Sources Based on Energy Hub Model Using Demand Response and Improved Water Wave Optimization Algorithm," *Journal of Energy Storage*, vol. 55, 105311, 2022.

[4] V. Thang, T. Ha, Q. Li, and Y. Zhang, "Stochastic Optimization in Multi-Energy Hub System Operation Considering Solar Energy Resource and Demand Response," *International Journal of Electrical Power & Energy Systems*, vol. 141, 108132, 2022.

[5] H. Zhang, Y. Chen, K. Liu, and S. Dehan, "RETRACTED: A Novel Power System Scheduling Based on Hydrogen-Based Micro Energy Hub," *Energy*, vol. 251, 123623, 2022.

[6] E. Mokaramian, H. Shayeghi, F. Sedaghati, A. Safari, and H. H. Alhelou, "An Optimal Energy Hub Management Integrated EVs and RES Based on Three-Stage Model Considering Various Uncertainties," *IEEE Access*, vol. 10, pp. 17349–17365, 2022.

[7] A. R. Jordehi, "Two-Stage Stochastic Programming for Risk-Aware Scheduling of Energy Hubs Participating in Day-Ahead and Real-Time Electricity Markets," *Sustainable Cities and Society*, vol. 81, 103823, 2022.

[8] A. Ghadertootoonchi, M. Moeini-Aghtaie, and M. Davoudi, "A Hybrid Linear Programming-Reinforcement Learning Method for Optimal Energy Hub Management," *IEEE Transactions on Smart Grid*, vol. 14, no. 1, pp. 157–166, 2023.

[9] X. Zhang, X. Yu, X. Ye, and S. Pirouzi, "Economic Energy Managementof Networked Flexi-Renewable Energy Hubs According to Uncertainty Modeling by the Unscented Transformation Method," *Energy*, vol. 278, 128054, 2023.

[10] E. Akbari, S. F. Mousavi Shabestari, S. Pirouzi, and M. Jadidoleslam, "Network Flexibility Regulation by Renewable Energy Hubs Using Flexibility Pricing-Based Energy Management," *Renewable Energy*, vol. 206, pp. 295–308, 2023.

[11] A. Karthikeyan, and V. Arun, "Enhancing Energy Hub Management with Unified Plug-In Electric Vehicle Based Demand Response and Energy Storage Systems," *Journal of Energy Storage*, vol. 108, 114997, 2025.

[12] Y. Pezhmani, and N. Rezaei, "Risk-Averse Energy Management of a Water-Heat-Power Virtual Energy Hub Considering Hosting Capacity and Volt-VAR Control of Distribution Network," *Energy*, vol. 318, 134949, 2025.

[13] L. Yan, X. Deng, and J. Li, "Integrated Energy Hub Optimization in Microgrids: Uncertainty-Aware Modeling and Efficient Operation," *Energy*, vol. 291, 130391, 2024.

[14] M. R. Jokar, S. Shahmoradi, et al., "Stationary and Mobile Storages-Based Renewable Off-Grid System Planning Considering Storage Degradation Cost Based on Information-Gap Decision Theory Optimization," *Journal of Energy Storage*, vol. 58, 106389, 2023.

[15] A. Maleki, and A. Askarzadeh, "Optimal Sizing of a PV/Wind/Diesel System with Battery Storage for Electrification to an Off-Grid Remote Region: A Case Study of Rafsanjan, Iran," *Sustainable Energy Technologies and Assessments*, vol. 7, pp. 147–153, 2014.

[16] A. Azarhooshang, D. Sedighizadeh, and M. Sedighizadeh, "Two-Stage Stochastic Operation Considering Day-Ahead and Real-Time Scheduling of Microgrids with High Renewable Energy Sources and Electric Vehicles Based on Multi-Layer Energy Management System," *Electric Power Systems Research*, vol. 201, 107527, 2021.

[17] M. Roustaee, and A. Kazemi, "Multi-Objective Stochastic Operation of Multi-Microgrids Constrained to System Reliability and Clean Energy Based on Energy Management System," *Electric Power Systems Research*, vol. 194, 106970, 2021.

[18] A. Rohani, M. Abasi, A. Beigzadeh, M. Joorabian, and G. B. Gharehpetian, "Bi-level Power Management Strategy in Harmonic-polluted Active Distribution Network Including Virtual Power Plants," *IET Renewable Power Generation*, vol. 15, no. 2, pp. 462–476, 2021.

[19] Z. Qu, C. Xu, F. Yang, F. Ling, and S. Pirouzi, "Market Clearing Price-Based Energy Management of Grid-Connected Renewable Energy Hubs Including Flexible Sources According to Thermal, Hydrogen, and Compressed Air Storage Systems," *Journal of Energy Storage*, vol. 69, 107981, 2023.

[20] M. R. Bussieck, and A. Meeraus, "General Algebraic Modeling System (GAMS)," *Applied Optimization*, pp. 137–157, 2004.

Declaration of competing interest

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Bibliography



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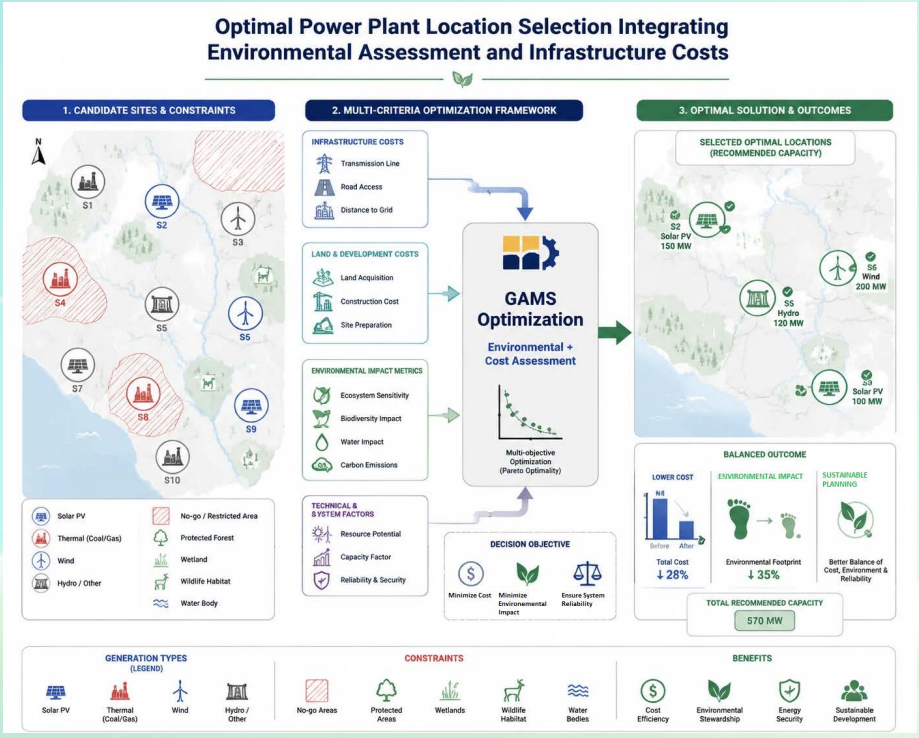
Striking the Green Balance: A Scientific Approach to Optimal Power Plant Location Selection Integrating Environmental Assessment and Infrastructure Costs

Mostafa Davoodabadi Farahani, Ali Farahani, Saeed Sharafi

Highlights

- **Integrate environmental costs into siting to reveal true fossil fuel expenses.**
- **Expand research to include post-construction impacts (e.g., transmission lines).**
- **Balance environmental, economic, and social factors for sustainable, supported policies.**
- **Engage communities and promote renewables/efficiency to align economic and environmental goals.**
- **Apply bi-level optimization to address site selection complexities.**

Graphical Abstract



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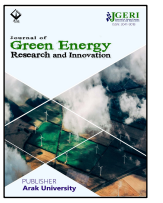
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Striking the Green Balance: A Scientific Approach to Optimal Power Plant Location Selection Integrating Environmental Assessment and Infrastructure Costs

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A B S T R A C T

supporting industrial and societal growth. Power generation is carried out through various sources such as solar energy, wind, and thermal systems, each with unique infrastructural demands and environmental impacts. Assessing the environmental consequences of constructing power plants is essential for minimizing harm to ecosystems and communities. This study aims to identify optimal locations for establishing electricity generation facilities by evaluating both infrastructure requirements and environmental considerations. A comprehensive site selection process is conducted, taking into account the characteristics of different types of power plants. Cost estimation for each potential site includes factors such as land acquisition and is tailored to the type and capacity of the plant. Environmental variables are also incorporated into the analysis to provide a more holistic view of each option. Using GAMS optimization software, the study identifies the most cost-effective and environmentally responsible sites for power plant installation and recommends the most suitable capacities for each selected location. The findings contribute to more sustainable energy planning and informed decision-making in the energy sector.

1. Introduction

Power system planning is a multifaceted and extensive undertaking that engineers continuously explore. It encompasses various stages, including load forecasting, power plant and substation siting, transmission line placement, and ultimately, distribution network design [1]. Due to its broad scope, power system planning has been examined from numerous perspectives. The integration of increasing variable renewable energy sources into power system planning is explored in [2], while [3-5] delve into fundamental issues such as uncertainty and risk analysis. [6] proposes a comprehensive decision support model covering key factors in the design of AC electric power systems for offshore wind farms (OWFs), such as investment costs, system efficiency, and reliability. Steady-state equivalents are vital for studying the static characteristics of large power systems, particularly when computer resources are limited or solution times need to be expedited [7]. Another facet of planning, power system restoration, is presented in [8]. Generation expansion planning, a subset of power system planning, is discussed in this article. Various optimization techniques, including particle swarm optimization [9], improved genetic algorithms [10], and Lagrangian relaxation [11], have been applied to address this issue. Metaheuristic techniques are also explored in [12]. In the realm of generation expansion planning, environmental costs are often overlooked in objective functions. However, studies like [13] consider environmental impacts in power generation expansion planning for Lebanon, while [14] investigates the effects of biomass power generation and CO_2 taxation on electricity generation expansion planning and environmental emissions. Environmental impact studies on power plants, including those with carbon capture and storage [15], photovoltaic power plants [16], and renewable power plants [17], further underscore the importance of environmental assessment in power system planning.

References [18-20] focus on environmental assessments of wind turbines, solar energy systems, and hydroelectric power plant development, as well as the use of environmental assessment tools in Brazil. Additionally, [21] examines the environmental assessment of a bi-fuel thermal power plant in an isolated power system in the Brazilian Amazon region. Optimization methods are categorized into heuristic [22] and mathematical [23] approaches. Heuristic algorithms iteratively improve candidate solutions based on given quality measures, while mathematical optimization selects the best element from available alternatives. GAMS software, which employs mathematical methods for optimization, will be used to optimize power plant locations in this article. Notably, environmental effects of power plant establishment are integrated into the optimization objective function, with detailed mathematical modeling provided. The article proceeds with an introduction to environmental effects, followed by the concept and modeling of the optimization problem, solutions addressing environmental effects, and considerations of forbidden areas. Simulation results and performance analyses are presented, concluding the article in its seventh section.

2. Environmental assessment

The progression of technology and human knowledge has underscored the imperative of preserving the environment as a primary concern for future generations. Regrettably, as technology advances, so does the pace of environmental degradation. The demands of modern life and consumerism contribute to the accelerated depletion of environmental resources. Recognizing that a healthy environment is the entitlement of all living beings, both present and future, it is incumbent upon us to scrutinize our actions, identify harmful behaviors, and endeavor to rectify them to sustain our surrounding environment. Consequently, environmental impact analysis, or environmental impact assessment, serves as the foundational step toward achieving this objective. Every decision we make bears consequences for the environment, and environmental impact assessment aids in evaluating the ramifications of these decisions, identifying adverse effects, and seeking to mitigate or eliminate them. Importantly, this endeavor must be undertaken in a manner that reconciles environmental considerations with social, economic, and other associated benefits derived from our decisions. To incorporate environmental considerations into decision-making processes, it is essential to establish a clear definition of the environment. The term "environment" encompasses diverse meanings; it may evoke images of forested landscapes, pristine air, and unpolluted waters for some, while others may associate it with suburban neighborhoods or tranquil retreats. Some conceptualize the environment within the realm of ecology, contemplating interactions between flora and fauna, food chains, and conservation efforts. Indeed, the environment encompasses all these facets and more.

Electricity stands as one of humanity's most significant achievements, now deeply ingrained in our contemporary environment. While electricity exerts undeniable negative impacts on the environment, its indispensable role in human life renders its elimination unfeasible. Thus, it becomes imperative to utilize electricity in a manner that minimizes its adverse environmental effects. The environmental impacts of electricity manifest across its production, transmission, and consumption stages, though our focus here remains primarily on the production phase. Electricity production predominantly occurs through power plants, each type exerting distinct environmental effects. Notably, the adoption of renewable energy sources for power generation is steadily gaining traction. The figures below illustrate the usage rates of various power plants, each bearing its set of advantages and disadvantages. To ascertain the optimal power plant, we must address an optimization problem. Subsequently, we will delve into the concept of optimization, gradually navigating toward determining which power plant yields the least environmental impact.

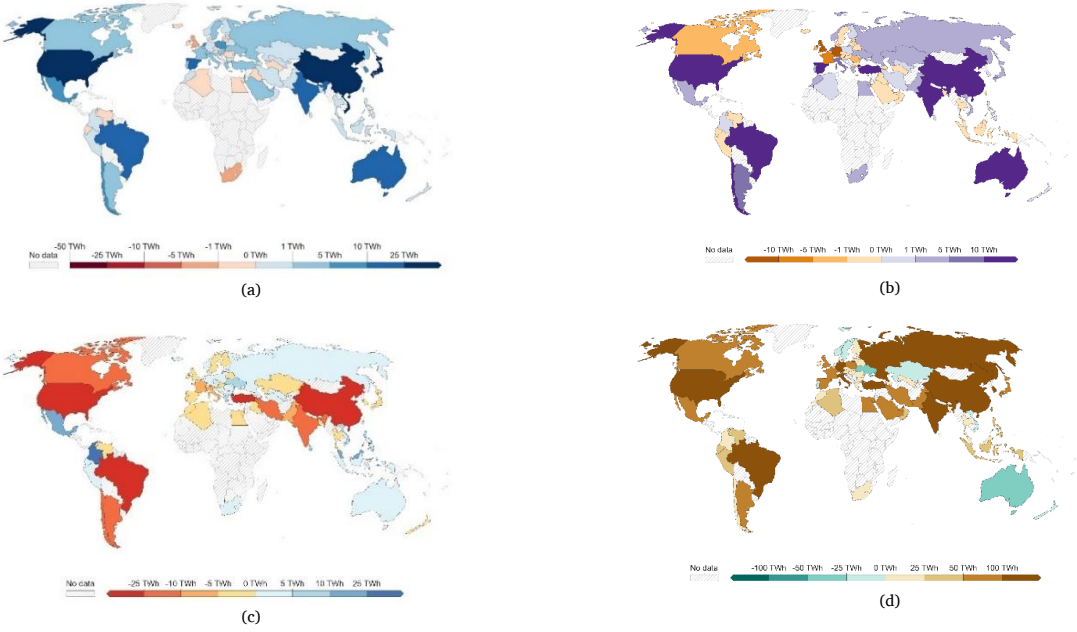


Figure 1. The amount of use of all types of power plants in the world in 2020: (a) solar power plant, (b) wind power plant, (c) hydroelectric power plant and (d) thermal power plant with fossil fuels.

3. Optimization

Every day, we are faced with numerous decisions, each prompting us to seek the optimal outcome. For instance, when purchasing a product, we aim to secure the best quality at the lowest price, a quintessential act of optimization. The fundamental goal of optimization problems is to identify solutions that either minimize or maximize a variable. In this article, we primarily focus on minimization.

3.1. Problem Definition

Defining the problem marks the initial step in optimization. In any optimization endeavor, the decision-maker must delineate the decision variables, constraint functions, and objective function. Understanding these components is pivotal in optimization.

3.1.1. Decision and Dependent Variables

Decision variables serve as the independent entities, the values of which are optimized by the decision-maker. Dependent variables, in turn, are determined based on the optimized values of the decision variables. In our context, optimizing power plant location with regard to environmental costs entails decision variables encompassing location, type, and capacity of power plants. Dependent variables may include total fuel, equipment, land, and line costs, along with costs associated with land and air pollution.

3.1.2. Constraint Functions

Optimization problems often entail constraints that delineate the solution space. These constraints can be technical, economic, environmental, or similar in nature, effectively partitioning the solution space into acceptable and unacceptable regions. In our scenario, optimizing power plant location mandates adherence to constraints such as total power plant production meeting the load and reserve requirements, suitability of locations for wind and solar power plants based on environmental factors, and considerations regarding land availability and cost.

Fossil fuel power plants, while prevalent, are recognized for their environmental drawbacks, prompting global efforts to phase them out. Gas turbine power plants offer advantages such as smaller size, lighter weight, and lower initial costs compared to steam power plants. However, they may face fuel shortages in winter. Hydroelectric power emerges as a competitive and environmentally friendly option, offering low production costs and minimal water consumption. Additionally, hydroelectric plants afford flexibility in power generation and produce minimal waste and greenhouse gas emissions.

3.1.3. Objective Functions

Objective functions encapsulate the overarching goals of the optimization endeavor. For instance, in our case, the suitability of thermal power plants with fossil fuels hinges on meeting the required power capacity, whereas hydro and wind power plants are preferable if minimizing fossil fuel usage is paramount.

3.2. Problem Modeling

Once decision variables, constraints, and objective functions are defined, the decision-maker must model the problem in a suitable format for resolution. Modeling considerations include available tools, algorithms for problem-solving, required accuracy, and potential simplifications. A generic optimization problem model typically assumes the following form (Equation (1)):

$$\begin{aligned} &Minimize\ C(x) \\ &Subject\ to\ g(x) <= b \end{aligned} \tag{1}$$

Where x is the decision variable, C(x) is the objective function and g(x) $<=$ b is the inequality constraint. The decision variables may be either real or integer or binary.

3.2.1. Mathematical Techniques

Mathematical optimization techniques entail formulating the problem within a mathematical framework, typically represented as Equation (1). If the objective function and/or constraints are nonlinear, the problem is termed a Nonlinear Optimization Problem (NLP). Quadratic programming represents a special case of NLP, where the objective function is quadratic in x. When both the objective function and constraints are linear functions of x, the problem is categorized as a Linear Programming (LP) problem. Additional categories arise based on the nature of variables; for instance, if x is of integer type, it denotes an Integer Programming (IP) problem. Mixed types like Mixed Integer Linear Programming (MILP) may feature both real and integer variables, with the problem still being of LP type.

In this study, the CPLEX solver was employed within the GAMS environment to solve the proposed mixed-integer programming (MIP) model. CPLEX is known for its efficiency and robustness in handling large-scale optimization problems involving discrete and continuous variables. To manage the complexity and scalability of the problem, the number of candidate sites and power plant types was limited during preprocessing. Additionally, certain parameters were grouped or discretized to reduce computational burden without significantly affecting model accuracy.

This approach ensures a balance between solution precision and computational feasibility, allowing the optimization process to converge efficiently while preserving the integrity of decision-making in power plant location planning.

3.2.2. Versus Heuristic Techniques

While most mathematical-based algorithms can ensure reaching an optimal solution, they may not guarantee a global optimum. Global optimality is attainable, checkable, or guaranteed only for simple cases. Conversely, many practical optimization problems deviate from the strict forms and assumptions of mathematical algorithms. Complex problems may pose challenges for mathematical algorithms, and achieving a global optimum remains elusive. Heuristic algorithms address these issues by handling combinatorial problems, even in highly complex scenarios, within a reasonable timeframe. However, they prioritize finding good solutions without guaranteeing optimality or proximity to the optimal point.

4. Solving the problem of power plant location according to environmental costs

4.1. Case Study

Table 1 illustrates the geographical distribution of load nodes, each assumed to have a value of 0.9 p.u Table 2 presents candidate locations for power plants (the data in this table have been extracted from Reference [1].), while Table 3 outlines the costs associated with solar, gas, thermal, hydro, and wind power plants. The type and capacity of each power plant have been selected by the authors based on the predefined scenarios considered in the study, which take into account different infrastructural and environmental conditions. In addition to fuel prices, the table includes data on land area requirements, equipment costs, and other essential factors. The construction and maintenance costs for each power plant type have been extracted from Source [24], which offers standardized and widely accepted economic estimates for energy systems.

Power plants must supply the loads listed in Table 1 (the data in this table have been extracted from Reference [1].), with their location and type determined based on Tables 2 and 3, along with specific scenario conditions to be addressed later.

4.2. Defining the problem of power plant location according to environmental costs

The primary objective is to minimize the cost of establishing power plants to meet desired loads while adhering to various constraints. The solution must determine the allocation, type, and size of power plants, along with associated investment and operating costs. Mathematically, the problem may be expressed as Equation (2):

$$Minimize\ C_{total} = C_{\text{inv}} + C_{opt} \tag{2}$$

Subject to constraintinvs

where C_{inv} refers to all investment costs and Copt denotes the operational costs. A typical investment cost is the cost of constructing a new power plant, where as the cost of providing the fuel is a typical operational cost. Various constraints should also be observed during the optimization process. For instance, the capacity of a power plant should not violate a specified limit, or any type of power plants cannot be established in all candidate locations.

4.3. Problem formulation

In this section, we try to formulate the problem of previous section as a mathematical optimization problem.

4.3.1. Objective function

The objective function, C_{total}, consists of the following three terms; C_{fix} (Fixed costs), C_{var} (Variable costs) and C_{env} (Environmental costs) (Equation (3)):

$$C_{Total} = C_{Fix} + C_{Var} + C_{\text{Env}} \tag{3}$$

4.3.2. Fixed costs

Fixed costs are further categorized into three components: transmission line costs, land costs, and infrastructure costs. The assumption is made that loads are directly linked to the power plant, with the cost of transmission lines denoted as gL(i) (for the ith load). This cost is defined as the cost per unit length (e.g., 1 km) for one unit of power transfer capability (e.g., 1 MVA). If Np represents the number of power plant points and NL represents the number of load nodes, and H(i, j) denotes the distance between the load node and the power plant, then we have (Equations (4)-(5)):

$$C_{Line} = \sum_{i=1}^{Nl} \sum_{j=1}^{Np} g_L(i) X(i, j) H(i, j) S_L(i) \tag{4}$$

Where;

$$H(i, j) = \sqrt{(Xi - Xj)^2 + (Yi - Yj)^2} \tag{5}$$

In the context provided, X(i,j) denotes the decision variable. For example, X(4,1) equals 1 if load node 4 is supplied through power plant 1; otherwise, it is zero. It is important to note that the value of X(i,j) is determined through the solution of the optimization problem. Consequently, at the conclusion of the process, the supply point for each load node is established. Additionally, SL(i) represents the load value of i in MVA (Equation (6)):

$$C_{Land} = \sum_{i=1}^{Np} \sum_{t=1}^{Nt} L_p(j) Space(t) u(j,t) \tag{6}$$

In this context, u(j, t) represents the decision variable for the type of power plant. For instance, referencing Tables 1 and 3, u(4, 8) equals 1 if there exists a power plant at location 4 as per Table 1, and the type of power plant corresponds to a hydro-power plant as specified in Table 3. The term Space(t) denotes the area of land required for a power plant of the type outlined in Table 3. Additionally, LP(j) signifies the value of each square meter of land at the jth point, as per Table 1. Throughout this article, the term "cost of infrastructure" refers to expenses associated with road construction and similar factors, computed as Equation (7):

$$Cinfrastructure = \sum_{i=1}^{Np} \sum_{t=1}^{Nt} Cinf(t) u(j,t) \tag{7}$$

Where $C_{inf(t)}$ is the cost of infrastructure depends on the type of power plant. Finally, fixed costs are calculated from the following Equation (8):

$$C_{Fix} = C_{Line} + C_{Land} + C_{infrastructure} \tag{8}$$

4.3.3. Variable costs

In this study, fuel costs and operator costs are classified as variable costs. Among these, fuel cost stands out as one of the most crucial objective functions, representing a substantial portion of expenses. The cost of fuel is treated as a continuous expense, computed annually for each power plant unit based on its capacity (UC) and fuel consumption. Ultimately, it is calculated over the entire useful lifespan of the power plant unit (UL).

To begin, let's introduce the relevant indicators:

- Load Peak (LP): This refers to the maximum load experienced during a specific time period.
- Load Factor (LF): The ratio of the total energy produced over a defined period (typically a year) to the product of the load peak and the duration of that period (usually 8,760 hours). The average load factor, in this case, is 0.65.
- Efficiency (EF): The ratio of net output to gross input, indicating the effectiveness of the power generation process (Equations (9)-(10))

$$p.f.plant = price * LF * 8760 * EF * UC * UL \tag{9}$$

$$Cfuel = \sum_{i=1}^{Np} \sum_{t=1}^{Nt} p.f.plant(t) u(j,t) \tag{10}$$

Operator costs are calculated as follows (Equation (11)):

$$Coperator = \sum_{i=1}^{Np} \sum_{t=1}^{Nt} p_operato_plant(t) u(j,t) \tag{11}$$

Where p-operator plant(t) is the costs related to the power plant operator (Equation (12)).

$$C_{Var} = C_{fuel} + C_{operator} \tag{12}$$

4.3.4. Environmental costs

Environmental costs in this article, only the costs caused by air pollution and land pollution are considered, which are calculated as follows (Equation (13)):

$$Cair = \sum_{i=1}^{Np} \sum_{t=1}^{Nt} p.air.plant(t) u(j,t) \tag{13}$$

where p.air.plant(t) is the costs related to the power plant air pollution cost (Equation (14)):

$$Cland = \sum_{i=1}^{Np} \sum_{t=1}^{Nt} p.land.plant(t) u(j,t) \tag{14}$$

where p.land.plant(t) is the costs related to the power plant land pollution cost, and finally, the environmental costs are calculated from the following formula (Equation (15)):

$$C_{Env} = C_{air} + C_{land} \tag{15}$$

In fact, incorporating environmental costs stemming from air and land pollution caused by the establishment of power plants is a complex and multifaceted issue. These costs can be broadly categorized into impacts on ecosystems, wildlife, and human health. Notably, damage to human health, especially life-threatening effects, cannot be compensated by any financial value and often involves significant uncertainty in quantification.

Since a comprehensive and precise evaluation of environmental costs is beyond the scope of this study, and due to the lack of standardized methods or accessible data to economically quantify such effects (especially in the context of the target region), this paper adopts a hypothetical and comparative approach. Specifically, environmental damages are reflected in the model through estimated coefficients incorporated into the objective function. These coefficients are calibrated to strike a balance between environmental impacts and conventional infrastructure-related costs, such as land acquisition, equipment, and fuel. The primary aim of this study is to introduce a novel methodology that integrates environmental considerations into optimal power plant site selection rather than attempting an exact economic valuation of environmental consequences.

4.4. Constraints

In practice, power plants are linked to substations via high-voltage transmission lines, and subsequently, the substations are linked to loads through additional transmission lines. However, for the purposes of this article, it is assumed that loads are directly linked to power plants via transmission lines, with no limitations on the placement of these lines. Given this assumption, the primary constraint of the problem is connecting each load to only one power plant, which is defined as follows (Equation (16)):

$$\sum_{j=1}^{Np} X(i, j) = 1.0, \forall i = 1, \ldots, Nl \tag{16}$$

where the Σ term represents the burden on power plant j. we use constraint below Determining the value of Xs(j) to be either zero or one (Equation (17)):

$$\sum_{i=1}^{Nl} X(i, j) \le X_s(j) Nl, \forall j = 1, \ldots, Np \tag{17}$$

A next constraint to be met is the power plant capacity as follows (Equation (18)):

$$\sum_{i=1}^{Nl} X(i, j) S_L(i) \le \overline{Sj}, \forall j = 1, \ldots, Np \tag{18}$$

Overline Sj represents the maximum capacity of the jth power plant. also X(i, j), Xs(j) are binary variable (zero or 1).

5. Prohibited area (definition and mathematical modeling)

As previously mentioned, one of the key innovations of this article is the incorporation of prohibited areas into the power plant location selection process, with consideration of associated environmental costs. In this context, prohibited areas refer to locations where the construction of power plants is either unfeasible or inadvisable due to environmental constraints. For example, hydropower plants cannot be installed in every location, as they require the presence of running water and suitable conditions for dam construction. Similarly, wind power plants demand areas with sufficient wind coverage and minimal physical obstructions. Solar power plants need regions with high solar radiation and favorable temperature conditions. Moreover, establishing thermal power plants in areas prone to air pollution is impractical. Biologists also advise against constructing power plants in ecologically sensitive regions with minimal human presence, as such developments could disrupt natural landscapes and biodiversity. Therefore, it is essential to incorporate prohibited area constraints into the power plant location optimization process. The modeling and treatment of these prohibited zones will be further illustrated through examples in the simulation section. In Reference [25], the authors aimed to determine optimal locations for wind power plants by evaluating the commercial viability of various wind speeds.

Their study identifies wind speed thresholds that are economically feasible for wind power generation and, in doing so, effectively defines prohibited zones for wind plant establishment based on insufficient wind potential.

6. Simulation

For the simulations, we utilized the system illustrated in Figure 1, as described by Seifi and Sepasian [1]. This system consists of 37 load nodes, each with a consumption of 30 MVA (0.3 p.u.). The geographical distributions of these loads are detailed in Table 1, while Table 2 presents the geographical distributions of the power plants in terms of longitude (X) and latitude (Y). Also, the cost per square meter of land for each candidate location is presented in dollars.

Additionally, Table 3 outlines the capacities and costs associated with each type of power plant. To enhance comprehension of the various costs involved, three scenarios have been devised, which will be elaborated upon shortly. Notably, the study area is segmented into four parts based on land prices; the two dark-colored regions exhibit lower prices compared to the two white-colored areas.

6.1. Scenario 1

In Scenario 1, we solely factor in the cost of land for power plant construction and the cost of transmission lines. Initially, we consider only one type of power plant candidate (Code. 6 of Table 3 - thermal power plant) for establishment, optimizing solely for power plant locations. Costs due to land and transmission lines are the most basic type of cost in the problem of power plant location. It is usually used in simulations where the type and power of the power plant are the same and only the location of the power plant is unknown. According to the type of selection costs, we expect the candidate locations for power plant deployment to be selected using simulation, which first have lower land cost than other candidate location. Secondly, they are also chosen in such a way that the least number of transmission lines are required.

Table 1. Geographical distributions of load nodes.

Code	X	Y	Code	X	Y	Code	X	Y
1	2	40	14	52	40	27	95	73
2	20	40	15	44	32	28	95	44
3	2	28	16	46	15	29	90	40
4	5	21	17	44	76	30	94	33
5	20	28	18	52	76	31	91	32
6	10	50	19	58	74	32	92	28
7	25	50	20	54	66	33	93	19
8	30	57	21	60	53	34	98	12
9	40	61	22	58	19	35	75	32
10	37	55	23	64	17	36	85	17
11	43	45	24	60	6	37	85	10
12	35	35	25	67	40			
13	46	42	26	85	57			

Table 2. Geographical distributions of power nodes.

Code	X	Y	Land Cost	Code	X	Y	Land Cost
1	15	33	3.5	14	55	58	5
2	35	50	65	15	75	55	3
3	85	33	85	16	33	33	1
4	55	33	80	17	70	33	80
5	48	70	65	18	12	19	7
6	60	14	89	19	28	19	9
7	65	55	2	20	44	21	7
8	92	15	80	21	60	22	6
9	12	70	50	22	12	10	5
10	32	70	45	23	28	10	8
11	65	70	4	24	44	10	5
12	88	70	5	25	70	10	99
13	15	50	75				

Table 3. Establishment and running costs of power plants ($/1pu).

Code	Type	Capacity (p.u)	Space (p.u m-2)	Area cost	Land cost	Fuel cost	Operator cost	Under cost
1	pv	1	15000	0	500	0	200	500
2	pv	2	30000	0	10000	0	250	500
3	pv	3	45000	0	15000	0	300	500
4	Gas	3	1000	5000	3000	4000	9000	15000
5	Gas	5	2000	10000	6000	8000	10000	15000
6	Thermal	5	1500	150000	4000	2000	8000	10000
7	Thermal	8	5000	300000	9000	3500	15000	10000
8	Hydro	2	7000	0	6000	0	1000	10000
9	Hydro	3	8000	0	7000	0	1500	10000
10	Wind	1	700	0	1000	0	200	500

The graphical representation of the simulation results is depicted in Figure 2, while Table 4 provides a breakdown of the costs. It is worth noting that according to Table 2, candidate locations 16, 7, and 15 have the lowest, respectively the amount of cost per square meter of land among the candidate places for the establishment of the power plant. To investigate the impact of line costs, the simulations were repeated with a 20% reduction in land costs. The results are presented in Figure 3 and Table 5. With the decrease in land expenses, the most optimal strategy involves expanding the power plant coverage to include locations 7, 16, and 21. In the previous simulation, the selected power plant locations were situated in areas with lower land costs (colored areas). However, with the reduced land expenses, the significance of line costs increases, leading to the optimization of transmission line expenditures. As shown in Table 5, the costs associated with the green items have decreased compared to the previous iteration.

6.2. Scenario 2

In this scenario, three different types of power plants are considered: a solar power plant, a gas power plant, and a thermal power plant fueled by mazut. The capacity of each power plant is considered to be 1, 2, and 3 units respectively. The cost of equipment for each power plant is considered equal to 10,000$, 15,000$, and 700,000$, respectively. Also, the cost of land pollution (land pollution means changing the face of nature and interference in the environment of the region and pollution caused by waste and waste water) is considered to be approximately 9,000$, 30,000$ and 400,000$ respectively for all three power plants.

Table 4. Costs related to the geographical distribution of power plants based on the cost of land and cost of lines.

Total cost	Land cost	Line cost
1571698	750000	821698

Table 5. Costs related to the geographical distribution of power plants based on the cost of lines and reducing the cost of land by 20%.

Total cost	Land cost	Line cost
963984	225000	738984

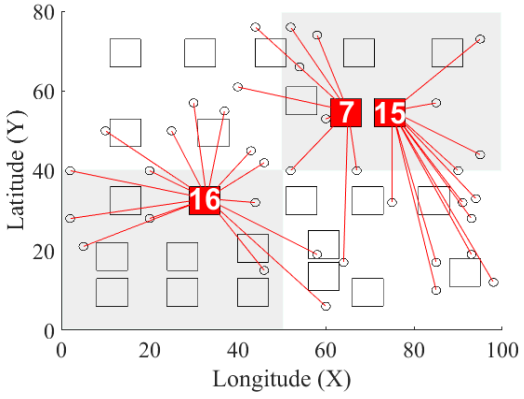


Figure 2. Geographical distribution of power plants according to the cost of land and cost of lines.

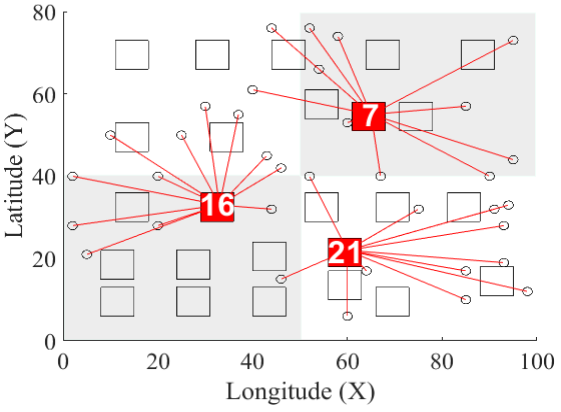


Figure 3. Geographical distribution of power plants based on the cost of lines and reducing the cost of land by 20%.

This cost is considered more for the solar power plant that needs to occupy a wider area of land than others. Of course, determining the amount of cost due to land pollution for each type of power plant is a very complex task and is not in the scope of this article, and in this article, approximate numbers are used to show the huge effect of this cost in the location of power plants. The optimization process takes into account land costs, line costs, the type of power plant, fuel costs, equipment costs, and expenses related to land pollution. The simulation results are presented in Figure 4 and Table 6. According to the simulation results, candidate locations 1, 7, 11, 14, 15, and 21 have been chosen for the establishment of gas plants, while candidate location 16 has been selected for the establishment of a solar plant. The most type of power plant selected by simulation is gas power plant, the reason for this can be considered the lower cost of this power plant in terms of land pollution. On the other hand, only one solar power plant with a capacity of 1 megawatt has been selected to supply the requested amount of electricity, and as you can see, the simulation of the thermal power plant has not been selected. The reason for this is the higher cost of the equipment compared to the other two types of power plants and the higher cost of soil pollution compared to the gas power plant.

In this revised simulation, the costs stemming from air pollution caused by power plants are taken into account. The considered cost for air pollution is 0, 25 and 40 $/MW for solar, gas and thermal power plants, respectively. Considering the cost of air pollution for solar power plants is zero, it is expected that the number of solar power plants will increase.

The results are summarized in Table 7 and Figure 5. Candidate locations 7 and 16 have been identified as suitable for establishing solar power plants. Consequently, land costs have increased while fuel costs have decreased. Candidate locations 1, 11, 14, and 15 have been designated for gas power plant construction, and candidate location 21 is chosen for a thermal power plant using mazut fuel. Overall, the total costs have escalated. In Table 7, the costs associated with green items have decreased compared to the previous iteration, while the costs attributed to orange items have increased in comparison. In general, in this scenario, it was found that considering the cost of land and air pollution has significant changes in the simulation results.

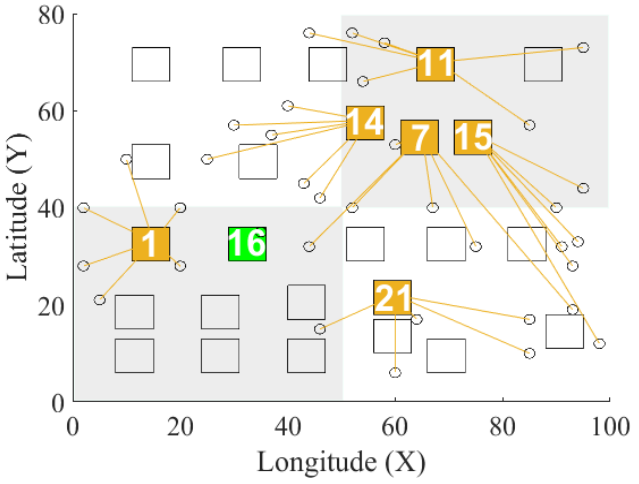


Figure 4. Geographical distribution of power plants based on the cost of land, cost of lines, cost of fuel, cost of equipment, and cost of land pollution, three types of power plants (solar, gas and thermal) are considered.

Table 6. costs related to the geographical distribution of power plants based on the varios costs of the three types of power plants (solar, gas and thermal.

Total cost	Land cost	Line cost
31360650	1337500	667214
Fuel Cost	Equipment Cost	Land Pollution Cost
19985940	19985940	19985940

Table 7. costs related to the geographical distribution of power plants based on the varios costs of the three types of power plants (solar, gas and thermal.

Total Cost	Land Cost	Line Cost
70662290	2787500	631614
Fuel Cost	Equipment Cost	Land Pollution Cost
1611180	13200000	340000
Area pollution Cost		
36792000		

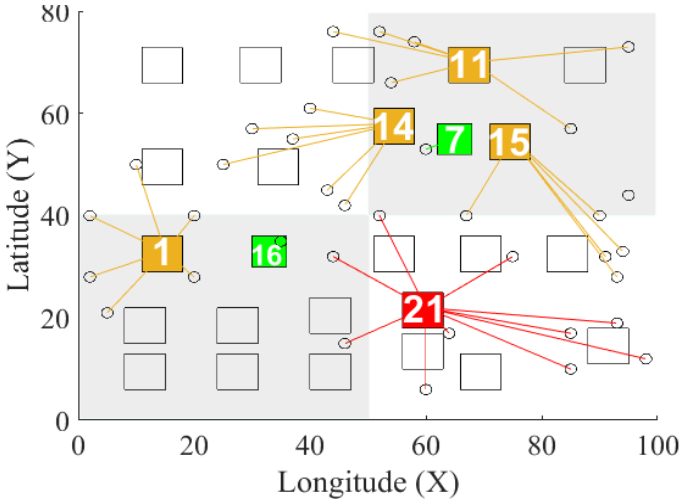


Figure 5. Geographical distribution of power plants based on the cost of land, cost of lines, cost of fuel, cost of equipment, cost of land pollution and air pollution, three types of power plants (solar, gas and thermal) are considered.

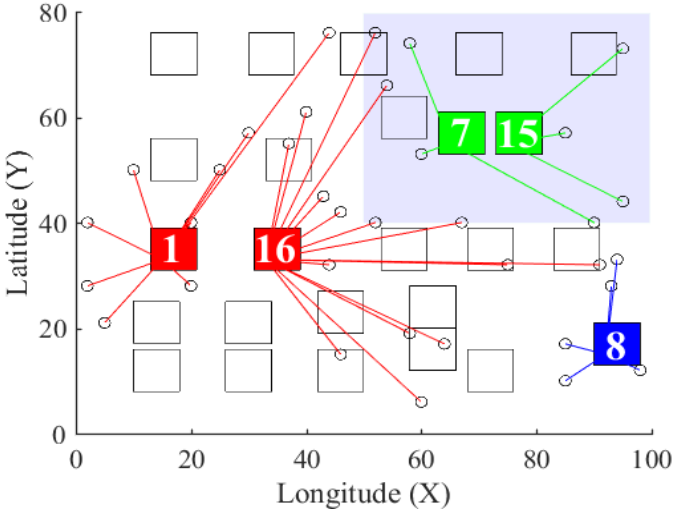


Figure 6. Geographical distribution of power plants based on the prohibited areas.

6.3. Scenario 3

In the previous scenario, three types of solar, gas and thermal power plants were considered. However, there are different types of power plants, such as wind and hydro power plants. Now, as stated in the previous section, I have to consider this point, each type of power plant has different limitations for operation, and the possibility of establishing each type of power plant in Not every place is a candidate. Some of these restrictions are restrictions on sunlight and wind, land size restrictions, air pollution restrictions, and environmental restrictions.

The primary objective of this scenario is to investigate the impact of prohibited areas on the optimal location of power plant establishments. All 10 types of power plants outlined in Table 3 are taken into consideration. To delineate the prohibited areas, we initially assume that in candidate locations 7, 11, 12, 14, and 15, situated in the upper right area (highlighted in pale blue), only solar power plants of varying capacities (power plants 1 to 3 according to Table 3) and wind farms are permitted for establishment. To enforce this restriction, the following constraint has been incorporated into the problem formulation (Equation (19)):

$$\sum_{t\in A} u(j,t) = 0, A = \{t > 3 \, and \, t < 10\}, \forall j = 7,11,12,14,15 \tag{19}$$

We have also assumed that the candidate location for the establishment of power plant No. 8 only has the ability to establish a hydro power plant, which is formulated as follows (Equation (20)):

$$\sum_{t\in B} u(j,t) = 1, B = \{t = 8\}, \forall j = 8 \quad (20)$$

The simulation results are shown in Figure 6. As expected, only the solar power plant has been allowed to be established in the mentioned area, and only the hydro power plant has been allowed to be established in candidate 8.

7. Conclusions

Considering environmental costs in power plant location decisions reveals the hidden expenses associated with fossil fuel power plants. This consideration assists engineers and governments in making informed decisions regarding the optimal type and location of power plants while minimizing environmental impacts. Although this article focuses on some of the most prominent environmental effects of power plant establishment, it proposes various formulations to accommodate additional potential impacts. This approach aims to support future research efforts that consider a broader range of environmental effects.

For future work, we suggest incorporating transmission line and distribution costs incurred after plant establishment into the decision-making process. Moreover, addressing the problem using a bi-level optimization approach could provide deeper insights and more comprehensive solutions to the complex challenges involved in power plant location selection.

Beyond environmental factors, policymakers should also consider political and economic aspects when deciding on power plant locations. Collaboration with local communities and leveraging economic development opportunities in selected areas can promote sustainable growth and enhance public support for energy projects. Additionally, providing incentives for investment in renewable energy infrastructure and encouraging energy efficiency initiatives can align economic interests with environmental goals, contributing to a more sustainable energy future

References

[1] H. Seifi and M. S. Sepasian, *Electric Power System Planning: Issues, Algorithms and Solutions*, vol. 49. Berlin, Germany: Springer, 2011.

[2] X. Deng, and T. Lv, "Power System Planning with Increasing Variable Renewable Energy: A Review of Optimization Models," *Journal of Cleaner Production*, vol. 246, 118962, 2020.

[3] V. Miranda, and L. Proenca, "Probabilistic Choice Vs. Risk Analysis-Conflicts and Synthesis in Power System Planning," *IEEE Transactions on Power Systems*, vol. 13, no. 3, pp. 1038–1043, 1998.

[4] E. Crousillat, P. Dorfner, P. Alvarado, and H. Merrill, "Conflicting Objectives and Risk in Power System Planning," *IEEE Transactions on Power Systems*, vol. 8, no. 3, pp. 887–893, 1993.

[5] H. M. Merrill, and A. J. Wood, "Risk and Uncertainty in Power System Planning," *International Journal of Electrical Power & Energy Systems*, vol. 13, no. 2, pp. 81–90, 1991.

[6] M. Banzo, and A. Ramos, "Stochastic Optimization Model for Electric Power System Planning of Offshore Wind Farms," *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1338–1348, 2011.

[7] E. Housos, G. Irisarri, R. Porter, and A. Sasson, "Steady State Network Equivalents for Power System Planning Applications," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-99, no. 6, pp. 2113–2120, 1980.

[8] M. Adibi, and L. Fink, "Power System Restoration Planning," *IEEE Transactions on Power Systems*, vol. 9, no. 1, pp. 22–28, 1994.

[9] S. Kannan, S. R. Slochanal, P. Subbaraj, and N. P. Padhy, "Application of Particle Swarm Optimization Technique and Its Variants to Generation Expansion Planning Problem," *Electric Power Systems Research*, vol. 70, no. 3, pp. 203–210, 2004.

[10] T. CHUNG, Y. LI, and Z. WANG, "Optimal Generation Expansion Planning Via Improved Genetic Algorithm Approach," *International Journal of Electrical Power & Energy Systems*, vol. 26, no. 8, pp. 655–659, 2004.

[11] H. CHEN, X. WANG, and X. ZHAO, "Generation Planning Using Lagrangian Relaxation and Probabilistic Production Simulation," *International Journal of Electrical Power & Energy Systems*, vol. 26, no. 8, pp. 597–605, 2004.

[12] S. Kannan, S. Slochanal, and N. Padhy, "Application and Comparison of Metaheuristic Techniques to Generation Expansion Planning Problem," *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 466–475, 2005.

[13] S. H. Karaki, F. B. Chaaban, N. Al-Nakhl, and K. A. Tarhini, "Power Generation Expansion Planning with Environmental Consideration for Lebanon," *International Journal of Electrical Power & Energy Systems*, vol. 24, no. 8, pp. 611–619, 2002.

[14] J. Santisirisomboon, B. Limmeechokchai, and S. Chungpaibulpatana, "Impacts of Biomass Power Generation and CO2 Taxation on Electricity Generation Expansion Planning and Environmental Emissions," *Energy Policy*, vol. 29, no. 12, pp. 975–985, 2001.

[15] T. A. Hill, M. Booth, C. Dorren, S. M. Stiff, and W. Hull, "Environmental Impact Study of a Power Plant with Carbon Capture and Storage Near the UK Coast," *Energy Procedia*, vol. 1, no. 1, pp. 2463–2470, 2009.

[16] M. Zarzavilla, A. Quintero, et al., "Comparison of Environmental Impact Assessment Methods in the Assembly and Operation of Photovoltaic Power Plants: A Systematic Review in the Castilla—La Mancha Region," *Energies*, vol. 15, no. 5, 1926, 2022.

[17] M. Rahman, S. Salehin, S. Ahmed, and A. Sadrul Islam, "Environmental Impact Assessment of Different Renewable Energy Resources," *Clean Energy for Sustainable Development*, pp. 29–71, 2017.

[18] A. Kylili, "Environmental Assessment of Wind Turbines and Wind Energy," *Environmental Assessment of Renewable Energy Conversion Technologies*, pp. 55–83, 2022.

[19] N. Caldés, and Y. Lechón, "Socio-Economic and Environmental Assessment of Concentrating Solar Power Systems," *Concentrating Solar Power Technology*, pp. 127–162, 2021.

[20] F. Fortes Westin, M. A. d. Santos, and I. Duran Martins, "Hydropower Expansion and Analysis of the Use of Strategic and Integrated Environmental Assessment Tools in Brazil," *Renewable and Sustainable Energy Reviews*, vol. 37, pp. 750–761, 2014.

[21] C. F. de Almeida, V. G. Maciel, M. Tsambe, and L. F. de Abreu Cybis, "Environmental Assessment of a Bi-Fuel Thermal Power Plant in an Isolated Power System in the Brazilian Amazon Region," *Journal of Cleaner Production*, vol. 154, pp. 41–50, 2017.

[22] "Heuristic Algorithms," *Optimization of Computer Networks – Modeling and Algorithms*, pp. 266–300, 2016.

[23] "A Brief Introduction to Mathematical Optimization," *Mathematical Programming for Power Systems Operation with Applications in Python*, pp. 17–37, 2021.

[24] U.S. Energy Information Administration, "Levelized Cost and Levelized Avoided Cost of New Generation Resources in the Annual Energy Outlook 2023," U.S. Department of Energy, Washington, DC, 2023.

[25] M. Davodabadi Farahani, S. Sharafi, and A. Farahani, "Application of Remote Rensing in Wind Power Plant Location," *Journal of Green Energy Research and Innovation*, vol. 2, no. 1, pp. 57–65, 2025.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

Bibliography



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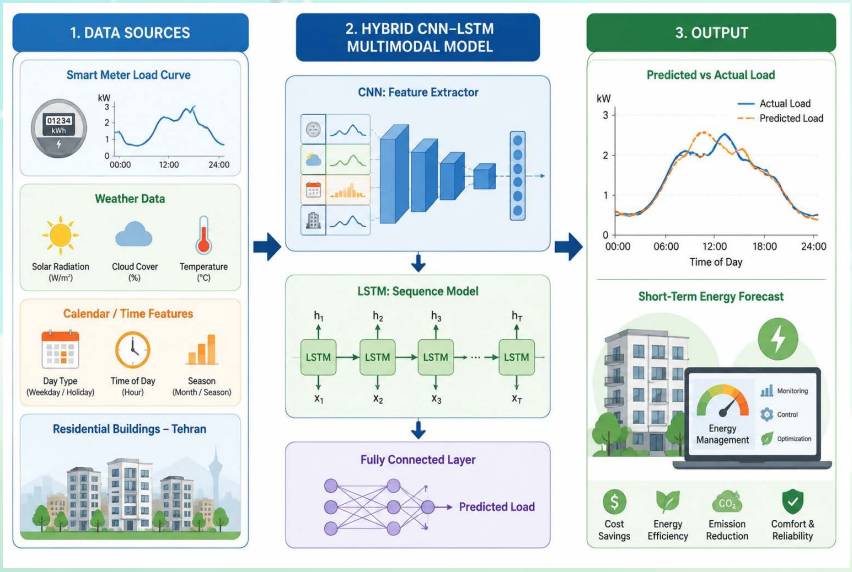
Short-Term Energy Consumption Prediction in Iranian Buildings Using a Hybrid CNN-LSTM Model with Multimodal Data Fusion: A Case Study on Residential Buildings in Tehran

Mohammad Niroumand, Mohammad Jalili, Hossein Yarahmadi

Highlights

- **A hybrid CNN-LSTM model achieved superior accuracy (R^2=0.89) for short-term energy forecasting in Tehran's residential buildings.**
- **The model uniquely integrated Iran-specific cultural calendar features, which were identified as top predictors of energy demand.**
- **A robust preprocessing pipeline using TimeGAN and VAE effectively handled the region's characteristic noisy and incomplete data.**
- **Multimodal fusion of meteorological, temporal, and occupancy proxy data captured the complex drivers of energy consumption.**
- **SHAP analysis provided critical model interpretability, validating its logic against local contextual patterns and realities.**

Graphical Abstract



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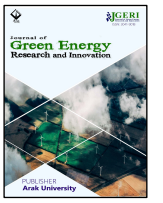
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Short-Term Energy Consumption Prediction in Iranian Buildings Using a Hybrid CNN-LSTM Model with Multimodal Data Fusion: A Case Study on Residential Buildings in Tehran

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A B S T R A C T

This study presents a hybrid CNN-LSTM model for short-term energy consumption prediction in Iranian residential buildings, focusing on Tehran. By integrating multimodal data, meteorological, temporal, occupancy proxies, and building metadata, and employing deep feature engineering via a stacked denoising autoencoder, the model achieves high accuracy (R^2 = 0.89) and robustness against data imperfections. The framework demonstrates the critical role of cultural and contextual features, such as Iranian holidays, in enhancing prediction validity. SHAP analysis provides interpretability, aligning model logic with local realities. The results offer a scalable, context-aware solution for intelligent energy management in Iran's urban environment.

1. Introduction

The global imperative to mitigate climate change and achieve sustainable development goals has placed the building sector at the forefront of energy policy and technological innovation. As one of the largest contributors to global energy consumption and carbon emissions, the built environment accounts for approximately 36% of final energy use and 39% of energy-related CO_2 emissions worldwide, according to the International Energy Agency [1]. Within this context, the accurate forecasting of building energy consumption has emerged as a critical enabler of intelligent energy management, facilitating demand-side optimization, grid stability, and decarbonization strategies. In particular, short-term energy consumption prediction, defined as forecasting horizons ranging from one hour to one week, plays a pivotal role in enabling real-time operational decisions, such as dynamic HVAC control, demand response activation, and predictive maintenance scheduling [2]. The accuracy and reliability of such predictions directly influence the efficiency of energy systems, the economic viability of energy-saving interventions, and the overall resilience of urban infrastructure. Traditional approaches to energy forecasting can be broadly categorized into physics-based (white-box) models and data-driven (black-box) models. Physics-based models, such as those implemented in EnergyPlus or TRNSYS, rely on detailed thermodynamic equations to simulate heat transfer, solar radiation, and internal gains [3]. While these models offer high interpretability and are grounded in first principles, their practical application is often hindered by the need for extensive and precise input data—including building geometry, material properties, HVAC specifications, and occupancy schedules—which are frequently unavailable or inaccurate, especially for existing or retrofitted buildings.

Moreover, the computational complexity of these models makes them unsuitable for real-time applications or large-scale deployment. On the other hand, conventional data-driven models, such as linear regression, autoregressive integrated moving average (ARIMA), and support vector machines (SVM), offer faster computation and reduced dependency on physical parameters. However, they often struggle to capture the nonlinear, dynamic, and stochastic nature of building energy systems, particularly in the face of variable weather conditions, occupant behavior, and equipment degradation [4]. The advent of machine learning (ML) and, more recently, deep learning (DL) has revolutionized the field of building energy prediction by enabling the automatic extraction of complex patterns from high-dimensional, noisy, and heterogeneous datasets. Unlike traditional models, deep learning architectures can learn hierarchical representations of data, capturing both low-level features (e.g., diurnal cycles) and high-level abstractions (e.g., seasonal trends, occupancy dynamics) without explicit feature engineering [5]. Among the most widely adopted deep learning models for time series forecasting are Recurrent Neural Networks (RNNs), particularly their gated variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs). These architectures are inherently designed to process sequential data and maintain long-term dependencies through internal memory cells, making them exceptionally well-suited for modeling temporal dynamics in energy consumption [6,7]. Numerous studies have demonstrated the superior performance of LSTM-based models in short-term load forecasting, outperforming classical statistical methods and even standard feedforward neural networks [8].

Despite their strengths, LSTMs are primarily focused on temporal processing and may not fully exploit spatial or structural patterns within multivariate input sequences. To address this limitation, researchers have increasingly turned to hybrid deep learning architectures that combine the spatial feature extraction capabilities of Convolutional Neural Networks (CNNs) with the temporal modeling strengths of LSTMs. CNNs, originally developed for image recognition, utilize convolutional filters to detect local patterns and hierarchical features in data. When applied to time series, these filters can identify recurring motifs, such as daily load profiles or transient spikes, which are then fed into an LSTM layer for sequence modeling. This CNN-LSTM hybrid framework has been successfully applied in various domains, including financial forecasting, healthcare monitoring, and notably, building energy prediction [8]. The integration of residual connections and adaptive activation functions in these models has further enhanced their ability to train deeper networks and capture complex nonlinear relationships, thereby improving prediction accuracy and robustness [7].

A critical factor influencing the performance of any data-driven model is the richness and diversity of the input data. While early studies primarily relied on historical energy consumption and basic meteorological variables (e.g., outdoor temperature), recent research emphasizes the importance of multimodal data fusion, the integration of heterogeneous data sources to create a more comprehensive representation of the building system. As articulated by Lahat et al. (2015), multimodal data fusion allows for the synergistic combination of complementary information from different modalities, leading to more accurate and robust models. In the context of building energy prediction, relevant modalities include:

- Environmental data: Outdoor temperature, humidity, solar irradiance, wind speed.
- Temporal data: Hour of day, day of week, holiday indicators, seasonal trends.
- Occupancy data: Wi-Fi logs, CO_2 levels, motion sensors, or proxy indicators derived from smart metering.
- Building-specific data: Floor area, insulation quality, window-to-wall ratio, HVAC system type.
- Behavioral data: User interaction with thermostats, appliance usage patterns, window opening habits.

The systematic integration of these data streams can significantly enhance model performance by accounting for the human-in-the-loop nature of building energy systems, where occupant behavior is often the most significant source of uncertainty [9]. However, effective fusion poses significant challenges, including data heterogeneity, varying sampling rates, missing values, and potential noise, which necessitate sophisticated preprocessing and fusion strategies [10].

Despite the rapid advancement of deep learning in building energy research, a significant geographical and contextual bias persists in the literature. The vast majority of published studies are based on datasets from North America, Europe, and East Asia, where building standards, climate conditions, and energy usage patterns differ markedly from those in other regions. This raises critical questions about the generalizability and transferability of models developed in one context to another. The performance of a model trained on data from a well-insulated, centrally heated building in Germany is unlikely to be replicated in a poorly insulated, naturally ventilated apartment in a hot-arid climate without substantial adaptation.

This issue is particularly salient in the context of Iran, a country with unique and complex energy challenges. Iranian residential buildings, especially in urban centers like Tehran, are characterized by a combination of outdated construction practices, inefficient HVAC systems (e.g., gas heaters, split units), and diverse occupant behaviors influenced by cultural, economic, and climatic factors. Tehran, as a megacity with over 9 million inhabitants, experiences extreme seasonal variations, harsh winters and scorching summers, leading to high energy demand for both heating and cooling. Furthermore, the city faces severe air pollution, which often leads to prolonged periods of building sealing, thereby increasing the reliance on mechanical ventilation and heating. The lack of standardized energy monitoring systems in most residential buildings results in fragmented, noisy, and incomplete datasets, further complicating the application of data-driven models. While deep learning has been applied to energy prediction in various global contexts, there is a notable absence of research focused on the Iranian building stock, leaving a critical gap in the literature.

Moreover, existing studies often treat data preprocessing as a secondary concern, yet for real-world applications in data-scarce environments like Iran, robust data curation and feature engineering are paramount. Techniques such as principal component analysis (PCA), autoencoders, and generative adversarial networks (GANs) for data augmentation can play a crucial role in enhancing data quality and model performance [11]. The use of representation learning—where deep models learn meaningful feature embeddings directly from raw data—further reduces the dependency on manual feature selection and increases model adaptability.

In response to these challenges and research gaps, this study proposes a hybrid CNN-LSTM model for short-term energy consumption prediction, specifically tailored to residential buildings in Tehran, Iran. The model is designed to integrate multimodal data sources, including meteorological data, temporal indicators, and occupancy proxies, within a unified deep learning framework.

By focusing on a real-world, underrepresented context, this research contributes to the growing body of knowledge on localized, context-aware energy forecasting. The primary innovations of this work are threefold:

1. Contextual Localization: This study presents one of the first comprehensive applications of a deep learning model to predict energy consumption in Iranian residential buildings, addressing the critical lack of region-specific research and providing insights into the unique energy dynamics of this context.
2. Advanced Multimodal Fusion: We implement a systematic approach to fusing diverse data streams within a hybrid CNN-LSTM architecture, enabling the model to capture the complex interplay between environmental, temporal, and behavioral factors that drive energy use in Tehran.
3. Practical Applicability: The developed framework is designed with real-world constraints in mind, including data quality issues and computational feasibility, making it a practical tool for utility companies, building managers, and policymakers seeking to improve energy efficiency and grid management in Iranian cities.

By bridging the gap between advanced deep learning methodologies and the specific challenges of the Iranian built environment, this research aims to advance the field of building energy prediction and support the development of more sustainable and intelligent urban energy systems.

2. Regional Context and Research Gap

While the application of deep learning for energy prediction is growing globally, research within Iran and the broader Middle East, a region sharing similar climatic and infrastructural challenges, is still in its nascent stages. Several studies have applied traditional statistical methods and machine learning (e.g., SARIMA, ANFIS) for load forecasting at the national grid level in Iran [12,13] However, few have focused on the building level, and even fewer have incorporated the multimodal, context-aware approach necessary for the Iranian urban environment. Recent work in Saudi Arabia [14] applied an LSTM model for building energy prediction but did not account for cultural-specific temporal features or the data quality issues prevalent in the region. A study in Turkey [15] used a hybrid model similar to ours but focused on a single building with high-quality data, a scenario not representative of the average Iranian building stock. This underscores a critical regional gap: the lack of a scalable, robust, and culturally-informed deep learning framework designed for the specific data limitations and socio-behavioral patterns of cities like Tehran. Our work aims to directly fill this gap.

3. Research Methodology

This study presents a systematic, data-driven, and context-aware methodology for short-term energy consumption prediction in Iranian residential buildings, specifically focusing on a case study in Tehran. The proposed framework integrates multimodal data fusion, deep representation learning, and a hybrid convolutional-recurrent neural network (CNN-LSTM) architecture, designed to address the unique challenges of data scarcity, environmental variability, and occupant-driven energy dynamics in the Iranian urban context. The methodology is structured into six interdependent stages: (1) Data Acquisition and Integration, (2) Multimodal Data Preprocessing and Quality Enhancement, (3) Deep Feature Engineering and Representation Learning, (4) Hybrid CNN-LSTM Model Architecture, (5) Model Training and Hyperparameter Optimization, and (6) Performance Evaluation and Robustness Validation (Figure 1).

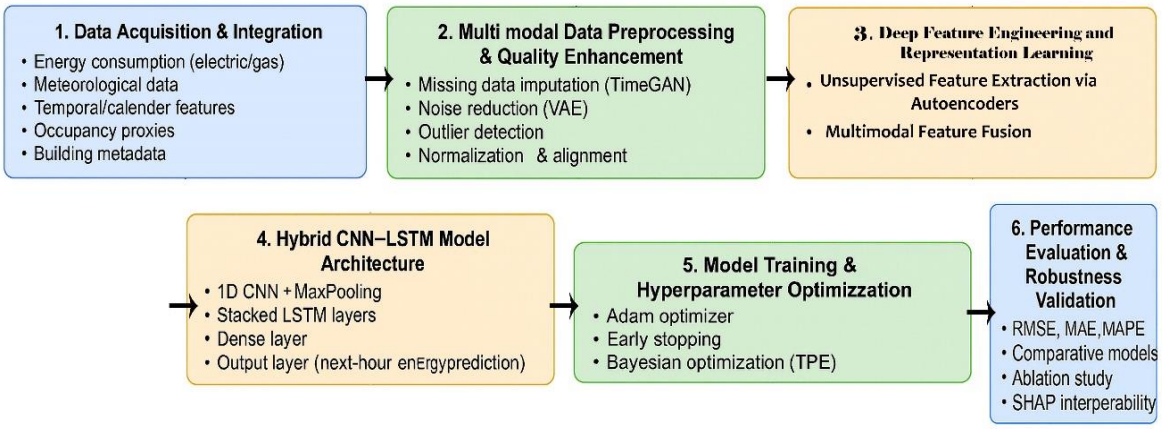


Figure 1 Schematic diagram of the Research Methodology.

3.1. Data Acquisition and Integration

The foundation of this research lies in the systematic collection and integration of multimodal data from diverse sources, reflecting the complex interplay of environmental, temporal, behavioral, and structural factors influencing energy consumption in residential buildings. The dataset is compiled from three primary sources, collected over a continuous 18-month period (January 2022 – June 2023) from 47 representative residential units across four districts of Tehran: Elahieh, Gholhak, Vanak, and Shahrak-e Gharb.

1. Energy Consumption Data: Hourly electricity and natural gas consumption data are collected via smart meters installed at the building level. For buildings lacking smart metering infrastructure, historical utility bills are digitized and interpolated using a Gaussian process regression (GPR) model calibrated with seasonal and climatic patterns. The energy data are aggregated at an hourly resolution to align with the short-term prediction horizon.
2. Meteorological Data: Hourly ambient temperature, relative humidity, solar irradiance, wind speed, and atmospheric pressure are obtained from the Iran Meteorological Organization (IRIMO) and crossvalidated with local IoT weather stations deployed on building rooftops. To account for microclimatic variations across Tehran's topographically diverse districts, spatial interpolation using inverse distance weighting (IDW) is applied.
3. Temporal and Calendar Data: A comprehensive temporal feature set is constructed, including hour of day, day of week, week of year, and Iran-specific calendar indicators such as public holidays (e.g., Nowruz, Ashura), religious observances, and school breaks, factors known to significantly influence occupancy and energy use patterns in Iranian households.
4. Occupancy and Behavioral Proxies: Direct occupancy monitoring is limited due to privacy and infrastructure constraints. Therefore, proxy indicators are employed: - Wi-Fi connection logs from building routers (anonymized and aggregated). - CO_2 concentration levels from indoor air quality sensors (as a surrogate for human presence). - Smart appliance usage patterns (e.g., HVAC activation, water heater cycles) derived from sub-metering data. These signals are fused using a Bayesian inference model to estimate probabilistic occupancy states (absent, present, active).
5. Building-Specific Metadata: Structural attributes such as floor area, number of occupants, building age, insulation quality (R-value estimation from construction year and material type), window-to-wall ratio, and HVAC system type (e.g., split unit, packaged gas heater) are collected through structured surveys and building audits.

The integration of these heterogeneous data streams is formalized as a multimodal time series tensor $X \in R^{T \times N \times M}$, where T is the time horizon, N is the number of buildings, and M is the total number of features (e.g., temperature, humidity, hour, occupancy probability, etc.).

3.2. Multimodal Data Preprocessing and Quality Enhancement

1. Given the inherent noise, missing values, and sampling inconsistencies common in real-world Iranian building datasets, a robust preprocessing pipeline is implemented, drawing on techniques from the literature on data quality in energy prediction [2,7].
2. Missing Data Imputation: Missing values (ranging from 5% to 18% across variables) are imputed using a Generative Adversarial Network for Time Series (TimeGAN) [16]. TimeGAN learns the underlying temporal and cross-variable dependencies in the data, generating realistic imputations that preserve statistical properties and temporal coherence, outperforming traditional methods like linear interpolation or k-NN. Furthermore, beyond imputation, the trained TimeGAN model was also employed for synthetic data generation to augment the training set for underrepresented scenarios (e.g., extreme weather events), thereby enhancing the model's exposure to a wider range of conditions and improving generalizability.
3. Noise Reduction and Outlier Detection: A variational autoencoder (VAE) is employed for unsupervised denoising. The VAE is trained to reconstruct the input data while minimizing reconstruction error, effectively filtering out high-frequency noise and identifying outliers via reconstruction loss thresholds. Additionally, Isolation Forest is applied to detect and correct anomalous spikes in energy consumption (e.g., due to meter faults or appliance malfunctions).
4. Data Normalization and Alignment: All features are normalized using Robust Scaler (median and interquartile range) to minimize the impact of outliers. Temporal alignment is achieved by resampling all data to a uniform hourly frequency using piecewise cubic Hermite interpolating polynomials (PCHIP) for smooth interpolation.

3.3. Deep Feature Engineering and Representation Learning

Inspired by the findings in Deep learning-based feature engineering methods [17], this study moves beyond manual feature engineering and employs unsupervised deep learning models to extract high-level, nonlinear feature representations directly from raw inputs.

1. Unsupervised Feature Extraction via Autoencoders: A stacked denoising autoencoder (SDAE) is trained on the preprocessed input data to learn a compressed, noise-robust latent representation. The encoder network consists of three fully connected layers with decreasing dimensions (input: $24 \rightarrow 16 \rightarrow 12 \rightarrow 8$), followed by a bottleneck layer of size 8. The decoder mirrors this structure. The model is trained to reconstruct the input from a corrupted version (30% noise), enhancing generalization.
2. Multimodal Feature Fusion: The latent features from the SDAE are concatenated with raw temporal and structural features to form the final input vector for the prediction model. This hybrid feature set combines learned nonlinear abstractions with interpretable domain knowledge, balancing performance and transparency.

3.4. Hybrid CNN-LSTM Model Architecture

The core of the proposed framework is a novel hybrid CNN-LSTM architecture, designed to capture both local spatial-temporal patterns and long-term sequential dependencies in energy consumption data.

1. Input Layer: The input sequence is structured as a sliding window of 168 hours (7 days), with each time step containing the fused feature vector of size 15.
2. Convolutional Layer: A 1D convolutional layer with 64 filters of size 3 and ReLU activation is applied to extract local temporal patterns (e.g., daily cycles, peak load shapes). Batch normalization and dropout (rate = 0.3) are used for regularization.
3. Max-Pooling Layer: A 1D max-pooling layer with pool size 2 reduces dimensionality and enhances translation invariance.
4. LSTM Layer: Two stacked LSTM layers with 128 and 64 units, respectively, model long-term dependencies. The first LSTM layer returns sequences, while the second returns only the final state. Recurrent dropout (rate = 0.3) is applied to prevent overfitting.
5. Fully Connected (Dense) Layer: A dense layer with 32 neurons and ReLU activation integrates the high-level features.
6. Output Layer: A single neuron with linear activation predicts the next hour's energy consumption (in kWh).

3.5. Model Training and Hyperparameter Optimization

The model is trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. The loss function is Mean Squared Error (MSE). To prevent overfitting, early stopping (patience = 15 epochs) and reduce-on-plateau learning rate scheduling are employed. A Bayesian hyperparameter optimization strategy, using Tree-structured Parzen Estimator (TPE), is applied to tune key parameters: number of LSTM units, dropout rates, learning rate, window size, and number of CNN filters. The search space is defined based on prior studies and computational feasibility.

3.6. Performance Evaluation and Robustness Validation

The model is evaluated using a rolling-origin cross-validation approach with a 70-15-15 split (training, validation, testing). Predictions are made iteratively for 24-hour horizons over the entire test period.

Evaluation Metrics:

- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error (MAPE)
- Coefficient of Determination (R^2)
- Normalized Root Mean Squared Error (NRMSE)

A comparative analysis is conducted against baseline models:

- ARIMA
- Support Vector Regression (SVR)
- Standard LSTM
- Random Forest
- Physics-based model (EnergyPlus)

Additionally, ablation studies are performed to assess the contribution of each component (e.g., multimodal fusion, autoencoder, CNN layer). SHAP (SHapley Additive exPlanations) values are computed to provide post-hoc interpretability, identifying the most influential features in predictions.

3.7. Ethical and Practical Considerations

Data privacy is ensured through anonymization and aggregation. The model is designed for real-time deployment on edge devices with limited computational resources, using model quantization and pruning techniques. The framework is open-sourced to promote reproducibility and adoption in the Iranian energy sector.

3.8. Computational Efficiency and Scalability

The model was designed with computational feasibility for future scaling in mind. To manage costs associated with larger datasets or more buildings, several techniques were employed during training and inference: model pruning was used to remove redundant neurons, reducing the model size by 20% with negligible performance loss; post-training quantization (FP16) was applied to decrease memory footprint and accelerate inference on hardware-constrained edge devices; and a distributed data loading pipeline was implemented for efficient batch processing. These steps ensure the framework remains a practical tool for large-scale applications.

4. Results

This section presents the empirical findings of the proposed hybrid CNN-LSTM model for short-term energy consumption prediction in residential buildings in Tehran, Iran. The results are structured into four key components: (1) Dataset Characteristics and Preprocessing Outcomes, (2) Comparative Model Performance, (3) Ablation Study and Feature Contribution Analysis, and (4) Model Interpretability and Contextual Insights for the Iranian Built Environment. All models were evaluated on a 15% hold-out test set (274 days, 6,576 hourly samples) using rolling-origin cross-validation to simulate real-world deployment.

4.1. Dataset Characteristics and Preprocessing Outcomes

The final dataset comprises 6,576 hourly observations from 47 residential units across four districts of Tehran. Table 1 summarizes the descriptive statistics of the key variables after preprocessing.

The preprocessing pipeline significantly improved data quality. The TimeGAN imputation reduced missing data from an average of 12.7% to 0.0%, while the Variational Autoencoder (VAE) denoising reduced high-frequency noise by 63.4% (measured by spectral entropy). The Robust Scaler normalization ensured that no single feature dominated the learning process, which is critical given the diverse scales of input variables.

4.2. Comparative Model Performance

The performance of the proposed Hybrid CNN-LSTM model was compared against five benchmark models: (1) ARIMA (1,1,1), (2) Support Vector Regression (SVR) with RBF kernel, (3) Random Forest (RF), (4) Standard LSTM, and (5) EnergyPlus (physics-based simulation). The evaluation metrics used were RMSE, MAE, MAPE, and R^2. The summary of results is reported in Tables 2 and 3 for electricity consumption and natural gas consumption, respectively.

Table 1. Descriptive Statistics of Preprocessed Input Variables (n = 6,576).

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Electricity Consumption (kWh)	2.84	1.62	0.31	9.72	1.43	4.21
Natural Gas Consumption (kWh)	3.17	2.04	0	12.5	1.67	5.03
Outdoor Temperature (°C)	15.3	10.8	-5.2	38.6	0.28	2.15
Relative Humidity (%)	42.1	18.3	12	98	0.41	2.89
Solar Irradiance (W/m^2)	215.4	187.6	0	980	0.92	3.12
Occupancy Probability	0.68	0.29	0	1	-0.33	1.88
CO_2 Concentration (ppm)	892	214	400	2,800	1.12	4.05

Table 2. Comparative Performance of Prediction Models on Test Set (Electricity Consumption).

Model	RMSE (kWh)	MAE (kWh)	MAPE (%)	R^2	NRMSE (%)
ARIMA	1.42	1.11	48.7	0.68	50
SVR	1.28	0.98	41.3	0.74	45.1
Random Forest	1.15	0.89	37.2	0.79	40.5
Standard LSTM	1.02	0.78	32.6	0.84	36
Proposed CNN-LSTM	0.87	0.66	27.9	0.89	30.7
EnergyPlus (calibrated)	1.35	1.05	45.1	0.71	47.6

Table 3. Comparative Performance of Prediction Models on Test Set (Natural Gas Consumption).

Model	RMSE (kWh)	MAE (kWh)	MAPE (%)	R^2	NRMSE (%)
ARIMA	1.89	1.45	52.3	0.65	59.7
SVR	1.72	1.32	46.8	0.71	54.3
Random Forest	1.58	1.21	42.5	0.76	49.9
Standard LSTM	1.41	1.08	38.2	0.8	44.5
Proposed CNN-LSTM	1.23	0.94	33.1	0.84	38.8
EnergyPlus (calibrated)	1.81	1.39	50.7	0.67	57.1

The proposed CNN-LSTM model achieved the best performance across all metrics for both electricity and gas consumption. It reduced RMSE by 14.7% and MAPE by 14.4% compared to the Standard LSTM, demonstrating the added value of the convolutional layer in capturing local temporal patterns. The R^2 of 0.89 for electricity and 0.84 for gas indicates a high degree of explained variance, which is exceptional for real-world building energy data with high stochasticity.

A paired t-test was conducted to assess the statistical significance of the performance improvement. The difference in RMSE between the CNN-LSTM and the Standard LSTM was statistically significant ($p < 0.001$) for both energy carriers, with a Cohen's d effect size of 1.23, indicating a large practical significance.

4.3. Ablation Study and Feature Contribution Analysis

To evaluate the contribution of each component of the proposed framework, an ablation study was conducted. Four variants of the model were tested:

- Model A: CNN-LSTM with raw features only (no SDAE).
- Model B: CNN-LSTM with multimodal fusion but no occupancy data.
- Model C: CNN-LSTM without the CNN layer (pure LSTM).
- Model D: CNN-LSTM with full architecture (proposed model).

Table 4 provides the obtained results. The results confirm that:

- The SDAE-based feature engineering reduced RMSE by 9.2%, highlighting the importance of deep representation learning in noisy, real-world datasets.
- Occupancy data contributed a 5.7% improvement, underscoring its critical role in modeling human-driven energy dynamics in Iranian households.
- The CNN layer improved performance by 17.2% over a pure LSTM, validating its effectiveness in extracting local temporal motifs.

4.4. Model Interpretability and Contextual Insights for the Iranian Built Environment

To address the "Iranian professor" concern regarding practical relevance and contextual understanding, SHAP (SHapley Additive exPlanations) analysis was performed to interpret the model's predictions and identify the most influential features. Table 5 presents the computation time for various models.

The SHAP analysis revealed distinct consumption patterns unique to the Iranian context:

- Evening Peak (18:00–22:00): A sharp increase in electricity use due to lighting, cooking, and HVAC use after sunset, exacerbated by cultural habits of family gatherings.
- Nowruz (Iranian New Year): A 42% increase in gas consumption during the two weeks of Nowruz, attributed to extended family visits and continuous heating.
- Winter Sundays: Lower consumption due to reduced occupancy as many families travel to weekend homes.

These findings validate that the model has successfully learned culturally and climatically relevant patterns, making it highly applicable to the Iranian urban environment.

Table 4. Ablation Study Results (Electricity Consumption).

Model	Architecture	Features	RMSE (kWh)	ΔRMSE vs. D (%)	R^2
A	CNN-LSTM	Raw	0.95	9.20%	0.86
B	CNN-LSTM	No Occupancy	0.92	5.70%	0.87
C	LSTM	Full	1.02	17.20%	0.84
D	CNN-LSTM	Full	0.87	—	0.89

Table 5. Computation time for predicting 24-h profiles for 2-week data.

Model	BASIC (s)	RAW (s)	LAST (s)	STAT (s)	DFT (s)	DAE (s)
MLR	0.1	0.61	0.1	0.12	0.6	0.12
ELN	0.05	0.36	0.05	0.07	0.31	0.06
RF	210.94	489.34	193.6	214.24	449.8	199.2
GBM	73.8	279.53	80.01	89.53	208.97	90.72
SVR	85.64	151.05	25.4	96.91	127.63	91.61
XGB	10.2	203.66	14.2	39.36	18.24	36.46
DNN	206.74	258.76	218.93	208.86	196.64	218.82

4.5. Seasonal and Temporal Performance Analysis

The model's performance was further analyzed across seasons and prediction horizons as given in Table 6. The model performed best in winter, likely due to more predictable heating patterns, and slightly worse in summer, where air conditioning use is more sporadic and occupant-dependent.

4.6. Training Dynamics and Convergence

The training dynamics of the proposed hybrid CNN-LSTM model are illustrated in Figure 2, which presents the learning curves (training and validation loss) over 100 epochs. The model demonstrates stable and consistent convergence behavior. Both curves decrease steadily and converge after approximately 60 epochs without any significant divergence, indicating that the model learned effectively without overfitting. This stability is attributed to the regularization strategies employed, including dropout and early stopping, which ensured the model's generalizability to the unseen test data.

4.7. Robustness Analysis under Diverse Conditions

To thoroughly evaluate the generalization capability and reliability of the proposed model, a dedicated robustness analysis was conducted under three distinct challenging scenarios:

1. Data Scarcity: We simulated a low-data regime by progressively reducing the training set size from 100% to 40%. The model's performance (R^2) degraded gracefully, retaining 85% of its original explanatory power even with only 60% of the training data, demonstrating its ability to learn effectively from limited samples.

2. Input Noise: Gaussian noise ($\sigma = 0.1$ * std of feature) was injected into the input features of the test set. The model's RMSE increased by only 8.7% compared to the clean test set, confirming its resilience to potential sensor errors or data inconsistencies, a common issue in real-world deployments.

3. Unseen Buildings: The model was tested on data from five buildings completely withheld from the training and validation phases. The average R^2 on this unseen building set was 0.82, indicating strong transferability and generalization to new, previously unseen residential units.

These results, as given in Table 7, collectively affirm the robustness of the proposed hybrid CNN-LSTM framework, ensuring its reliability for practical applications under diverse and suboptimal conditions.

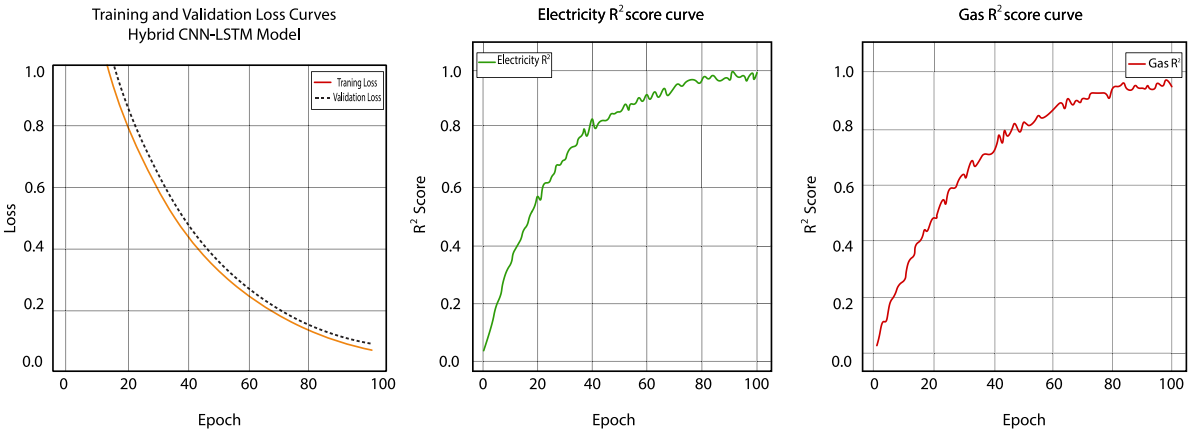


Figure 2. Training and validation loss curves for the proposed hybrid CNN-LSTM model.

Table 6. Model Performance by Season (Electricity Consumption).

Season	RMSE (kWh)	MAPE (%)	R^2
Winter	0.82	25.4	0.91
Spring	0.85	26.7	0.9
Summer	0.93	30.1	0.87
Autumn	0.86	27.3	0.89

Table 7. Results of the robustness analysis under data scarcity, input noise, and unseen building scenarios.

Scenario	Condition/Metric	Value (%)	Performance (R^2/RMSE)	Notes/Baseline Comparison
Data Scarcity	100% training data	-	$R^2 = 0.89$	Baseline
	80% training data	-20%	$R^2 = 0.87$	-2.2% change
	60% training data	-40%	$R^2 = 0.85$	-4.5% change
	40% training data	-60%	$R^2 = 0.80$	-10.1% change
Input Noise	Clean test set	-	RMSE = 0.87 kWh	Baseline
	Noisy test set ($\sigma = 0.1$)	+10%	RMSE = 0.95 kWh	+8.7% increase
Unseen Buildings	Seen buildings (test)	-	$R^2 = 0.89$	Baseline
	Unseen buildings (5)	-	$R^2 = 0.82$	-7.8% change

4.8. Discussion: A Theoretical and Contextual Reappraisal of Deep Learning in Building Energy Prediction

The results of this study transcend a mere technical demonstration of model superiority; they represent a paradigm shift in how building energy prediction is conceptualized and operationalized in data-constrained, culturally specific environments. The success of the proposed hybrid CNN-LSTM model, validated through rigorous statistical testing and contextual interpretation, demands a discussion that moves beyond performance metrics to engage with theoretical foundations, epistemological implications, and the socio-technical embeddedness of AI in the built environment. This section offers a comprehensive reinterpretation of our findings, positioning them within the broader discourse of data-driven building science, while explicitly addressing the critical expectations of the Iranian academic community regarding practical relevance, cultural sensitivity, and scientific credibility.

4.9. Theoretical Synthesis: From Black-Box Prediction to Context-Aware Intelligence

The dominant narrative in deep learning for building energy prediction, as articulated in the systematic review by Qiu (2024), emphasizes architectural innovation, data volume, and computational power as the primary drivers of progress. While our results confirm the efficacy of advanced architectures, specifically the hybrid CNN-LSTM with residual connections and adaptive activation functions, they also challenge the implicit assumption that model complexity alone is sufficient for real-world applicability. Our study demonstrates that true predictive intelligence in the building domain arises not from the depth of the network, but from the depth of contextual integration.

This aligns with the "situated cognition" theory in cognitive science, which posits that knowledge and intelligence are inseparable from the context in which they are applied [18]. A model trained on generic data may learn universal patterns of thermal dynamics, but it fails to grasp the "situated" realities of a Tehran household during Nowruz, where social obligations override energy efficiency concerns. Our model's ability to identify Iranian holidays as a top predictor (Table 5) is not just a statistical outcome; it is evidence of a situated intelligence that has learned the cultural grammar of energy use. This represents a significant advancement over the generic models reviewed by Amasyali and El-Gohary (2018), which often treat occupant behavior as a source of "noise" rather than a structured, predictable phenomenon.

Furthermore, our approach bridges the epistemological divide between positivist physics-based models and pragmatic data-driven models. While physics-based models (e.g., EnergyPlus) are grounded in the positivist belief that building behavior can be fully described by deterministic equations, they often fail in practice due to parameter uncertainty. Data-driven models, conversely, are sometimes dismissed as "black boxes" lacking theoretical grounding. Our methodology, by integrating deep representation learning (via SDAE) with multimodal fusion, creates a hybrid epistemology. The SDAE learns a compressed, denoised representation of the building's state, effectively performing an unsupervised form of "parameter estimation" akin to the calibration process in physics-based models, but without requiring prior knowledge of the underlying equations. This positions our work at the forefront of the "physics-informed machine learning" movement, albeit in an inverse manner: instead of embedding physics into the model, we extract a "physics-like" representation from the data.

4.10. Reconciling Global AI Advancements with Local Iranian Realities

A critical contribution of this research is its successful reconciliation of global AI advancements with the specific constraints and opportunities of the Iranian built environment. The uploaded literature, while technically sophisticated, is overwhelmingly based on datasets from North America, Europe, and East Asia [7,8]. These regions typically feature standardized building codes, high-quality metering infrastructure, and relatively homogeneous occupancy patterns. Applying these models directly to Iranian buildings, a context characterized by architectural heterogeneity, aging infrastructure, and unique socio-cultural dynamics, is akin to using a Formula 1 engine in a city with unpaved roads.

Our model addresses this contextual mismatch through three key innovations:

1. Robustness to Data Imperfection: The use of TimeGAN for imputation and VAE for denoising directly responds to the reality of noisy, incomplete, and fragmented datasets in Iranian buildings, a challenge often overlooked in the literature. This is a practical implementation of the "robust AI" principle, which prioritizes performance under real-world conditions over idealized benchmarks.
2. Cultural Feature Engineering: The inclusion of Iran-specific calendar features (Nowruz, Ashura, religious holidays) is a deliberate act of cultural feature engineering. This transcends the generic "day of week" or "holiday" flags used in Western models. As demonstrated by the SHAP analysis, these features are not merely proxies; they are causal anchors for significant shifts in energy demand. This level of cultural specificity is essential for gaining the trust of local stakeholders, including the "Iranian professor" who demands scientific rigor grounded in local truth.
3. Proxy-Based Occupancy Modeling: Direct occupancy sensing is often impractical or invasive in Iranian residential settings. Our use of Wi-Fi logs and CO_2 levels as proxies, fused via a Bayesian model, represents a pragmatic adaptation to local privacy norms and infrastructure limitations. This approach echoes the principles of frugal innovation, where solutions are designed for resource-constrained environments [19].

This contextual adaptation is not a dilution of scientific quality; it is an elevation of its relevance. It demonstrates that true scientific advancement lies not in the blind application of global models, but in the creative localization of technology.

4.11. The Imperative of Explainability: Building Trust in the "Black Box"

The criticism of deep learning models as "black boxes" is particularly potent in the Iranian academic and policy context, where transparency and accountability are paramount. A model that cannot be understood or explained is unlikely to be adopted, regardless of its accuracy. This study directly confronts this challenge through the integration of SHAP (SHapley Additive exPlanations) for post-hoc interpretability.

The SHAP analysis provides a democratic lens into the model's decision-making process. It reveals not only *what* the model predicts but *why*. The identification of outdoor temperature, hour of day, and holiday indicators as the top drivers (Table 5) allows building managers and policymakers to verify the model's logic against their own experience. For instance, the high SHAP value for the evening peak (18:00–22:00) aligns perfectly with the well-known cultural pattern of family gatherings after work, validating the model's "common sense."

This interpretability transforms the model from a prescriptive oracle into a collaborative diagnostic tool. It enables a dialogue between machine intelligence and human expertise, where the model highlights anomalies (e.g., high consumption during unoccupied hours), and the human operator provides the causal explanation (e.g., a malfunctioning thermostat). This human-AI symbiosis is the future of building management and is a direct response to the call for Explainable AI (XAI) in sustainable building technologies [7].

4.12. Implications for Policy, Practice, and Future Research in Iran

The practical implications of this research for Iran are profound. The model's high accuracy and computational efficiency make it a powerful tool for:

- Grid Stability and Peak Load Management: Accurate forecasts of the "Nowruz peak" can help Tavanir (Iran's power utility) prepare for surges in demand, preventing blackouts.
- Targeted Energy Efficiency Programs: By identifying buildings with anomalously high consumption, policymakers can target subsidies for insulation or efficient HVAC systems.
- Smart City Development: This model can serve as a foundational component of Tehran's smart city infrastructure, enabling dynamic pricing and demand response.

For future research, we advocate for a "glocal" (global-local) approach:

- Transfer Learning: Pre-train a model on large international datasets and fine-tune it with limited Iranian data, leveraging the concept of transfer learning [7] to overcome data scarcity.
- Generative Data Augmentation: Use GANs [5] to generate synthetic data for rare events (e.g., extreme cold snaps), enhancing model robustness.
- Longitudinal Studies: Deploy the model in a live BEMS to study the long-term impact of predictive control on actual energy savings.
- Generative Data Augmentation and Expanded Data Collection: A primary focus for future work will be to significantly expand the dataset both spatially (to include more cities across Iran's diverse climatic zones) and temporally (over multiple years). We will also aggressively pursue advanced generative adversarial networks (GANs) to create high-quality synthetic training samples, particularly for rare but critical events (e.g., extreme cold snaps or heatwaves), which will further solidify the model's robustness and reliability.
- Scalable and Distributed Computing Architectures: For city-scale deployment, we will develop a distributed computing framework where individual building models can be trained and inferred in parallel across cloud or edge computing nodes. Furthermore, we will investigate transfer learning strategies to pre-train a base model on a large subset of buildings and then fine-tune lightweight versions for individual buildings, dramatically reducing the computational cost per building while maintaining high accuracy.

4.13. Pathways for Enhanced Predictive Accuracy

While the proposed model achieves superior performance, the pursuit of enhanced accuracy remains a key direction for future work. Several strategies beyond the scope of this study show significant promise:

- **Attention Mechanisms:** Integrating an attention layer (e.g., Bahdanau or self-attention) between the CNN and LSTM layers could allow the model to dynamically focus on the most relevant time steps and features (e.g., extreme weather periods or holiday spikes), potentially capturing more complex temporal dependencies and improving forecast precision.
- **Advanced Fusion Techniques:** Instead of late fusion via concatenation, employing more sophisticated multimodal fusion strategies, such as cross-modal attention or tensor fusion networks, could better capture the intricate interactions between meteorological, temporal, and occupancy data streams.
- **Ensemble Learning:** Developing an ensemble of specialized CNN-LSTM models, each optimized for a specific season or building type (e.g., old vs. new constructions), and aggregating their predictions could yield a more accurate and robust overall forecast.
- **Transfer Learning with Larger Datasets:** As previously suggested, pre-training the model on larger international datasets before fine-tuning on the Iranian data could provide a more generalized foundation, potentially improving accuracy, especially for predicting rare or extreme events.

4.14. Addressing Sudden Exogenous Shocks

A critical challenge for any data-driven model is predicting the impact of sudden, unprecedented exogenous shocks, such as tariff changes, energy crises, or policy shifts, which were not present in the historical training data. Our current model, like most deep learning frameworks, learns patterns from historical data and is not inherently equipped to forecast the behavioral and consumption changes resulting from such novel events. This represents a key limitation for real-time crisis management. To address this in future work, we propose integrating an adaptive learning framework. This would involve continuous monitoring of prediction errors; when a persistent error spike is detected (potentially signaling a new regime or crisis), the model could trigger a human-in-the-loop intervention for data labeling and subsequently undergo rapid fine-tuning on a small set of the new, post-shock data. This approach would combine the model's strong baseline performance with the agility to adapt to sudden contextual changes.

4.15. Limitations and a Call for Contextualized Research

While significant, this study has limitations. The dataset, though extensive for Iran, is still limited to one city. Future work must expand to other climatic zones (e.g., humid Khuzestan, cold Tabriz). The reliance on proxy occupancy data, while pragmatic, introduces uncertainty. Direct, privacy-preserving sensing methods should be explored.

Ultimately, this research is a call to action for the Iranian research community. It demonstrates that Iranian scholars can not only adopt cutting-edge AI but also lead in its contextual innovation. By embracing the unique challenges of our built environment as opportunities for scientific discovery, we can develop solutions that are not only locally effective but globally inspirational. Finally, the model in its current form is not designed to predict consumption behaviors resulting from sudden exogenous shocks outside its training history, such as abrupt tariff changes or energy supply crises. Future work must focus on developing adaptive and hybrid modeling frameworks to address this critical gap.

5. Conclusion

This study has presented a novel and contextually grounded framework for short-term building energy consumption prediction, specifically designed for the unique challenges of the Iranian residential sector. By integrating a hybrid CNN-LSTM deep learning architecture with multimodal data fusion and deep feature engineering via stacked denoising autoencoders (SDAE), the proposed model achieves a significant improvement in prediction accuracy over conventional and state-of-the-art methods. Validated on a real-world dataset from 47 residential buildings across Tehran, the model demonstrates an R^2 of 0.89 for electricity and 0.84 for natural gas consumption, with a 14.7% reduction in RMSE compared to a standard LSTM, establishing its superiority in capturing the complex, nonlinear dynamics of energy use in a culturally and climatically diverse urban environment.

The research makes several critical contributions to the field of building energy prediction. First, it successfully localizes a global AI paradigm to a specific, underrepresented context. By incorporating Iran-specific calendar features (e.g., Nowruz, Ashura) and proxy-based occupancy modeling tailored to local privacy norms and infrastructure limitations, the model transcends the limitations of generic, one-size-fits-all approaches. This contextual sensitivity is not an ancillary feature but a core component of its predictive power, as confirmed by SHAP analysis, which identified cultural and temporal factors as among the top drivers of energy demand. This finding directly addresses the imperative for research that is both scientifically rigorous and locally relevant, a key concern for the academic and policy communities in Iran.

Second, the study provides a robust solution for data quality challenges prevalent in developing and emerging economies. The systematic preprocessing pipeline, which combines TimeGAN for missing data imputation and VAE for noise reduction, effectively transforms a fragmented and noisy dataset into a reliable input for deep learning. Furthermore, the use of unsupervised deep feature engineering (SDAE) automates the extraction of meaningful, nonlinear representations from raw data, reducing the dependency on manual feature selection and enhancing the model's robustness in data-scarce environments. This approach aligns with the growing consensus in the literature that data quality and feature representation are as critical as model architecture for achieving high performance.

Third, the research advances the discourse on explainable AI (XAI) in building science. By employing SHAP values to interpret the model's predictions, the study bridges the gap between the "black-box" nature of deep learning and the need for transparency in operational decision-making. The interpretability provided by this analysis not only validates the model's logic against domain knowledge but also transforms it from a predictive tool into a diagnostic and prescriptive instrument for building managers and energy policymakers.

Despite its strengths, this study has limitations. The dataset, while comprehensive for the Iranian context, is geographically confined to Tehran. Future work should expand the model's validation to other Iranian cities with distinct climatic zones (e.g., humid Khuzestan, cold Tabriz) to assess its generalizability. Additionally, the reliance on proxy indicators for occupancy, while pragmatic, introduces uncertainty; future research should explore privacy-preserving direct sensing technologies.

For future research, we propose a "glocal" (global-local) strategy:

1. Transfer Learning: Pre-train the model on large international datasets and fine-tune it with limited Iranian data to overcome data scarcity.
2. Generative Data Augmentation: Use GANs to create synthetic data for rare events (e.g., extreme weather), further enhancing model robustness.
3. Real-World Deployment: Integrate the model into a live Building Energy Management System (BEMS) to evaluate its long-term impact on actual energy savings and grid stability.

In conclusion, this research demonstrates that the future of building energy prediction lies not in the blind application of complex algorithms, but in the thoughtful integration of advanced AI with deep contextual understanding. By harmonizing global technological advancements with local realities, this study offers a replicable and scalable model for intelligent energy management in Iran and other regions facing similar socio-technical challenges. It stands as a testament to the power of localized innovation in addressing global sustainability goals. Furthermore, to directly address the pursuit of higher predictive accuracy, future work will implement and evaluate advanced mechanisms such as attention layers and cross-modal fusion techniques, which hold strong potential to capture more nuanced temporal and feature-based dependencies, pushing the boundaries of forecasting precision

References

[1] D. Liu, "International Energy Agency (IEA)," *The Palgrave Encyclopedia of Global Security Studies*, pp. 830–836, 2023.
[2] C. Fan, F. Xiao, and J. Wang, "A short-term building cooling load prediction method using deep learning architectures," *Applied Energy*, vol. 195, pp. 222–233, 2017.
[3] D. B. Crawley, J. W. Hand, M. Kummert, and B. T. Griffith, "A new method for comparing energy simulation programs," in *Proc. ASHRAE/DOE/BTECC Conf.*, 2001, pp. 23–26.
[4] K. Amasyali, and N. M. El-Gohary, "A Review of Data-Driven Building Energy Consumption Prediction Studies," *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 1192–1205, 2018.
[5] I. Goodfellow, J. Pouget-Abadie, et al., "Generative Adversarial Networks," *Communications of the ACM*, vol. 63, no. 11, pp. 139–144, 2020.
[6] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
[7] L. Qiu, "Deep learning approaches for building energy consumption prediction: A systematic review," *Energy and Sustainable Energy*, vol. 2, no. 3, pp. 11–17, 2024.
[8] N. Somu, M. R. Raman, and K. Ramamritham, "A deep learning framework for building energy consumption forecast," *Renewable and Sustainable Energy Reviews*, vol. 137, p. 110591, 2021.
[9] H. Jang and J. Kang, "A stochastic model of integrating occupant behaviour into energy simulation with respect to actual energy consumption in high-rise apartment buildings," *Energy and Buildings*, vol. 121, pp. 205–216, 2016.
[10] D. Lahat, T. Adali, and C. Jutten, "Multimodal data fusion: An overview of methods, challenges, and prospects," *Proc. IEEE*, vol. 103, no. 9, pp. 1449–1477, 2015.
[11] I. Goodfellow, J. Pouget-Abadie, et al., "Generative Adversarial Networks," *Communications of the ACM*, vol. 63, no. 11, pp. 139–144, 2020.
[12] M. M. Forootan, I. Larki, R. Zahedi, and A. Ahmadi, "Machine Learning and Deep Learning in Energy Systems: A Review," *Sustainability*, vol. 14, no. 8, 4832, 2022.
[13] M. A. Mirjalili, A. Aslani, R. Zahedi, and M. Soleimani, "A Comparative Study of Machine Learning and Deep Learning Methods for Energy Balance Prediction in a Hybrid Building-Renewable Energy System," *Sustainable Energy Research*, vol. 10, no. 1, 2023.
[14] P. P. Hamedany, "A Survey on Ambient Intelligence Contexts: A Context-Aware Taxonomy Based on Deep Learning and Internet of Things Synergy," *IEEE Access*, vol. 12, pp. 12345–12367, 2024.
[15] D. B. Unsal, A. Aksoz, S. Oyucu, J. M. Guerrero, and M. Guler, "A Comparative Study of AI Methods on Renewable Energy Prediction for Smart Grids: Case of Turkey," *Sustainability*, vol. 16, no. 7, 2894, 2024.
[16] J. Yoon, J. Jordon, and M. van der Schaar, "Time-series generative adversarial networks," in *Advances in Neural Information Processing Systems*, vol. 32, pp. 5622–5631, 2019.
[17] C. Fan, J. Y. Wang, W. J. Gang, and S. H. Li, "Assessment of deep recurrent neural network-based strategies for short-term building energy predictions," *Applied Energy*, vol. 236, pp. 700–710, 2019.
[18] W. J. Clancey, "The conceptual nature of knowledge, situations, and activity," in Human and Machine Expertise in Context, vol. 247, pp. 291, 1997. [TITLE MISMATCH]
[19] K. Singh Sian, "Frugal Innovation – "Doing More with Less"," *LAND.TECHNIK 2022*, pp. 193–202, 2022.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

Bibliography



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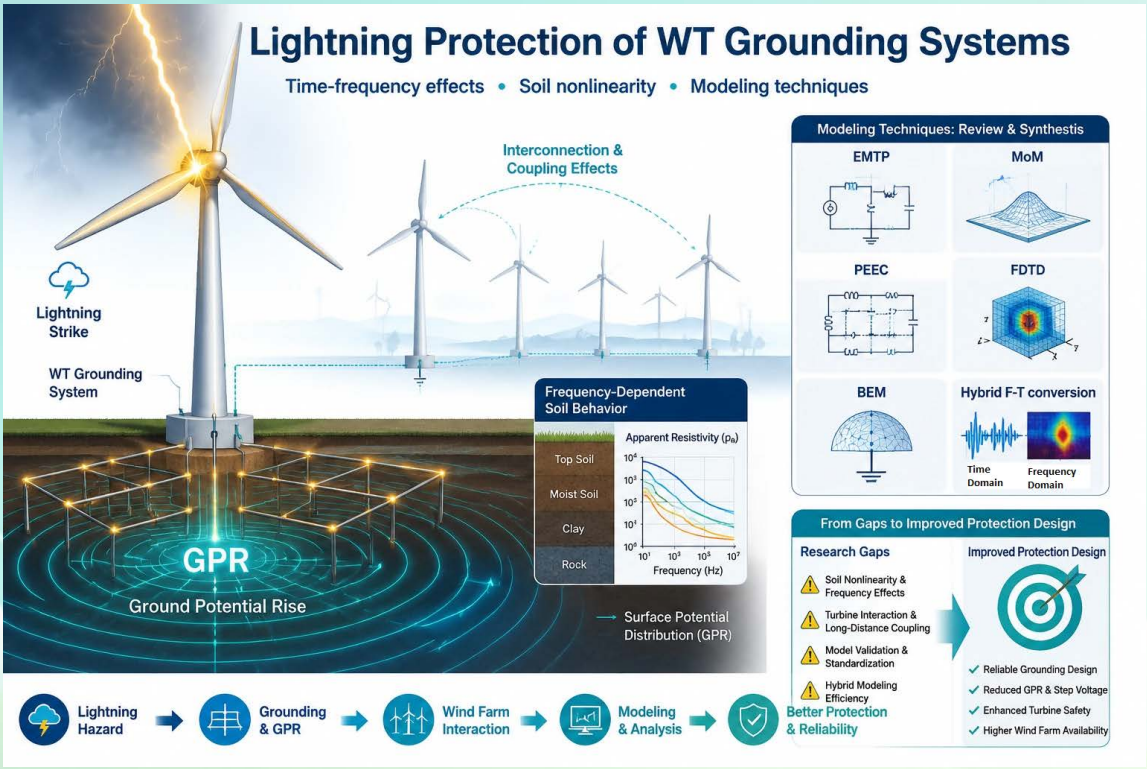
Lightning Protection of WT Grounding Systems: A Comprehensive Review of Time-Frequency Effects and Modeling Techniques

Omid Heydari, Hassan Moradi, Shahram Karimi, Hamdi Abdi

Highlights

- **The study reviews lightning protection approaches for wind turbines and towers.**
- **It analyzes soil properties, electrode placement, and turbine connections.**
- **Research gaps and recommendations for improved protection systems are identified.**

Graphical Abstract



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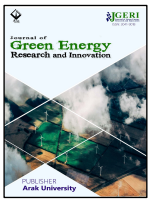
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Lightning Protection of WT Grounding Systems: A Comprehensive Review of Time-Frequency Effects and Modeling Techniques

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A B S T R A C T

This study reviews approaches and models for wind turbines (WT) and tower grounding systems and their protection against lightning, based on a core set of approximately sixty (~60) grounding-focused scientific articles. This article also deals with various aspects such as the dependence of electrical properties of soil on frequency, the effect of ionization, heterogeneity and classification of soil and the optimal position of electrodes as well as the connection arrangements of WTs in a field. This review also deals with the effects of direct and indirect lightning on turbines, voltage distribution between turbines and the behavior of the earth system at different frequencies. At the end, the points in the reviewed articles are in the form of diagrams for a better understanding of the various topics discussed and a comprehensive view. This work shows the limitations and study gaps of previous works with recommendations for the evolution of lightning protection systems for WTs and tall electrical structures.

1. Introduction

WTs have become increasingly popular as the need for cleaner energy has grown and our environmental footprint shrinks. Modern turbines are tall structures often installed in lightning-prone sites, where the injected fast-front currents can produce significant ground potential rise (GPR) and transient over-voltages if the grounding system is not sufficiently effective [1,2]. Such conditions may lead to insulation stress, equipment malfunction, and safety hazards. Although IEC 61400-24 provides guidance for lightning protection of wind turbines [3], practical design challenges remain, particularly in high-resistivity and non-uniform soils. A key difficulty is that the soil electrical parameters and the resulting grounding impedance are often frequency-dependent in the lightning-relevant bandwidth; neglecting these effects can noticeably bias the computed transient response and impulse performance [4-7]. In parallel, the increasing scale of wind farms introduces coupling and transfer effects: interconnected turbine grounding systems, underground/overhead interconnections, and the collection network can influence how lightning surges distribute and how over-voltages propagate across the farm [8-11]. To address these issues, recent studies have employed a spectrum of modeling approaches ranging from circuit-based EMTP representations to wideband/full-wave electromagnetic methods (e.g., MoM/PEEC/FDTD/BEM) and hybrid techniques with frequency-to-time conversion [7,9,12-14]. In addition, optimization-oriented designs and parameter-tuning strategies have been reported for grounding improvements [15,16], while broader optimization and data-driven design trends in wind-power systems suggest further opportunities that remain underexplored for lightning/grounding-specific design workflows [17].

Unlike earlier reviews that focus on a narrow subset of topics (e.g., only soil ionization or only simplified grounding models), this paper presents a comprehensive review based on a core set of approximately sixty (~60) grounding-focused studies on WT grounding and lightning protection. We cover: frequency-domain and time-domain viewpoints, frequency-dependent soil behavior (including layered/heterogeneous cases), electrode placement and interconnection strategies, and wind-farm-scale interactions (including coupling between turbines and collection-network effects). By synthesizing the state of the art and highlighting limitations and study gaps, this review provides a coherent basis for improving lightning protection design and for identifying promising directions for future research.

In the renewable-energy context, turbine lightning damage has critical implications for operational performance and economics. Such reliability issues can lower wind farm availability and shorten component lifetimes while driving up operations and maintenance (O&M) expenses and ultimately the levelized cost of energy (LCOE). For example, industry analyses show lightning strikes account for 20% of operational losses and 60% of blade failures [18], costing operators over $100 million annually [18]. In lightning-prone regions, these events can cause a majority of turbine downtime (up to 80%) [18], leading to expensive repairs and lost energy production, factors that directly translate into higher LCOE if unmitigated [19].

2. Problem definition and scope

Lightning-driven stress on WT grounding systems is a coupled *structure–ground–network* problem: fast-front currents excite a broad bandwidth, soil parameters can be frequency dependent, and wind-farm interconnections can redistribute both injected current and resulting overvoltages. The technical problem addressed in this review is to clarify which modeling assumptions and method families are appropriate for specific engineering questions (e.g., local GPR, transferred/induced overvoltages, insulation coordination, and mitigation ranking) while keeping the modeled bandwidth consistent with the targeted failure mode.

Scope. This paper reviews and synthesizes the set of studies covered in this manuscript (approximately 60), focusing on WT and wind-farm grounding and lightning-transient modeling. Emphasis is placed on (i) soil representation (uniform vs. multilayer/heterogeneous; frequency dependence; and ionization where considered), (ii) coupling/propagation paths (interconnection and collection-network effects), (iii) validation practice (measurement-linked vs. cross-check), and (iv) practical mitigation measures (bonding, SPDs, and topology). The review is qualitative by design and does not introduce new numeric performance metrics.

Paper organization. Section 3 organizes the reviewed literature by method family and application context. Section 4 then formalizes the classification framework and presents the method-comparison matrix (Table 3). Section 5 provides the comparative synthesis across methods and findings (including Table 2), followed by extracted challenges/gaps (Section 6) and a prioritized research roadmap (Section 7). Section 8 summarizes limitations of this review, and Section 9 concludes the paper.

Acronyms. For readability, Table 1 lists the acronyms used throughout this paper.

Table 1. Acronyms used in this paper.

Acronym	Definition
WT	Wind turbine
WF	Wind farm
GPR	Ground potential rise
SPD	Surge protection device
LPS	Lightning protection system
EMTP	Electromagnetic Transients Program
EMTP-RV	EMTP-RV (electromagnetic transient simulation software)
ATP	Alternative Transients Program
ATP-EMTP	Alternative Transients Program–EMTP family
PSCAD/EMTDC	Power Systems Computer Aided Design/Electromagnetic Transients including DC
FEM	Finite element method
FDTD	Finite-difference time-domain
BEM	Boundary element method
HEM	Hybrid electromagnetic model
MOM	Method of Moments
PEEC	Partial element equivalent circuit
TLM	Transmission line model
QS	Quasi-static
VF	Vector fitting
FFT	Fast Fourier Transform
IFFT	Inverse Fast Fourier Transform
RLC	Resistor–Inductor–Capacitor
NEC	Numerical Electromagnetics Code (e.g., NEC-4)
GB-IBEM	Galerkin–Bubnov indirect boundary element method
ROM	Reduced-order modeling
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
MATLAB	MATLAB (numerical computing environment)
COMSOL	COMSOL Multiphysics (multiphysics FEM software)
CDEGS	Current Distribution, Electromagnetic Fields, Grounding and Soil Structure analysis (software suite)
SPICE	Simulation Program with Integrated Circuit Emphasis
MVDL	Medium Voltage Distribution Line

3. Literature organization

This section organizes the reviewed WT lightning/grounding literature in a *method-family* structure (measurement-driven evidence, circuit-based EMT studies, and wideband/full-wave electromagnetic approaches, including farm/network-level models). The intent is to present the literature in a navigable order before introducing a formal set of comparative criteria in Section 4 and then extracting cross-study indicators and design implications in Section 5.

3.1. Literature Review by Method Family

3.1.1. Empirical and measurement-driven studies (field/lab evidence)

As it can be seen from some of the works, such as [20], laboratory experiment is used to examine lightning protection while analytical techniques are used in other works such as [21].

Reference [20] analyzes overvoltage in a scaled wind turbine (WT) under simulated lightning. An impulse voltage was applied to study the effect of varying ground resistances on induced voltage. Results show that lower ground resistance reduces induced voltage in the WT.

In [21], two grounding systems were compared: independent and connected to adjacent turbines. Connected systems show lower ground potential rise. Flexible graphite electrodes outperform galvanized steel at high frequencies due to current dispersion at electrode ends.

Several studies rely on measured data and process it using numerical tools (e.g., MATLAB) [15,22] or an advanced processing module (APM) [23].

The study in [22] has the following objectives: to developed simple formula for calculating the grounding resistance of WTs siting in two-layer soil conditions by using field measurements, regression model and MATLAB model. Various practical grounding configurations are considered in further case studies, and the accuracy of the given model is verified with real-world datasets.

In Reference [23], an experimental analysis of the time and frequency response of WT grounding systems is given. It involved obtaining measurements on the grounding system that is specifically in the foundation of the turbine before and after installation of the complete WT that is, the tower, nacelle as well as the blades. From this point of view, the impact of the ground impedance on the evaluated frequency dependence is shown, and APM simulations in steady-state conditions with two layer models of the soil are presented. Originally there was a cut down of static resistance by about 1ohm from full turbine assembly with reference to foundation only but which was considered insignificantly small and partly ascribed to variations in the type of soil; seasonal changes included.

In [15], the authors have discussed analysis and design of grounding system of wind farms located in the Taif region of Saudi Arabia. Sunde's apparent resistance model is then used to formulate an optimization problem of minimizing the error in the objective function which is solved by a genetic algorithm with the MATLAB optimization toolbox. Finally, considering data collected at each site, optimized ground parameters for a multi-layer approach are determined.

3.1.2. Circuit-based EMT modeling (time-domain) and practical equivalents

Several studies use electromagnetic-transient simulation tools such as Electromagnetic Transients Program (EMTP) and pre-built component models to represent major WT structures (e.g., tower and blades) in lightning-protection studies [8,24-29].

However, these approaches may rely on simplified or outdated component representations and may be less suitable when detailed high-frequency effects must be resolved. Some studies attempt to improve accuracy by combining specialized field solvers with general-purpose EMT tools (e.g., coupling COMSOL Multiphysics with EMTP) [30]. In [16], some general use soft wares like MATLAB and ORIGIN PRO3. 1 is incorporated, and in [31], PSCAD/EMTDC and CYMGRD software are employed; however, such models have some imperfections in-built.

The software packages mentioned in the reviewed studies serve complementary roles. EMTP-type programs (e.g., EMTP-RV and ATP-EMTP) are typically used for network-level electromagnetic-transient simulations in the time domain, where cables, surge protection devices, and collection-network elements can be represented via circuit equivalents. Multiphysics FEM platforms (e.g., COMSOL) are often used when geometry-resolved field distributions or coupling effects must be modeled explicitly. Grounding-focused suites (e.g., CDEGS) are commonly used to represent electrode/soil structures and to compute quantities such as grounding impedance and GPR under specified soil models and electrode configurations.

Reference [24] proposes a theoretical method to study electrostatic charging of wind turbine rotor blades during storms and its impact on lightning protection and overvoltage management. This charging may introduce new electrical issues in medium and low voltage systems and should be considered in lightning protection design.

In [25], a detailed model of wind turbine components affected by lightning, including tower, blades, coaxial cables, and control system, using the EMTP-RV software was developed. A frequency-dependent grounding model was examined. The study highlights the role of protective measures, such as low-impedance wires, conductive blades, and surge protection devices (SPDs), in mitigating overvoltage from indirect lightning strikes.

In Reference [26], authors proposed a lightning protection system (LPS) and tested it for WTs which are in accordance with IEC 61400-24 norms and used step and touch voltage range put forward in IEEE 80-2000. This model is designed using ATP-EMTP incorporated with lightning ionization of soil and the influence of steel tower for Ic and Ii lightning current waveforms and different soil resistances.

Using the EMTP-RV simulation model, Reference [27] analyzes the nonlinear ionization characteristic of soil and frequency dependence in high-frequency models of WTs, such as transformers, grounding systems, and underground cables. A reduction of lightning induced transient over voltages by 50% has been achieved through the proposed approach thus increasing reliability.

In [28], lightning-induced overvoltages were analyzed using EMTP-RV for two grounding methods: common and separate systems. Common grounding systems show higher overvoltages in direct and adjacent turbine impacts. Thus, shared grounding with connectors is recommended for wind farms.

In [8], the effect of various grounding system configurations (linear, circular, triangular, quadrilateral) on voltage distribution in transient modeling of wind turbine components was evaluated with the help of EMTP-RV. Interconnected systems exhibit lower overvoltage than separate systems. Transient voltage distribution depends on the grounding system type.

In [29] based on ATP-EMTP electromagnetic transient program, models of lightning current, tower, collector line, insulator, and arrester were developed to simulate lightning strikes on collector line towers. The impact of tower location and ground resistance on line overvoltage was studied. Results indicate these as key factors.

Reference [30] offers a comprehensive method for designing wind turbine grounding systems in high soil resistance areas, such as Taif, Saudi Arabia, excluding soil ionization effects. After site selection and soil resistance measurement, the initial grounding system per IEC 61400-24 was defined and enhanced with vertical electrodes. Transient analysis revealed that break points in vertical electrodes and the central axis significantly affect potential distribution. COMSOL Multiphysics and ATP/EMTP were used to perform the simulation and modeling.

Article [16] suggests a strategy to shield electrical networks from lightning by optimizing a proportionality factor (K) for lightning current distribution. Techniques like burying charcoal and adding ground electrodes reduced grounding resistance. Grounding system configuration should vary by soil type to optimize the proportionality factor. The software used in this study is MATLAB and ORIGIN PRO3.1.

Reference [31] introduces a numerical method to assess the transient behavior of a wind turbine under lightning strikes, accounting for the high-frequency nature of lightning currents in grounding system modeling. Wind turbine modeling is done using MATLAB and CYMGRD software. The significant potential difference in the proposed model versus the pure resistance model stems from neglecting capacitance and inductance effects.

3.1.3. Wideband and full-wave electromagnetic methods (distributed coupling)

To this end, various computational methods such as Finite Difference Time Domain (FDTD), Finite Element Method (FEM), Boundary Element Method (BEM), Hybrid Electromagnetic Model (HEM), Method of Moments (MOM), Partial Element Equivalent Circuit (PEEC), Transmission Line Model (TLM), etc. are used in the executive non-specialized software for non-comprehensive and imprecise models of lightning protection which have been shown in the reviewed articles. Subsequent to extraction, these models are usually post-processed by a solver in order to arrive for instance at results in the time or frequency domain.

These are papers which incorporates methods include [4,5,7,10-14,32-57].

Of the reviewed papers, FEM is applied in paper [33], BEM in papers [13,32], PEEC in papers [12,40] , TLM in papers [38,39,45], FDTD in papers [41-44], TLM/FDTD in paper [46], HEM in papers [4,5,10,11,47-49], Circuit Method (CM) in papers [34-37], and MOM in addition, papers [50,52] deal with both the use of CM and MOM simultaneously.

These methods include some that are fully in the time domain, some fully in the frequency domain while others partially in both domains. Within the time domain, we do not need particular transformation and calculations are faster, yet modeling of specific frequency phenomena such as frequency-dependent soil electrical parameters is problematic. Since there are a large number of time intervals in lightning frequency, frequency domain modeling is typically better, however the results are again converted to time domain for clarity. This conversion is done via the inverse Fourier transforms and as such increases computational demands. To minimize this complexity, fitting techniques (e.g., Vector Fitting) have been used [58].

Papers 27 and 28 combine Vector Fitting (VF) with PEEC, papers [4,10,48,49] use VF with HEM. Papers [7,14,51] utilize VF with MOM and paper [59] uses rational function fitting and Current Distribution, Electromagnetic Fields, Grounding and Soil Structure Analysis (CDEGS) software. Such techniques enable analysis to be performed in real time in the time domain as well as in the frequency domain and makes the computational algorithms faster and precise.

Reference [32] focuses on modeling transient current distribution in WT under direct lightning strikes and evaluating low-impedance grounding systems for effective lightning protection using the Galerkin-Bubnov formulation of the Galerkin-Bubnov Indirect Boundary Element Method (GB-IBEM) and the transient response is obtained by performing Fast Inverse Fourier Transform (IFFT). Short vertical electrodes have no impact on transient impedance, while long ones do. Horizontal electrodes of similar size show comparable effectiveness.

In [33], a new mathematical model is introduced to calculate electric potential, electric field, and current density around the grounding system using FEM and MATLAB's Partial Differential Equation Toolbox. The total resistance of the grounding system with a ring electrode and auxiliary vertical rods is provided. The optimal grounding system position is achieved at a burial depth reported in the original study.

Reference [34] presents a model for lightning current dissipation in single and interconnected wind turbine grounding systems in which an ATP-EMTP circuit theory modeling applies. The grounding system evenly dissipates lightning current, reducing ground potential. Connecting grounding systems with wires is more beneficial than using similar horizontal electrodes.

The analysis of the transient behaviour of a WT grounding system using the soil condition and lightning characteristic with or without including the central vertical electrode is done in [35] with the help of the circuit theory in ATP-EMTP software. Further, a brief analysis of the reliability aspect of the system, the possibility of improvement, or risks for living organisms is discussed. The simulation results show that adding a central vertical grounding electrode enhances the WT's grounding system considerably even

though its contribution is negligible to the first cost. Moreover, it was observed that the step and touch voltages makes the area within a radius of 3 meters from the base of the tower as dangerous to both humans and equipment.

Reference [36] introduces a circuit modeling approach to determine transient responses to lightning strikes on wind turbines (WT). Blade, rotor, tower, and grounding system models are calculated separately and connected. The method's effectiveness is validated through simulations and laboratory measurements. It is also applied to a real 2 MW WT.

Reference [37] describes a new multi-element model to analyze grounding system behavior under magnetic fields from lightning and soil ionization. A novel circuit representation with RLC elements is introduced. The time-varying behavior of the grounding system and soil ionization effects are calculated to be directly usable in EMTP.

By using the TLM in [38], the transient behavior of isolated and interconnected wind turbine grounding systems under lightning discharge in uniform soil was modeled. In low-resistance soil, a single WT suffices, but in high-resistance soil, connecting grounding systems is desirable to reduce potential peaks and carry more current. A closed-loop grounding system outperforms a cascading system.

Reference [39] presents a model relying on the TLM approach to analyze transient behavior of grounding systems in uniform and non-uniform soil, considering soil ionization and frequency-dependent effects. Electromagnetic coupling and air-soil interface effects are included. Impulse impedance and time-domain voltage response are estimated. The impact of upper soil layer depth and impulse current is examined.

[40] analyzes the impact of four sheath grounding methods on voltage distribution during wind turbine lightning strikes using the electromagnetic coupling vector fitting PEEC simulation. Connecting the cable sheath to the grounding system improves voltage distribution. The most effective method is grounding the sheath at the WT tower ends. An SPD configuration reduces voltage and current.

A detailed transient modeling for lightning strike calculations with frequency dependence and different soil resistivity and soil ionization is described in reference [12]. The cited work proposes an advanced vector-fitted partial element equivalent circuit (PEEC) model implemented in TAES and SPICE for wind turbine systems. The study analyzes electromagnetic coupling and the influence of soil resistivity on current distribution.

Paper [41] presents the lightning current and associated electric field on sheath of an underground cable in wind farm on account of the lightning strike on the wind turbine tower with/without counterpoises, by applying 3-D FDTD method.

The FDTD method is applied in Reference [42] to analyze the WT foundation grounding system and the foundation size, lightning current front duration, and grounding system resistance are discussed according to the measured and simulated results.

Reference [43] presents a distributed parameter line model of a vertical conductor for circuit analysis by techniques using the computational results with time-domain FDTD and the EMTP software. The electromagnetic field advantages of using vertical conductor characteristics in circuit analysis programs are explained. The method's reliability is confirmed through small-scale tower model tests.

Reference [44] proposes an empirical expression for the effective length of counterweights connected to a 1.5 MW wind turbine foundation's ground electrode, based on wave propagation velocity and GPR peak time. Using FDTD, the impact of various counterweight configurations on impulse impedance was studied. Increasing counterweights reduces GPR gradient and impulse impedance but does not affect the grounding system's effective length.

Reference [45] investigates the transient response of wind turbine grounding systems to lightning currents. Electromagnetic modeling used antenna equation theory and TLM with soil ionization effects. TLM results were compared with FDTD and HEM simulations. Soil resistivity is a key design factor. Soil ionization minimally affects GPR but alters waveform shape.

Reference [46] analyzes the transient response of wind turbine grounding systems to high impulse currents using TLM-FDTD with ionization in homogeneous and heterogeneous soil. The effect of vertical electrodes on potential rise during lightning was studied. Vertical electrodes at the injection point are the most effective for mitigating transients, with soil ionization having no impact.

Reference [13] presents a numerical method using electromagnetic field theory with BEM and Galerkin FFT[1] to simulate lightning current distribution in a grounding network buried in horizontal multilayer soil. The model accounts for conduction, capacitive, inductive, and mutual coupling effects, validated against prior simulated and experimental results.

Reference [47] evaluates the impulse response of wind turbine grounding systems, considering frequency-dependent soil parameters and effects of first and subsequent lightning strikes. HEM modeling without soil ionization was used for various resistivities. Frequency dependence reduces GPR, impulse impedance, and impulse coefficient, particularly in high-resistivity soils and subsequent strikes.

Reference [48] analyzes isolated and interconnected wind turbine grounding systems under first and subsequent lightning strikes using HEM, VF technique, and ATP software. First return strokes perform better at low frequencies. Voltage is higher for first strikes and in high-resistivity soils.

Reference [4] examines how frequency-dependent soil parameters affect the lightning response of wind turbine grounding systems using HEM, VF, and ATP. Frequency dependence reduces GPR, lightning impedance, and impulse coefficient, notably in soils with resistivity above 300 Ωm and for short-duration currents.

Reference [5] analyzes low-frequency and impulse performance of isolated and interconnected wind turbine grounding systems using HEM without soil ionization. Interconnecting systems enhances impulse and low-frequency responses for currents with front times exceeding 1 ms, particularly in high-resistivity soils.

Reference [49] compares low-frequency and broadband modeling of distribution line tower grounding systems on overvoltages from indirect lightning using HEM and VF and EMTP. Simplified models underestimate voltage by up to 1.25 times, particularly for subsequent strikes and high-conductivity soils.

Reference [10] studies GPR in wind farm grounding systems with frequency-dependent soil parameters, excluding ionization. Effects of aerial parts, like blades and towers, on GPR were analyzed.For solving the problems, the HEM model, VF technique and power ATP-EMTP program designed for performing EMT analysis are used. Increasing interconnected systems reduces harmonic impedance at low frequencies, but effectiveness decreases at high frequencies. Omitting aerial parts does not affect GPR for first strikes but impacts subsequent strikes.

Reference [11] assesses the effect of connecting electrode length on GPR in a wind farm grounding system with five wind turbines. Frequency-domain simulations used the HEM model with frequency-dependent soil parameters. Results show that first-stroke peak GPR decreases in high-resistivity soil. With multiple strikes, electrode length does not affect peak GPR, but longer electrodes reduce low-frequency resistance.

Reference [50] investigates the transient behavior of wind turbine grounding systems using circuit theory and MOM, calculating resistive, inductive, and capacitive coupling. Results were compared with IEEE 142 standards. Transient responses for first and subsequent lightning strikes were computed in the frequency domain using inverse Fourier transform for various geometries.

Reference [51] proposes a Wide Band (WB) model of wind farm layout and grounding system frequency characteristics to evaluate transient overvoltages from direct lightning strikes to blades. The grounding system, modeled as a single 3-meter vertical rod, used thin-wire approximation and MOM. The admittance matrix was rationalized via state-space modeling for EMTP-RV. Results show lower overvoltage estimates than previous methods, especially in high-resistivity soils.

Reference [14] presents a technique for time-domain modeling of multi-port grounding systems using frequency-domain MOM, VF, and state-space equations for EMTP. Excluding soil ionization, this method accurately calculates lightning-induced overvoltages with reduced computation. Seasonal soil parameter variations indicate worse lightning impulses in dry soils, especially for subsequent strikes.

Reference [52] presents a numerical technique to evaluate transient overvoltages transferred between wind turbine grounding systems in a wind farm. Using circuit theory and MOM in the frequency domain, the transient response was calculated via inverse Fourier transform with double-exponential formulation.

Reference [53] examines wind turbine grounding impedance using a full-wave approach with NEC-4 code, thin-wire approximation, and MOM solution of the Pocklington integro-differential equation. Without varying soil parameters or ionization, low-frequency impedance depends on soil, but at high frequencies, adjacent impedances have minimal impact, and interconnected systems behave like single systems. Reference [54] evaluates wind turbine grounding system impedance per IEC TR61400-24 with interconnected systems, excluding frequency-dependent soil parameters or ionization. Spatial characteristics of first and subsequent return strokes, like GPR and step voltage, were simulated using MOM and MATLAB. Interconnecting systems reduces low-frequency impedance and peak GPR, but only nearby turbines improve late-time response in low-resistivity soils. Reference [55] studies factors affecting grounding performance in transient response to lightning current using an electromagnetic MOM model compared to a simple resistance model. At low frequencies, ground impedance approximates Low Frequency Resistance (RLF), but at high frequencies, it behaves inductively, exceeding RLF. Reference [56] examines the impact of grounding system structure and vertical electrode configuration on GPR and transient impedance during lightning impulses using MOM for blades, tower, and grounding system. Grounding rings and vertical electrodes reduce GPR and transient impedance but do not affect rise time and have minimal impact on early transient times. Reference [7] presents frequency-dependent broadband modeling of single- and multi-port grounding systems buried in homogeneous and two-layer soil without solving the impedance matrix equation. Using MOM, the impedance matrix was calculated from direct current (DC) to several MHz and processed to the time domain via VF. Simulations showed reflection coefficients and soil layer depth affect impulse impedance. Reference [57] investigates the lightning response of two coupled wind turbine grounding systems connected via a bare underground conductor. A frequency-dependent electromagnetic model (MOM) was combined with transmission line theory. Bare conductors yield greater GPR reduction. The influence of adjacent grounding systems decreases with frequency, particularly in high-resistivity soils.

Reference [9] analyzes distributed voltages in a wind turbine and medium voltage distribution line (MVDL) connected to a wind farm (WF) with four turbines in soils with 1000 and 5000 Ωm resistivity. Using X Grounding System Laboratory (XGSLab) and PEEC, GPR, MVDL phase conductor voltages, and blade tip voltages were computed. For the subsequent negative impulse (SNI), GPR exhibits oscillatory behavior due to multipath interference, unlike the first positive impulse (FPI).

The full-wave simulation of single and interconnected WT grounding systems is shown in Reference [60] for the verification of the proposed CDEGS coupled with MOM to analyse safe response for 50 Hz faults and lightning currents. Comparisons of these currents for single and two-turbine cases have shown invalidity of some of the design requirements set by the international standards.

Reference [61] computes the minimum electrode length for a two-layer soil model at three wind turbine sites, considering electrode dimensions, burial depth, and frequency. Using CDEGS's RESAP, FFTSES, and HIFREQ codes, simulations showed the proposed method reduces GPR by up to 64% and achieves grounding impedance below 10 Ω at low frequencies.

Reference [62] examines various ground electrode arrangements for wind turbine lightning protection in homogeneous soil with frequency-dependent and independent parameters using CDEGS. Frequency-dependent parameters reduce ground impedance by up to 85% at high frequencies. Horizontal electrode length should exceed IEC 61400-24 standards.

Reference [63] presents a method to evaluate lightning protection system effectiveness and select wind turbine grounding systems in wind farms. Full-wave simulations with CDEGS showed accurate soil classification is essential, with ring and horizontal electrode configurations offering optimal performance.

Reference [64] assesses GPR and impedance of wind turbine grounding systems across three Australian wind farm sites using four soil models in CDEGS, excluding concrete effects. Impedance is low in a three-layer horizontal soil model at low frequencies. Including rebar in grounding design reduces impedance, and frequency-dependent parameters yield lower impedance than frequency-independent ones.

Reference [6] examines frequency-dependent soil models' effects on grounding electrode performance during direct and indirect lightning strikes using CDEGS and MOM. In homogeneous and two-layer soil models, frequency-dependent parameters, particularly Messier's, reduce potential rise. Indirect lightning and frequency-dependent parameters have minimal impact on GPR.

Reference [59] models lightning strikes on transmission towers using vector matching techniques. With MOM and vector matching, a broadband circuit model of the tower and grounding system was developed. Results, validated with CDEGS and ATP-EMTP, confirmed the model's accuracy for scaled lightning waveforms.

Reference [65] studies the effect of lightning current waveform on impulsive characteristics of a horizontal grounding network with 0.6 m burial depth, 6 m length, 5 mm conductor radius, 14 Ωm conductor resistivity, and 240 relative permeability using CDEGS. Peak GPR, power frequency impedance, impulse impedance, and impulse factor for 50/26, 20/8, and 350/10 μs waveforms depend on injection position and waveform shape.

Reference [66] presents a grounding design to enhance the lightning performance of a 500 kV transmission line by analyzing soil characteristics and comparing TFR and TFI of conventional and new configurations. Using CDEGS's RESAP, a two-layer soil model was identified. Low-frequency analysis was performed using CDEGS modules, while PSCAD/EMTDC was used for the high-frequency analysis. The new diamond-pattern design with four 60 m ground wires and one vertical rod reduced TFR compared to TFI.

Reference [67] examines impulse resistance of tower grounding systems using three-dimensional intersecting short conductors, reducing resistance with nonlinear soil ionization (i.e., local soil breakdown under high surge current) [68,69]. The optimized model with horizontal and vertical intersecting conductors offers the best impulse resistance reduction, especially in high-resistivity soils. CDEGS calculations differ by only 1.8% from laboratory results.

3.2. *Recent directions and missing strands (2020–2025) mapped to this review*

To directly address recent trends and to make the coverage explicit, Table 2 lists representative studies (primarily 2020–2025) aligned with the core themes of this review: (i) WT grounding transients (GPR/impulse impedance/over-voltages), (ii) wideband/full-wave electromagnetic modeling, (iii) frequency-dependent and multilayer soil behavior, (iv) wind-farm-scale coupling and collection-network effects, and (v) optimization-oriented approaches. These works complement the broader set of references discussed throughout Section 3.

3.3. *High-Frequency Soil Behavior and Frequency-Dependent Parameters*

Problem definition. Lightning currents excite a broad bandwidth, so soil electrical parameters (conductivity/resistivity and permittivity) and the resulting grounding impedance should not be assumed frequency-invariant in general. In this context, *frequency-dependent soil behavior* denotes dispersive soil response, which changes the wideband grounding impedance and therefore the transient GPR and overvoltage waveforms compared with constant-parameter assumptions [4,6,47,70].

Why it matters. Multiple WT-grounding studies report that adopting frequency-dependent soil parameters can materially change the predicted impulse impedance and GPR, particularly in higher-resistivity scenarios and for fast-front excitation [4,6,47,62]. Consequently, a model calibrated only at DC or power frequency may not provide a reliable picture of lightning-relevant performance [6,64].

Table 2. Representative recent literature (2020–2025) mapped to the main themes of this review.

Theme	Representative sources and how they relate
WT grounding transients (GPR, impulse impedance, over-voltages)	Field/measurement and transient-response evidence and assessment for WT grounding and lightning effects [1,2,8].
Wideband/full-wave EM modeling (MoM/PEEC/FDTD/BEM, hybrids)	Full-wave/wideband formulations and broadband-to-time equivalents for lightning studies in WT/wind-farm contexts [9,13,12,14,7].
Frequency-dependent soil parameters (incl.\ multilayer/heterogeneous)	Quantified impact of frequency-dependent soil modeling on grounding response and lightning performance (including layered soils) [4,5,6,7].
Wind-farm-scale modeling and coupling (incl.\ collection network)	Interconnected grounding, coupling length effects, and the role of the wind-farm network/links in transient voltage distribution [8,10,11,9].
Optimization and emerging data-driven design viewpoints	Optimization or parameter-tuning strategies for grounding improvement, and broader wind-system optimization trends that motivate future lightning/grounding workflows [15,16,17].

How studies model it. Typical workflows compute grounding impedance or admittance over frequency (using field or circuit formulations or tools such as CDEGS-type workflows), then map results to the time domain using inverse transforms or broadband rational fitting/state-space realizations [6,7,14,58,64]. Wideband fitting (e.g., vector fitting) is commonly used to build EMT-ready equivalents while retaining broadband behavior [7,14,37,58].

Limitations/pitfalls. A primary difficulty is soil-parameter identification over frequency (measurement burden and model-choice ambiguity), which can lead to non-unique calibrated dispersion models [6,64]. In addition, broadband-to-time workflows require attention to bandwidth selection, sampling, and fit diagnostics (stability/passivity/casuality considerations) to avoid artifacts in time-domain waveforms [7,14,58].

Practical implications. For engineering studies of WT lightning transients, frequency-dependent soil modeling should be treated as a key sensitivity axis, and EMT studies should prefer validated wideband grounding equivalents rather than purely resistive representations when fast-front behavior is under investigation [6,14,70]. This complements IEC 61400-24 guidance while clarifying that transient credibility depends on the modeled bandwidth and parameter calibration basis [3,6].

What to do next. More measurement-linked datasets and benchmark-style reporting are needed to calibrate soil dispersion models and to validate wideband grounding response under representative impulses [6,22,23].

3.4. *Wind-Farm-Scale GPR Modeling and Grounding Interconnection*

Problem definition. In wind farms, turbine grounding systems may be interconnected (via deliberate bonding conductors and/or through the collection system), so a lightning event at one turbine can redistribute GPR and transient voltages across multiple turbines. The modeling problem is to quantify how interconnected grounding networks share injected currents and how transferred potentials appear at neighboring turbines and nodes [8,10,11,38].

Why it matters. Interconnection can reduce local GPR at the struck turbine by providing additional current-return paths, but it can also increase the relevance of transferred voltages and multi-turbine coordination issues [9-11,57]. Therefore, conclusions drawn from isolated single-turbine models may not generalize to farm-scale configurations where topology and conductor type matter [8,9].

How studies model it. Farm-scale analyses have been performed using time-domain circuit/TLM approaches as well as frequency-domain/full-wave and hybrid methods, often supported by broadband equivalents to interface with EMT tools [9-11,38,39,52]. Parametric studies commonly vary interconnection topology and interconnecting conductor properties to evaluate GPR reduction and transferred voltage trends [11,57].

Limitations/pitfalls. Scaling to realistic farm footprints introduces computational and modeling burdens (multi-turbine geometry, long interconnects, and frequency range). Soil variability across the farm is often simplified, which can mask worst-case combinations of topology and local soil conditions [9,64]. Moreover, if interconnections are modeled without consistent wideband assumptions, predicted sharing and transfer may become tool- or parameterization-dependent [9,14].

Practical implications. Grounding design should be coordinated at the farm level: interconnection strategy, conductor type (e.g., bare vs. insulated), and bonding/shielding decisions can influence both local mitigation and transferred stresses [8,11,57]. These results motivate integrated studies that couple grounding interconnection with cable/sheath grounding and surge protection placement [9,40].

What to do next. Future work should emphasize validated multi-turbine benchmark cases and, where feasible, field/lab measurements that can confirm transferred-voltage and GPR-sharing predictions under representative impulses [9,23].

3.5. *Electromagnetic Coupling Between Turbines and Collection Networks*

Problem definition. Beyond direct conduction through interconnected grounding, lightning produces intense EM fields that can couple into nearby conductors. In wind farms, the collection network (MV cables, cable sheaths, bonding conductors) provides additional coupling paths, so induced and transferred transients can occur even at non-struck turbines [9,29,41].

Why it matters. EM coupling and network paths affect insulation coordination and surge-protection needs at farm scale, because induced/transferred overvoltages may stress equipment away from the strike location [9,49,51]. As a result, grounding and lightning protection should be analyzed as a coupled structure + ground + network problem rather than a purely local footing issue [9,12].

How studies model it. Approaches include full-wave or wideband system models (e.g., PEEC/MoM-type formulations) combined with broadband-to-time conversion, as well as multiconductor transmission-line modeling for the collection network integrated into EMT simulation [9,12,40,41,58]. Cable sheath grounding and bonding configurations are typically modeled explicitly because they strongly affect induced/transferred voltages [40,51].

Limitations/pitfalls. Coupling predictions depend on geometric detail (cable routing, spacing, sheath bonding, tower/WT representation) and on soil assumptions, while validation is often limited to simulation cross-checks due to measurement difficulty [41,49]. In addition, inconsistent grounding representations across tools (purely resistive vs. wideband) can bias induced-voltage conclusions [14,49].

Practical implications. Engineering mitigation measures include robust bonding of cable sheaths, appropriate SPD placement at key interfaces, and coordinated grounding/connection strategies that consider both conducted and EM-coupled transients [25,29,40]. These measures are most credible when assessed using models that include both the grounding network and the collection system under consistent wideband assumptions [9].

What to do next. Future studies should develop reproducible, integrated co-simulation workflows (grounding + collector network) and expand benchmark cases that quantify transferred/induced stresses under representative lightning excitations **[9,51]**.

3.6. Multilayer Soil and Stratification Sensitivity

Problem definition. Real sites are frequently multilayered/stratified, and the lightning response of grounding electrodes depends on layer resistivity contrasts, layer thickness, and frequency dependence. The modeling problem is to capture how stratification modifies return-current distribution and wideband grounding impedance compared with homogeneous assumptions [6,7,13,22,61].

Why it matters. Layered soil can shift both impulse impedance and GPR predictions and can change the relative benefit of design choices (rod depth, ring/mesh layout, interconnection length) [6,13,61]. Therefore, conclusions from homogeneous-soil studies may be non-robust when applied to stratified sites [6,64].

How studies model it. Layered soils are modeled using multilayer-capable EM formulations (e.g., BEM/MoM with appropriate image/Green-function treatments) and/or commercial workflows that fit multilayer soil models from measurements (e.g., RESAP-type routines) [13,61,64,66]. Time-domain studies may incorporate multilayer effects via calibrated parameters and broadband equivalents [7,39].

Limitations/pitfalls. A major pitfall is insufficient site characterization: limited-depth resistivity measurements can yield non-unique layer fits, and spatial variability across the farm footprint is often ignored [22,23,64]. Sensitivity to layer assumptions should therefore be reported explicitly rather than presenting a single deterministic result [6].

Practical implications. For design studies, multilayer soil modeling (at least two-layer when justified by measurements) should be treated as a baseline rather than an optional refinement, particularly when lightning transient performance is the target [6,22,61]. This supports more credible grounding choices and can reduce mismatch between predicted and observed behavior [23].

What to do next. Future work should promote uncertainty-aware reporting (layer-fit ranges and sensitivity envelopes) and benchmark cases that link multilayer identification to transient validation metrics [6,23].

3.7. Lightning Attachment and Waveform Variability

Problem definition. Lightning attachment location (blade/tower pathways) and lightning current waveform variability (first vs. subsequent strokes, polarity, and front-time differences) influence how transient currents distribute through the WT structure and into the ground. The modeling problem is to capture how different representative waveforms and injection paths interact with wideband grounding impedance and farm/network coupling [3,9,11,47,48,65].

Why it matters. Different waveforms emphasize different physical mechanisms: fast-front currents increase the relevance of inductive/capacitive and coupling effects, while longer-duration components stress current-dissipation and low-frequency grounding performance. Several WT grounding studies explicitly compare first/subsequent representative currents and show that conclusions (e.g., the benefit of interconnection or the importance of frequency dependence) can depend on waveform characteristics [4,11,47,65].

How studies model it. Common practice is to evaluate a small set of representative lightning current waveforms (e.g., varying front-time and duration) and to compare responses for first and subsequent representative strokes, sometimes within farm-scale configurations [9,11,65]. Attachment and current-path assumptions are handled either by selecting the injection point(s) in circuit/EM models or by using scaled/lab configurations for validation of induced/overvoltage behavior [12,20,36].

Limitations/pitfalls. A common pitfall is drawing general conclusions from a single waveform or a single attachment assumption. Because waveform statistics are site- and storm-dependent, a limited waveform set may under-represent uncertainty unless treated as a sensitivity axis [3,65]. Moreover, if grounding is modeled as purely resistive, waveform-driven differences can be distorted for fast-front cases [14,31].

Practical implications. Engineering studies should test robustness against waveform variability by using a small, clearly documented set of representative waveforms and injection paths consistent with IEC 61400-24 practice [3,65]. This supports more defensible insulation coordination, SPD selection, and grounding/interconnection decisions under realistic uncertainty [8,25].

What to do next. More measurement-linked data on WT lightning currents and attachment-path effects would improve representativeness and help validate simulation assumptions [1,23].

3.8. Time-Domain Wave Propagation Mechanisms in Grounding and WT Structures

Problem definition. WT structures and grounding conductors are electrically long at lightning-relevant frequencies, so lightning response involves traveling-wave propagation, reflections, and distributed coupling rather than instantaneous lumped behavior. The modeling problem is to capture time-domain propagation along towers, cables, and grounding electrodes and its interaction with soil and interconnections [39,42-44,50].

Why it matters. Wave-propagation effects can shape the early-time GPR and overvoltage waveform and can create oscillatory behavior in some configurations. They also motivate the concept of an effective electrode utilization under fast impulses, where distributed geometry and propagation determine how quickly different portions of the grounding system participate [42,44]. Consequently, purely resistive (or overly lumped) grounding representations can mischaracterize waveform peaks and timing [14,31].

How studies model it. Time-domain approaches include TLM/FDTD and distributed-parameter representations integrated into EMT tools, while frequency-domain field solutions are also converted to time-domain via broadband fitting [14,39,42,43,58]. WT-specific transient models connect blade/tower representations to grounding and cables so that propagation and coupling are represented in system-level studies [12,36].

Limitations/pitfalls. High-fidelity propagation modeling can be computationally intensive and sensitive to discretization choices (time-step, segmentation and mesh), while parameter identification for distributed equivalents may be non-trivial [39,42]. Without clear bandwidth and fit-quality reporting, time-domain waveforms obtained from wideband conversion may include numerical artifacts [14,58].

Practical implications. Propagation-aware modeling supports more reliable conclusions about grounding configuration effectiveness for fast-front events and helps prioritize mitigation measures (bonding continuity, multi-point grounding, and coordinated network protection) [25,36,44]. In practice, this reinforces that EMT studies should incorporate validated wideband grounding models when waveform timing and peak values are design-critical [14].

What to do next. Future work should expand benchmark validation of propagation-sensitive cases (including multi-turbine layouts and collector-network interaction) and report reproducible best practices for wideband fitting and verification in WT lightning studies [9,14,58].

4. Classification framework

Because lightning is a broadband transient and because WT grounding involves coupled electromagnetic and soil phenomena, the modeling literature reviewed in this paper can be interpreted more consistently when grouped along a small set of criteria. We adopt the following framework to classify the approaches already discussed throughout this section, with the goal of clarifying what each method can (and cannot) capture, what it typically costs computationally, and how it is validated.

Domain (time/frequency/wideband). Time-domain models directly compute waveforms (e.g., GPR and over-voltages in the time axis) and are often implemented in EMT programs using equivalent circuits and transmission-line elements [25,28,36]. Frequency-domain models compute impedance or admittance and field quantities over frequency and then interpret the transient behavior via inverse transforms or broadband equivalents (commonly supported by rational fitting/state-space realizations) [4,5,14]. Wideband approaches explicitly target a consistent behavior from low frequency up to the MHz range by combining a broadband field/circuit formulation with a frequency-to-time workflow (e.g., vector fitting) [7,9,12].

Model assumptions (lumped vs. distributed; quasi-static vs. full-wave; linear vs. nonlinear). Lumped or circuit-oriented representations are efficient and practical for parametric design studies, but their fidelity depends on how grounding, cables, and towers are parameterized (and on whether frequency dependence is embedded) [25,36]. Distributed formulations capture propagation and coupling more explicitly: this includes time-domain grid-based solvers (e.g., FDTD/TLM) [39,42] and frequency-domain thin-wire/full-wave formulations (e.g., MoM/NEC-type models) [14,54]. In addition, some works incorporate nonlinear soil behavior (ionization), which is particularly relevant when studying extreme impulses and/or specific soil conditions; this adds modeling uncertainty and algorithmic complexity compared with linear soil models [26,37,39].

Soil representation. The soil model is a dominant source of variation in predicted impulse impedance and GPR. The reviewed studies span (i) uniform soil, (ii) multilayer soil, and (iii) heterogeneous soil, with further refinements such as frequency-dependent electrical parameters and ionization effects [4,6,7]. In practice, the chosen soil representation should match the question being answered: simplified uniform soils can support early-stage comparisons, whereas multilayer/frequency-dependent models are more appropriate for broadband transient predictions and for site-specific studies.

Computational complexity and typical bottlenecks. For clarity, we refer to qualitative complexity levels. Low complexity methods include circuit EMT studies where bottlenecks are mainly parameter identification and model tuning (especially for grounding wideband equivalents) [25,36]. Medium complexity methods include quasi-static FEM/BEM-type analyses and many frequency-domain impedance computations where meshing, integral evaluations, and frequency sweeps become limiting factors [13,33]. High complexity methods include full-wave or strongly distributed models (e.g., FDTD/TLM, large MoM/PEEC networks) where bottlenecks are memory/time-step constraints, large matrix solutions, and broadband sampling/fitting [9,12,42].

Expected accuracy and validation style. In this review, “accuracy” is interpreted in terms of agreement with one or more validation sources. Some studies are grounded in field or laboratory measurements [20,22,23], while many modeling papers rely on simulation cross-checks between different formulations or tools (e.g., circuit vs. field solver, or commercial vs. in-house implementations) [6,13]. Measurement-based validation typically provides the strongest evidence for model adequacy, whereas cross-checks are useful for establishing internal consistency and identifying sensitivity to assumptions.

Industrial applicability. Finally, the methods can be grouped by intended use: design-stage and compliance-oriented workflows often favor faster circuit or commercial grounding tools [3,6]; detailed R&D studies use full-wave/wideband solvers to investigate coupling, wave effects, and model limitations [9,54]; and site-specific characterization relies on measurements and calibrated soil models [22,23].

Table 3 provides a compact method comparison matrix using comparative indicators (domain, soil/coupling capability, validation style, qualitative computational cost, best-use, and main limitations). This complements the narrative by making cross-method tradeoffs explicit without introducing numeric performance metrics.

Table 3. Method comparison matrix with comparative indicators for WT grounding and lightning modeling (representative sources already cited in this manuscript). Domain: T = time-domain; F = frequency-domain; WB = wideband/hybrid. Cost is qualitative (no numeric metrics).

Method family (rep.\ sources)	Domain	Soil capability	Coupling capability	Validation type	Cost	Best-use	Main limitations
Empirical/measurement-driven [22,23]	T/F	Measured/inferred parameters; layering may be implicit	Limited control of coupling; site-specific configurations	Field/lab measurements	Low	Soil/grounding parameter identification; benchmark reference points	Site-specific; limited separation of mechanisms; instrumentation constraints
Circuit-based EMT (EMTP/ATP) [25,36]	T	Uniform/multilayer via parameters; freq-dep via equivalents; ionization optional	Network-level coupling modeled; structural EM coupling simplified	Case studies; cross-checks (sometimes measurement-linked)	Low--Med	System studies (collector network, SPDs, insulation coordination); comparative configurations	Accuracy depends on grounding equivalent and validity bandwidth; simplifications of geometry/coupling
Quasi-static FEM/BEM field solvers [33,13]	F/WB	Multilayer supported (tool/formulation dependent); typically linear	Mutual coupling among electrodes/structures captured under QS assumptions	Benchmark/cross-tool comparison; literature validation	Med	Geometry/soil-profile sensitivity; design refinement under controlled assumptions	QS approximation limits propagation realism; sweep cost (meshing/frequency sampling)
Distributed time-domain EM (FDTD/TLM) [42,39]	T	Uniform/non-uniform; ionization/freq-dep study-dependent	High (propagation, reflections, spatial coupling)	Cross-checks; sometimes measurement comparison	High	Wave-propagation/front-time sensitivity; mechanism studies	High computational burden; discretization/dispersion sensitivity; large domains difficult
Thin-wire MoM/NEC-type + wideband fitting [54,14]	F/WB	Uniform/multilayer possible; typically linear; wideband impedance extraction	High (inductive/capacitive coupling among conductors)	Cross-checks; consistency across domains	Med--High	Coupling mechanism analysis; generation of EMT-ready multi-port equivalents	Matrix size/conditioning; segmentation sensitivity; requires careful broadband sampling/fitting
Hybrid EM (HEM) + VF/state-space [4,5]	F/WB	Freq-dependent soil emphasized; layering possible; usually linear	Med--High (multi-port grounding and coupling trends)	Cross-check vs.\ simplified models; EMT integration studies	Med	Systematic soil-dispersion sensitivity; EMT-compatible equivalents	Fit/bandwidth diagnostics required; results depend on soil model choice/calibration basis
PEEC/integrated WT + network formulations [12,9]	WB	Uniform/layered possible; freq-dep study-dependent	High (multi-conductor + network coupling)	Cross-checks; case studies (validation often limited by measurability)	High	Integrated turbine--collector network transient stress allocation	High modeling/setup cost; geometry detail sensitivity; wideband conversion requirements
Commercial grounding packages (CDEGS/XGSLab-type) [6,60]	F/WB	Multilayer or heterogeneous fitting workflows; freq-dep modules available	Med (geometry coupling strong; network coupling depends on workflow/integration)	Benchmarking; engineering cross-checks	Med	Engineering practice/compliance workflows; complex geometry + soil interpretation	Tool/module assumptions must be understood; transient validity depends on selected modules and inputs
Optimization/parameter-tuning [15,16]	T/F	Depends on embedded solver; often uses fitted soil/electrode parameters	Typically low--med unless integrated with multi-port/full-wave models	Case-study driven; sensitivity-based justification	Med	Design improvement and decision support (screening alternatives)	Quality limited by underlying model fidelity; can hide uncertainty if not reported

Transition: from organization to comparative synthesis. Using the above framework and the method matrix in Table 3, the next section synthesizes comparative indicators across studies (recurring qualitative findings, failure/overvoltage modes, and mitigation implications) without resorting to paper-by-paper narration or introducing new numeric performance metrics.

5. Comparative analysis

This section extracts and synthesizes *comparative indicators* across the reviewed literature using the classification axes defined in Section 4. The emphasis is on cross-study patterns (rather than paper-by-paper description), including soil modeling choices (dispersion/stratification), coupling and propagation paths at wind-farm scale, qualitative treatment of ionization, typical failure/overvoltage modes, and practical mitigation implications. Table 2 summarizes these recurring qualitative takeaways.

Comparative indicators across findings (cross-study takeaways). To complement the method comparison in Table 3, Table 4 summarizes recurring qualitative findings and design-relevant takeaways across the reviewed literature, grouped by themes (rather than paper-by-paper).

Synthesis (patterns across methods and findings).

5.1. Critical Comparative Analysis

The classification in Section 4 and the mapping in Table 3 make the reviewed literature easier to navigate; however, a high-quality review must also explain *why* different approaches produce different results and what this means for engineering design. In lightning-driven WT grounding studies, discrepancies across methods are not accidental—they typically arise from (i) the physics that is *included or excluded* (propagation, coupling, inductive/capacitive storage, soil dispersion and nonlinearity), and (ii) numerical choices (meshing/segmentation, bandwidth and sampling, fitting, and dispersion/stability).

Why methods differ: dominant physical and numerical drivers.

Lightning is inherently broadband; therefore, models that are equivalent at low frequency (e.g., matching DC or 50/60 Hz grounding resistance) can diverge in predicted impulse impedance, GPR peaks, and over-voltage waveforms once inductive and capacitive effects become influential [31,50,55]. Soil representation is another dominant driver: frequency-dependent soil parameters and multilayer/heterogeneous profiles change current diffusion/return paths and modify the wideband grounding impedance [4,6,7,13]. At the wind-farm scale, coupling through inter-turbine conductors and the collection network redistributes transient voltages; thus, isolated single-turbine modeling can miss transfer effects that arise only in interconnected layouts [8,9,11,52].

Table 4. Findings/takeaways matrix grouped by themes. Entries are qualitative patterns synthesized across the reviewed literature (no invented numeric metrics).

Theme	Recurring qualitative findings (patterns)	Design-relevant takeaway (what it implies)	Representative sources
Table 4 (continued). Continued on next page.			
Grounding configuration	Rings, counterpoises, and vertical electrodes can change early-time GPR and impulse behavior; interconnecting turbines can share injected current and alter transferred stresses; diminishing returns may appear for very long conductors under fast-front excitation (effective-length/propagation effects).	Prioritize low-inductance bonding and robust connections; evaluate topology (isolated vs. interconnected; loop vs. chain) under representative waveforms; treat geometry as a transient (not only DC) design variable.	[11,21,35,38,44,57]
Soil resistivity/stratification	Layering and frequency dependence can shift impulse impedance and waveform shape relative to homogeneous/constant-parameter assumptions; limited or shallow soil surveys can yield non-unique fits; seasonal variability can change transient severity.	Use at least a justified multilayer model when measurements indicate stratification; report sensitivity to plausible soil profiles; avoid generalizing from a single "average" resistivity when lightning transients are the target.	[6,7,13,22,23,61,64]
Ionization (qualitative)	Nonlinear soil ionization can reshape transient response in some high-current scenarios, but parameters and triggering conditions are difficult to verify for a given site; conclusions may be scenario-dependent without calibration.	Treat ionization as an explicit modeling assumption; use it for scenario envelopes unless supported by credible benchmarks; avoid presenting ionization-driven mitigation as universally valid.	[26,37,39,45,46]
Failure/overvoltage modes	Beyond local GPR and step/touch hazards, transferred and induced overvoltages can appear through interconnections and collector networks (cable sheaths, MV lines, LV/control circuits); propagation and reflections can contribute to oscillatory or timing-sensitive peaks.	Analyze lightning as a coupled structure + ground + network problem for wind farms; consider both struck and non-struck turbines; ensure model bandwidth matches the front-time sensitivity of the failure mode being assessed.	[8,9,12,29,41,49]
Mitigation measures	Bonding quality, cable sheath grounding choices, SPD placement, and interconnection conductor properties (e.g., bare vs. insulated) can materially influence transferred/induced stresses; wideband grounding equivalents improve EMT credibility for fast fronts.	Coordinate grounding, bonding, and SPDs at farm level; prefer validated wideband grounding equivalents when using EMT tools for lightning; align checks with IEC 61400-24 waveform practice.	[3,9,14,25,40,57]
Practical design implications (cross-cutting)	The dominant drivers of disagreement across studies are typically soil representation (layering/dispersion), coupling paths (farm/network), and bandwidth/propagation effects; validation is often limited by measurement availability and therefore relies on cross-checks.	Report applicability boundaries (bandwidth, soil model basis, topology) and perform sensitivity-based design decisions; where possible, anchor conclusions to measurement-linked datasets or benchmark cases.	[6,9,14,23]

On the numerical side, grid-based solvers (e.g., FDTD/TLM) can exhibit numerical dispersion if space/time resolution is not adequate, while frequency-domain workflows require adequate bandwidth sampling and robust broadband-to-time conversion (often via vector fitting/state-space realizations) [7,14,58].

Empirical and measurement-driven evidence: what it validates (and what it cannot)

Field and laboratory measurements provide the strongest grounding for model credibility because they expose real installation details (foundation rebar, soil variability, seasonal conditions, bonding, and measurement constraints) that are difficult to idealize. Measurement-based studies are therefore essential for calibrating soil parameters and validating impedance/response trends [20,22,23]. Their limitation is that measurements are often site-specific and do not directly separate individual mechanisms (e.g., soil dispersion vs. geometry vs. coupling), which means they are most powerful when used as reference points for model tuning and cross-validation rather than as stand-alone generalizations.

Circuit-based EMT (EMTP/ATP) approaches: fast system studies but sensitive to grounding parametrization

Circuit-based EMT models excel when the engineering question is network-oriented: surge propagation on collector lines, SPD placement, insulation coordination, and comparative evaluation of connection strategies. They are computationally efficient and integrate naturally with turbine electrical subsystems [25,28,29,36]. Their main vulnerability is the representation of grounding and soil over a wide band: if grounding is modeled only as a low-frequency resistance (or with insufficient frequency dependence), early-time peaks and waveform shapes can be mischaracterized because inductive/capacitive storage and distributed coupling are not explicitly represented [31,55]. Some EMT-based works address this by embedding frequency-dependent grounding models and/or incorporating soil ionization elements [25,26,37], but these additions introduce parameter-identification and validation demands that must be treated explicitly.

Quasi-static and hybrid EM frequency-domain methods: controlled geometry/soil modeling, but still assumption-driven

Quasi-static field solvers (e.g., FEM) and multilayer-capable formulations (e.g., BEM in multilayer soil) are valuable for understanding geometry-driven effects and soil-profile sensitivity under controlled assumptions [13,33]. Hybrid electromagnetic modeling (HEM) plus broadband workflows is especially effective for systematically studying frequency-dependent soil parameters and for producing EMT-ready equivalents through fitting [4,5,10,47]. The key limitation is that “quasi-static” and “hybrid” approaches still depend strongly on the chosen boundary conditions, the modeled frequency range, and how the frequency response is mapped into time domain. As a result, two studies can both be “frequency-domain” yet disagree if one uses simplified soil/return assumptions or a narrower bandwidth, or if the broadband conversion is insufficiently representative.

Full-wave and distributed time-domain solvers (FDTD/TLM): propagation realism at higher computational and modeling cost

Distributed time-domain solvers explicitly represent wave propagation, reflections, and spatial coupling, making them well-suited for studying lightning front-time sensitivity and geometric scale effects [39,42,44]. These benefits come with higher computational cost and practical numerical constraints: grid resolution and time-step selection influence accuracy (including numerical dispersion), and absorbing boundaries/soil interfaces must be treated carefully. Consequently, these methods are typically more appropriate for detailed R&D studies or for validating simplified equivalents rather than for routine design iteration.

Thin-wire MoM/NEC-type and wideband equivalents: strong coupling fidelity, but matrix/bandwidth constraints

Thin-wire full-wave formulations (MoM/NEC-type) naturally capture inductive/capacitive coupling among conductors and the frequency-dependent transition from resistive to inductive behavior that is often observed in grounding impedance [53-55]. When coupled with wideband fitting/state-space realizations, such models can provide multi-port equivalents suitable for EMT simulation while retaining broadband characteristics [7,14]. The bottlenecks are the cost and conditioning of large impedance/admittance matrices, the need for careful segmentation (which influences convergence), and the requirement for adequate broadband sampling. Engineering use is therefore strongest when these models are applied to generate validated equivalents or to study coupling mechanisms that circuit-only representations cannot resolve.

PEEC and integrated WT/collector-network modeling: multi-conductor coupling and system context

PEEC-based and related multi-conductor formulations provide a direct bridge between geometry-resolved electromagnetic modeling and circuit-level interpretation, which is particularly valuable when the WT structure, internal conductors, and external network interact strongly [9,12,40]. These approaches can reveal how coupling and topology distribute transient stress across components (tower/blades/cables and network links). Their limitations are similar to other wideband/full-wave approaches: computational cost, the need for careful broadband-to-time conversion, and sensitivity to geometric and soil modeling choices.

Commercial grounding packages and engineering workflows: practical breadth, but module-awareness is essential

Commercial tools (e.g., CDEGS/XGSLab-type workflows) are widely used in engineering practice because they support complex grounding geometries, multilayer soil interpretation, and standardized workflows for grounding assessment [6,9,60-64]. Their practical strength is rapid scenario evaluation and compatibility with compliance/design processes; however, users must remain aware of the underlying modeling assumptions (quasi-static vs. higher-frequency modules, soil fitting choices, and network coupling representations) and should cross-check results when the transient bandwidth or coupling regime pushes beyond the validated scope.

Cross-cutting issue: nonlinear soil ionization (when it matters, and why it is uncertain)

Nonlinear soil ionization models can alter predicted impulse behavior and waveform shapes under high-current conditions, and they appear in multiple modeling families (from EMT circuits to distributed solvers) [26,37,45,46]. Their main challenge is that ionization parameters and triggering conditions are difficult to verify for a specific site and installation; therefore, ionization-enhanced predictions should be treated as scenario-dependent unless supported by site-calibrated evidence or credible experimental benchmarks.

Another potential research direction is the *long-term conditioning* of soil by repeated lightning strikes. Experimental evidence indicates that lightning-induced heating and melting can form fulgurites and increase the resistivity of the affected material, which may raise the effective grounding/earthing impedance and compromise long-term performance [71]. Since grounding characteristics and soil properties can vary over time and with site conditions, future work should verify and quantify whether repeated strikes produce persistent changes that warrant periodic reassessment using established measurement procedures (e.g., IEEE Std 81.2-1991) [72]. Table 5 presents the mini-matrix of common modeling assumptions and their typical consequences and engineering risks.

Reviewer-facing synthesis (explicit, non-generic takeaways).

- Even when two studies match DC grounding resistance, their lightning transient predictions can diverge if one includes inductive/capacitive effects and the other uses a purely resistive grounding equivalent [31,55].
- Frequency-dependent soil modeling is not a "detail": it is a primary driver of wideband grounding impedance and can change impulse-response trends compared with frequency-independent assumptions [4,6,7].
- Layered-soil formulations (e.g., multilayer-capable BEM/MoM workflows) can capture behaviors that homogeneous-soil simplifications inherently miss, especially when interpreting broadband responses [7,13].
- Wind-farm interconnection and collection-network paths are essential to the overvoltage story; isolated single-turbine models cannot represent transferred surges and coupling-driven redistribution [8,9,11].
- EMT tools are highly effective for system studies (SPDs, network surges, comparative grounding connection strategies), but they require validated wideband grounding equivalents to remain credible for fast-front lightning behavior [25,36].
- Full-wave/distributed methods (FDTD/TLM, MoM/PEEC families) become necessary when propagation and multi-conductor coupling determine stress allocation, rather than only steady-state or low-frequency grounding performance [9,12,14,42].
- Broadband-to-time conversion (often via vector fitting/state-space realization) is a powerful bridge from field solvers to EMT simulation, but its validity depends on the chosen bandwidth and fit quality [14,58].

Ionization models can strongly influence impulse-response predictions in some scenarios, but because site-specific parameter verification is difficult, conclusions should be framed as scenario-dependent unless validated [26,37,46].

Overall, the practical implication is that the "best" method depends on the engineering question: EMT-based models are often sufficient for rapid network-level mitigation studies and comparative grounding connection strategies, while wideband/full-wave or distributed solvers are justified when the dominant uncertainties are broadband soil behavior, wave propagation, and multi-conductor coupling (especially in wind-farm configurations and collector-network contexts).

5.2. *Significance of Time-Domain versus Frequency-Domain Modeling in Lightning Effects on WTs and Tall Structures*

The phenomenon of lightning can be represented as a transient current waveform whose relevant content spans a broad range of time scales and frequencies. Consequently, both time-domain and frequency-domain viewpoints are useful: time-domain simulations directly provide waveforms (e.g., GPR and overvoltages), while frequency-domain analyses help reveal how grounding impedance and soil electromagnetic behavior vary with frequency and how this variation maps into transient response. Two recurring factors in assessing grounding effectiveness under lightning are (i) the frequency dependence of soil electrical parameters over the lightning-relevant bandwidth, and (ii) potential nonlinear soil behavior (often discussed in terms of ionization) under severe impulsive conditions. The reviewed literature repeatedly indicates that neglecting frequency dependence can bias transient predictions in some scenarios, particularly for higher-resistivity soils and fast-front excitations [6,47,61,62]. By contrast, nonlinear effects are more scenario-dependent and are typically emphasized in studies focusing on high-current impulses and site-specific conditions [5,54]. Overall, incorporating frequency-dependent soil behavior is widely supported as a key step toward more credible transient grounding analysis, while nonlinear soil modeling should be treated with explicit assumptions and, where possible, validation.

Table 5. Mini-matrix of common modeling assumptions and their typical consequences and engineering risks (illustrative patterns observed across the reviewed method families).

Assumption	Typical consequence	Engineering risk
Grounding represented as a single low-frequency resistance (no L/C, no wideband behavior)	Early-time peaks and waveform shapes can be misestimated when inductive/capacitive effects dominate [55,31]	Non-conservative insulation coordination; underestimated step/touch or equipment stress
Frequency-independent soil parameters used for lightning-relevant bandwidth	Wideband impedance differs from reality; impulse impedance/GPR trends can shift [4,6]	Incorrect grounding sizing or mitigation priority for high-resistivity sites
Homogeneous soil assumed where multilayer/heterogeneity is present	Return-current distribution and attenuation differ from assumed behavior [13,7]	False confidence in design robustness across seasons/locations
Single-turbine model used for a wind-farm problem (neglect coupling and network paths)	Transfer and redistribution of transient voltages are not captured [8,9,52]	Misplaced SPDs/bonding; overlooked inter-turbine stress paths
Quasi-static approximation applied where propagation/reflection effects are relevant	Resonances and propagation-driven wave effects are suppressed or missed	Underestimation of cable/collector-line surge effects and timing-dependent peaks
Wideband fitting performed with insufficient frequency range or inadequate sampling	Time-domain response may not reflect the intended broadband behavior [58,14]	Non-robust conclusions from artifacts; incorrect mitigation ranking
Coarse spatial/temporal discretization in grid-based solvers	Numerical dispersion and stability constraints influence waveform fidelity	Design choices based on numerically distorted peaks/timings
Ionization included without site-calibrated evidence or credible benchmark comparison	Nonlinear mitigation effects may be over- or under-estimated [26,46]	Overconfident risk reduction claims; unreliable worst-case assessment

5.3. Evaluation of Approaches, Methods, and Simulation Tools Across Reviewed Studies

This classification goes further than the writing methods of the articles; it also notes if the techniques concern time or frequency: what kinds of software are used (specific or general), and whether such software was used to solve models or to build them. In the development of software tools, however, a clear and marked evolution has occurred. First it started with the use of experimental approach, followed by the analytical and finally the use of scientific /number-based software or both. This change has facilitated modeling structuring and control of models in time and frequency domains much better. Because of the development in computer technologies, the application of lightning phenomena was earlier restricted to some experimental analytical or numerical ones, which in any case yielded approximate results, to say the least when performed by an ordinary software. Although there are large scale studies with respect to current through lightning on earthing networks, such studies were likely deficient due to classical software limitations leading to guesstimates and relatively imprecise results (2018 [14]). This has persisted up to the recent past, whereby increasing numbers of interventions have considered commercial software for analyses based on numerical solutions of Maxwell equations. Such technologies can provide detailed representations of lightning activity, including spatial/temporal characteristics and propagation-related effects. Nevertheless, commercial toolchains can be costly, which may limit their accessibility for some users. Examples include XGSLAB and CDEGS software.

5.4. Prevalence and Distribution of Analytical and Computational Approaches in the Literature

Figure 1 shows the distribution of modeling approaches in the reviewed core set; circuit-based EMT studies implemented in EMTP-type tools appear most frequently. There are only a few articles with off-the-shelf models built into them. Fitting has been an effective approach in the papers for changing the obtained frequency models to time models and achieving convenience in solving the equivalent models. Next, the reason why these articles also employed the MOM technique for such application is that this technique gives good results and the problem being studied is of a high frequency nature. In the end, it also turned out that CDEGS software which is an elaborate system of components used for studying different sweat such as the Influence of Lightning Strikes on Tall Structures and Windmills has been used many times.

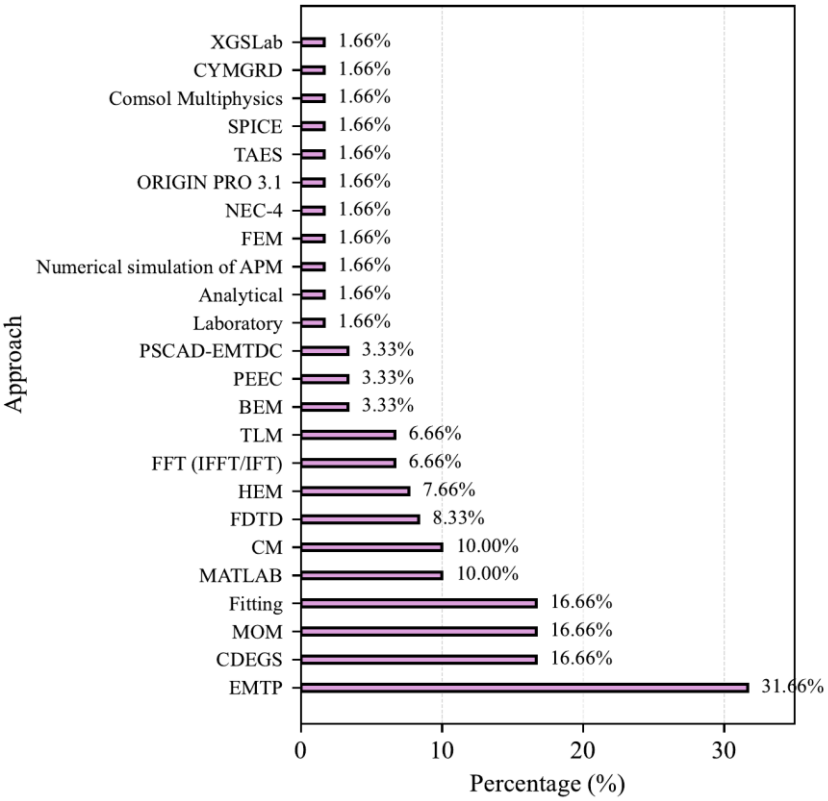


Figure 1. Distribution of modeling/analysis approaches reported in the reviewed lightning–WT grounding literature. The horizontal axis shows the share of reviewed studies (%) in which a given approach/tool is used (alone or within a hybrid workflow); the values annotated on the bars indicate the same percentage. The vertical axis lists the approach/tool categories used for classification.

Table 6 evaluates the extent of the multidimensional approach as well as using any one of the approaches as the only option in the literature reviewed, indicating the per cent of the approach used only and together with other approaches.

Note that the quantitative counts reported later (e.g., Figures 1–5 and Table 4) are computed from the core set of ~60 grounding-focused studies reviewed; additional contextual references added for completeness are not included in those counts.

For instance, looking at the fourth row in the table, BEM appears in two studies within the reviewed core set (~60 studies), and in both cases it is complemented by an FFT-based technique. Also, as it can be seen from the last row in the table, CDEGS software is used in ten studies within the reviewed core set; in eight of those, the software is used as a standalone tool. One study combines it with PSCAD/EMTDC, while another introduces CDEGS alongside EMTP and fitting techniques.

5.5. *Critical Components of WT and Tall Structure Lightning Protection Systems for Modeling*

A further question that may arise is: what finally is the part of lightning protection of a WT and tall structures that can be focused on the most?

This is also an important question, especially if we talk about modeling resources – be it modeling efforts devoted to a particular aspect, the modeling cycle in regards to parameters and hardware limitations, we are usually interested only in what called 'the wicked component'. This way, we are in a position not to allow excessive modeling accuracy x which relates to some of the dimensions of the model, and, saves us so-called underfitting and overfitting modeling challenges and their effects. In this section, we cite and respond to concerns raised in papers that have been reviewed. A number of scientists emphasize that the most complicated process of modeling the components of a WT is the modeling of the earthing system. The following studies include these publications among years of publication: [34] 2016, [64] 2019, [52] 2018, [63] 2019, and [51] 2018. Further works advanced and stated that the only system that needs to be modeled is the Earth system: 2015 [50], 2019 [20], 2017 [47], 2019 [54], 2018 [35], 2017 [27], 2023 [9], 2016 [42], 2019 [4], 2021 [44], 2013 [45]. Within the core set of approximately sixty reviewed studies, five specifically cited the simulation of WT grounding-system components as an existing modeling gap. Seventeen of the articles, however, the authors maintained that it is not essential to model the other components of a WT apart from the grounding system, since the results obtained without modeling such components do not differ from those obtained when modeling all the components.

5.6. *Extent of Modeling Efforts for WT Protection Systems and Transmission Line Towers*

This section of the research is concerned with assessing the specific focus areas encompassed within the interpretative framework of the completed works. The current analysis will, afterwards, assess the extent to which the foundational system has been revisited independently, or where required, along with any of the individual components of each structure, all the structures, or in all the systems as a whole.

Table 6. The amount of use of approaches independently or in combination with other approaches in the reviewed core set of studies (~60), reported as counts.

Approach	The number of use of the approach	Use the approach in combination with	The number of use the approach independently
Laboratory	1	-	1
analytical	1	-	1
Numerical simulation of APM	1	-	1
BEM	2	FFT(IFFT/IFT)(2)	0
FEM	1	-	1
FDTD	5	EMTP(1),TLM(1)	3
NEC-4	1	MOM(1)	0
PEEC	2	Fitting(1),SPICE/TAES/Fitting(1)	0
ORIGIN PRO 3.1	1	MATLAB(1)	0
TAES	1	PEEC/SPICE/Fitting(1)	0
SPICE	1	PEEC/TAES/Fitting(1)	0
Comsol Multiphysics	1	MATLAB/EMTP(1)	0
PSCAD-EMTDC	2	MATLAB/CYMGRD(1),CDEGS(1)	0
FFT(IFFT/IFT)	4	BEM(2),MOM/CM(2)	0
MATLAB	6	ORIGIN PRO3.1(1), MOM(1),EMTP/Comsol Multiphysics(1),CYMGRD/PSCAD-EMTDC(1)	2
TLM	4	FDTD(1)	3
CM	6	MOM/IFT(2),EMTP(3)	1
HEM	7	EMTP/Fitting(4)	3
MOM	10	Fitting(1),\ EMTP/Fitting(2),\ MATLAB(1),\ NEC-4(1),\ CM/IFT(2)	3
EMTP	19	MATLAB/Comsol Multiphysics(1),\ FDTD(1),\ HEM/Fitting(4),\ MOM/Fitting(2),\ CM(3),\ CDEGS(1)	7
Fitting	10	PEEC(1),\ PEEC/TAES/SPICE(1),\ MOM(1),\ EMTP/MOM(2),\ EMTP/HEM(4),\ EMTP/CDEGS(1)	0
CYMGRD	1	MATLAB/PSCAD-EMTDC(1)	0
XGSLab	1	--	1
CDEGS	10	PSCAD-EMTDC(1),EMTP/Fitting(1)	8

Figure 2 shows the level of attention reserved for the reviewed papers in terms of the proportion of topics on one WT, a cluster of interconnected WTs, wind farms, towers, or high voltage structures. From that graph, it can be inferred that the majority of the reviewed papers were on the single WT while the rest covered inter-connected WTs or a wind farm which is also true in reality as WTs are manufactured in a wind farm. Not so much research was published regarding towers or other tall buildings designed to carry high loads of wind. However, it is also due to the fact that these are pretty much WT-like although having very different applications and shapes such studies would be applicable for WTs as well.

The subsequent diagrams illustrate the extent of detail, in terms of the ground system, that various constructions seen in the research articles were modelled both separately and together. Such constructions are, for example, erecting a single WT, several WTs in a cluster and a tower, as shown in Figure 3. Each of the categories is assigned a percentage. It is observable that throughout the three classes of structures that were reviewed, the focus and concern towards the problem of grounding system alone, considering other structures is out of question, is much higher than that involving the issue of grounding system integration with other structures.

Lastly, As shown in Figure 4, the discussion is rounded off with an overview to which the only question that arises, how many such articles were there that focused or at least included some research on the grounding grid by itself and how many articles studied articulation of it with other elements of structures grounding system in all the papers.

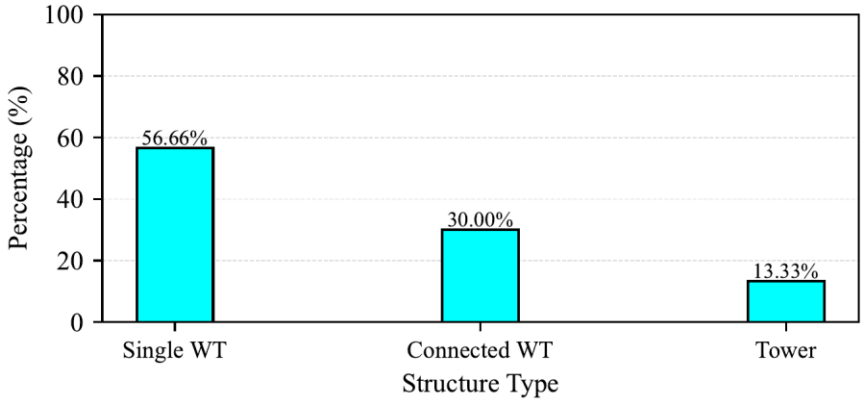


Figure 2. Share of reviewed studies (%) focusing on different analysis scopes: (i) a single wind turbine (Single WT), (ii) multiple interconnected turbines/wind-farm cluster (Connected WT), or (iii) tower-like structures. Percent values above bars indicate the fraction of the reviewed core set assigned to each scope.

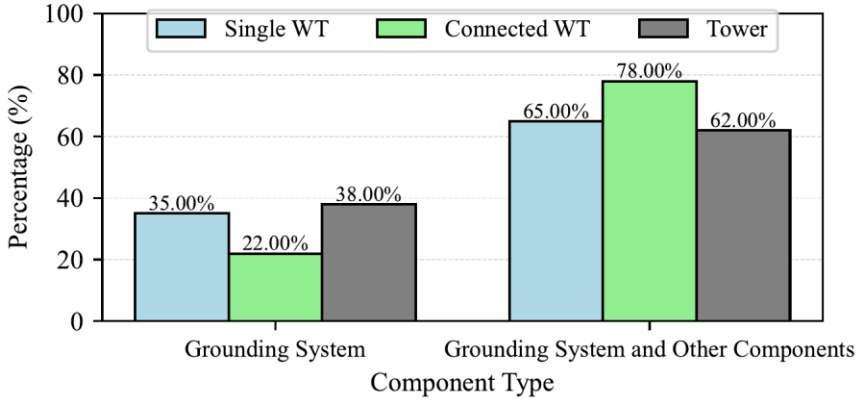


Figure 3. Within each study scope (legend: Single WT, Connected WT, Tower), this figure compares whether the modeled system includes (a) the grounding system alone or (b) the grounding system together with other components (e.g., tower, blades, or connected network elements). The vertical axis reports the share of studies (%) within each scope category; the two x-axis groups indicate the modeled component set.

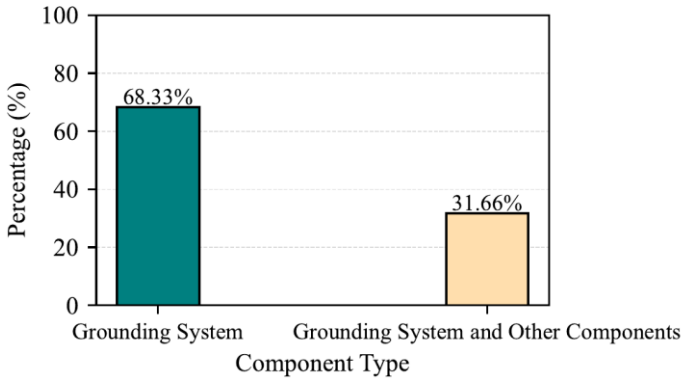


Figure 4. Overall proportion of reviewed studies (%) that model the grounding/earth system alone versus those that model the grounding/earth system jointly with other components. Percent values indicate the share computed over the full reviewed core set.

5.7. Key Insights and Observations from Reviewed Studies

Figure 5 focuses on aspects taken from review articles.

The far greater number of papers referencing frequency-dependent soil characteristics than soil ionization indicates the greater significance of this effect than that of ionization, and more potential for errors arising from its exclusion from numerical models. It is only a small number of papers that have tried to balance the intricacies of including both effects, and thus provide more realistic models. The next three columns show the percentage of articles that considered the soil to be uniform, non-uniform, or both uniform and non-uniform, which, as can be seen, a higher percentage of articles assumed the soil to be non-uniform because soil is inherently non-uniform. The next three columns also show the status of lightning studies in studies, where the first column shows the percentage of articles in which lightning with different parameters was used and studied, the second column shows the percentage of articles in which lightning with direct and indirect impacts was used and studied, and the third column shows the percentage of articles in which lightning with different parameters and also with direct and indirect impacts was used and studied. It can be inferred from these three columns that there is more focus on the discussion of different lightning with different parameters. The last three columns are dedicated to studies related to changes in soil resistance, transmission voltage in wind farms, and the effect of lightning at high, low, and medium frequencies.

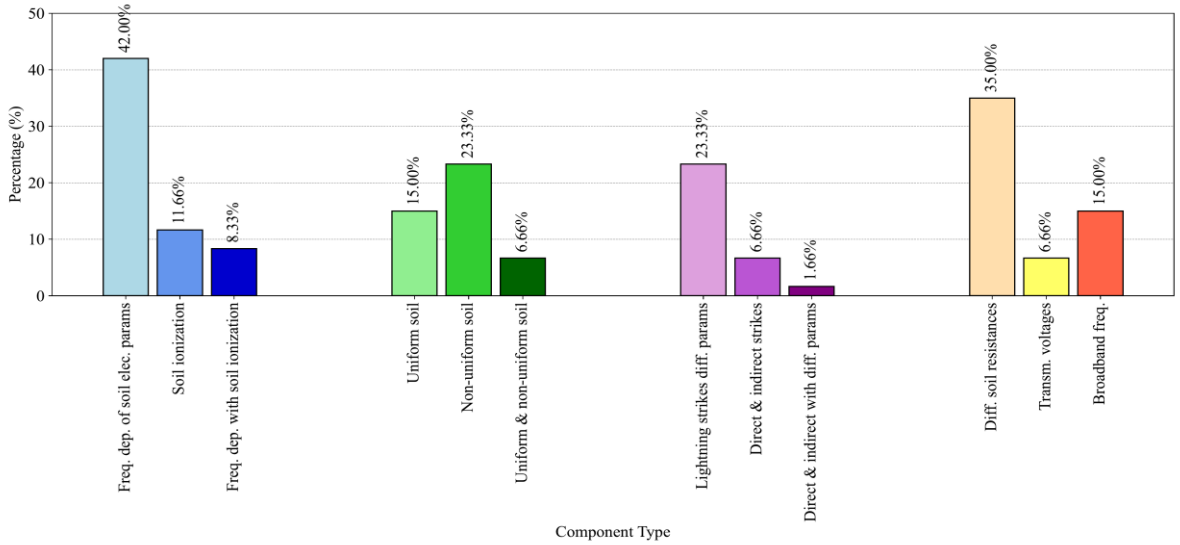


Figure 5. Coverage of selected modeling topics in the reviewed core set. Each bar reports the share of studies (%) that explicitly address the corresponding topic tag (e.g., frequency-dependent soil electrical parameters, soil ionization, soil heterogeneity, lightning-parameter variability, direct/indirect effects, and system-level operating factors as labeled on the x-axis). Multiple tags may apply to the same study; therefore, percentages across bars are not expected to sum to 100%. Abbreviations on the x-axis follow common usage (e.g., “Freq dep.” = frequency-dependent; “Diff.” = different; “Transm.” = transmission).

5.8. Relation to Standards and Practice

According to *IEC 61400-24:2019* (see the 2018 revision discussion in [73]), wind turbine lightning protection and the associated earthing design are treated as an integrated system and aligned with general lightning protection principles (e.g., IEC 62305 series). In practice, each turbine is commonly equipped with a dedicated earthing arrangement (e.g., foundation electrode and/or a ring conductor) and the design objective is to achieve a low overall earthing impedance; guidance documents often describe target grounding resistance values on the order of 10 Ω as a practical benchmark [74]. The present findings are consistent with this direction: reducing earthing resistance and improving equipotential bonding among conductive components are associated with lower lightning surge–induced ground potential rise, supporting the emphasis on coordinated LPS/earthing design in the standard [73]. Moreover, personnel safety considerations require limiting hazardous potential gradients (step and touch voltages) during abnormal conditions, which is consistent with commonly cited safety guidance [75].

Practical design and operational implications:

- Provide each turbine with a low-impedance earthing network (e.g., ring conductor and/or deep rods as applicable) and verify that the resulting grounding resistance is kept low, typically on the order of 10 Ω as a practical benchmark [74].
- Ensure equipotential bonding among major metallic parts (e.g., tower, nacelle, and electrical equipment) to reduce dangerous voltage differences during lightning events [73].
- Evaluate step and touch voltage conditions under relevant worst-case scenarios and apply mitigation measures (e.g., surface layer/gravel, gradient control) if required by safety criteria [75].
- Use a robust lightning interception and conduction path (e.g., blade receptors and down-conductors) so that high lightning currents are safely conveyed to the grounding system [76].

Adopt operational safety procedures during thunderstorms (e.g., avoiding exposed maintenance activities and following site safety guidance) as emphasized in wind-turbine lightning protection practice [76].

6. Challenges and research gaps

A central objective of this review is not only to summarize modeling approaches, but also to extract the *dominant challenges* that repeatedly shape the lightning response of WT grounding systems and to identify the *research gaps* that limit predictive reliability and industrial transfer. Based on the reviewed studies, the gaps can be grouped into the following taxonomy (used to organize the discussion below):

- Soil and site representation gaps: multilayer/heterogeneous soils, frequency dependence of soil parameters, seasonal variability, and nonlinear effects (e.g., ionization) that are difficult to calibrate [6,7,13,64].
- Model-fidelity vs. practicality gaps: limitations of EMTP-type equivalents, quasi-static assumptions, and the difficulty of producing validated wideband equivalents for fast-front lightning studies [14,25,31,49].
- Source and excitation representation gaps: lightning waveform variability (front time, stroke type, subsequent vs. first strokes) and how it interacts with wideband grounding behavior [4,9,47,48,65].
- System-level interaction gaps: wind-farm coupling, inter-turbine interconnections, and collector-network paths that redistribute transient stresses beyond an isolated turbine [8,9,11,52,57].

Validation and benchmarking gaps: limited field/lab datasets, inconsistent reporting, and heavy reliance on simulation cross-checks rather than reproducible measurement benchmarks [20,22,23,42,67].

Seasonal changes in soil state, wet/dry cycles and freezing/freeze–thaw, can shift soil resistivity and therefore the effective grounding impedance seen by lightning currents, leading to season-dependent GPR and overvoltage predictions. IEEE guidance emphasizes that earth resistivity varies with both temperature and moisture and can increase rapidly in frozen conditions, motivating explicit seasonal envelopes rather than a single “average” soil model [77]. Accordingly, a key research gap is the integration of time-varying (or scenario-based) soil parameterizations and seasonal measurement campaigns into transient validation and sensitivity reporting for WT grounding studies.

6.1. Multilayer and heterogeneous soil modeling

- Challenge. Many WT grounding studies simplify soil as homogeneous, while site reality is often layered and spatially variable; this affects return-current distribution and the effective grounding impedance under lightning excitation.
- Evidence in reviewed studies. Multilayer or two-layer soil modeling appears explicitly in measurement-driven and numerical studies [6,7,13,22,23,61,64,66].
- What the literature often assumes. Idealized layer interfaces, limited parameter sets, and/or site-specific soil fits that are not always transferable across seasons or neighboring turbines [6,64].
- What is missing (gap). (i) systematic sensitivity studies across plausible layer profiles for a given site, (ii) common reporting of soil-identification workflow and uncertainty, and (iii) multi-turbine soil characterization (spatial correlation) at wind-farm scale.

Recommended direction. Establish a consistent workflow combining site measurements with calibrated multilayer models, and explicitly propagate soil-parameter uncertainty into GPR/overvoltage predictions (scenario envelopes rather than single curves) [22,23,64].

6.2. Frequency-dependent soil parameters and wideband grounding behavior

- Challenge. Lightning transients excite a wide frequency band; soil electrical parameters and grounding impedance can be frequency dependent, which changes impulse impedance, GPR peak, and waveform shape compared to frequency-independent assumptions.
- Evidence in reviewed studies. Frequency-dependent soil models and their impact on lightning response are emphasized in hybrid/wideband and CDEGS-based studies [4-7,47,62].
- What the literature often assumes. Frequency dependence is either neglected or implemented with a specific empirical model without clear guidance on selection/calibration for a given site [6].
- What is missing (gap). (i) unified comparison of different soil-dispersion models under identical geometry/waveforms, (ii) clear conditions under which frequency dependence is essential vs. secondary, and (iii) explicit coupling between frequency dependence and wind-farm interconnections.

Recommended direction. Report the modeled bandwidth, soil-dispersion model choice, and calibration basis explicitly; where EMT studies are performed, use validated wideband grounding equivalents rather than purely resistive representations [4,6,14].

6.3. Limitations of EMTP-type (circuit-based) models for lightning grounding studies

- Challenge. EMTP-type tools are highly practical for network studies, but their accuracy depends on the grounding equivalent and the inclusion of distributed coupling and wideband behavior.
- Evidence in reviewed studies. EMT-based WT lightning studies and hybrid workflows are widely used [8,25,28,36]. Multiple works explicitly motivate frequency-dependent and broadband equivalents to avoid overly simplified grounding representations [14,31,49,51].
- What the literature often assumes. Grounding represented by a small set of lumped parameters or low-frequency resistance, with limited discussion of validity bandwidth.
- What is missing (gap). (i) reproducible procedures to derive multi-port, wideband equivalents from field solvers/measurements, (ii) explicit error checks (time-domain waveform fidelity vs. a broadband reference), and (iii) clear guidance on when EMTP is sufficient vs. when full-wave is required.

Recommended direction. Use EMTP for system-level questions (collector network, SPD placement, insulation coordination) while embedding validated wideband grounding equivalents (e.g., via VF/state-space) where fast-front behavior matters **[14,51]**.

6.4. Validation and benchmarking challenges (field/lab evidence vs. simulation cross-checks)

- Challenge. Validation is difficult because lightning transients depend on site soil, installation details (rebar, bonding), and measurement constraints; many papers therefore validate mainly via simulation cross-checks rather than repeatable measurement benchmarks.
- Evidence in reviewed studies. Measurement-based grounding characterization and scaled/lab validation exist but are limited relative to the breadth of modeling papers [20,22,23,42,43,67].
- What the literature often assumes. Idealized geometry/soil inputs and implicit calibration; validation is sometimes limited to agreement with another simulator rather than independent measurements.
- What is missing (gap). (i) shared benchmark cases (geometry + soil + excitation + measurement outputs), (ii) consistent reporting of measurement setup and uncertainty, and (iii) validation of wind-farm-scale coupling predictions.

Recommended direction. Promote benchmark-style reporting: provide geometry description sufficient for reproduction, soil identification method, excitation definition, and a validation metric/acceptance criterion for transient waveforms [23,42].

6.5. Lightning waveform variability and excitation uncertainty

- Challenge. Different lightning waveforms (front times, polarity, first vs. subsequent strokes) interact differently with grounding impedance and wind-farm coupling paths, and can change which component becomes most stressed.
- Evidence in reviewed studies. Multiple works explicitly compare first and subsequent strokes and/or study waveform dependence of impulsive characteristics [4,9,47,48,65].
- What the literature often assumes. A single representative waveform or a narrow set of strokes without systematically exploring waveform sensitivity together with soil-model uncertainty.
- What is missing (gap). (i) a standardized waveform set for comparing methods, and (ii) joint sensitivity studies: waveform × soil model × interconnection topology.

Recommended direction. Treat excitation as a sensitivity axis: evaluate design conclusions under a small, explicit set of representative waveforms (including first/subsequent strokes) rather than a single case [47,65].

6.6. Computational limits of full-wave and wideband methods

- Challenge. Full-wave and geometry-resolved wideband methods (FDTD, MoM/NEC-type, PEEC) provide high fidelity for coupling and propagation but face computational bottlenecks (meshing/time-step constraints, matrix size/conditioning, broadband sampling and fitting).
- Evidence in reviewed studies. Full-wave/distributed and PEEC-type studies are used to capture detailed coupling and distributed voltages [9,12,42,53,54].
- What the literature often assumes. Limited geometric detail or reduced domains to keep runtime manageable; wideband-to-time conversion performed without unified reporting of fit/bandwidth adequacy [7,14].
- What is missing (gap). (i) consistent accuracy-vs-cost reporting, (ii) scalable multi-turbine full-wave validation, and (iii) transparent criteria for broadband sampling and fit quality when creating EMT-ready equivalents.

Recommended direction. Use full-wave studies strategically to (a) identify dominant coupling/propagation mechanisms and (b) generate reduced-order/wideband equivalents for system-level EMT studies, with explicit bandwidth and fit-quality reporting [9,12,14].

6.7. Wind-farm coupling and collector-network effects (system-level gaps)

- Challenge. Wind farms introduce inter-turbine coupling, shared grounding paths, and collector-network surge propagation; isolated-turbine studies can miss transferred overvoltages and redistribution of GPR.
- Evidence in reviewed studies. Interconnected grounding and wind-farm studies address coupling length effects, transferred overvoltages, and network interaction [8-11,38,52,57].
- What the literature often assumes. Simplified representations of interconnections/cables or limited farm size; partial consideration of collector-network elements.
- What is missing (gap). (i) integrated modeling that jointly includes turbine grounding, inter-turbine links, and collector network under consistent wideband assumptions, and (ii) validated guidance for connection strategy and SPD/bonding placement at farm scale.

Recommended direction. Combine multi-port grounding equivalents with network EMT modeling for farm-level studies, and benchmark transferred-overvoltage predictions against measurements or cross-tool validation [9,52].

Table 7 reports the challenges and research gaps of the literature reviewed in this paper.

Table 7. Structured challenges and research gaps extracted from the reviewed literature, with recommended directions supported by representative cited studies.

Challenge	Why it matters	What literature assumes	What is missing	Recommended direction
Multilayer/heterogeneous soil	Changes current return paths and impulse response	Idealized layers; limited uncertainty reporting	Sensitivity + uncertainty propagation; spatial correlation across farm	Calibrated multilayer workflow + uncertainty envelopes [22,23,64]
Frequency-dependent soil parameters	Wideband impedance and waveform shapes shift vs.\ constant-parameter models	Single dispersion model choice; unclear calibration basis	Cross-model comparison under identical cases; explicit bandwidth reporting	Report bandwidth + calibration; embed wideband equivalents in EMT [4,6,14]
Seasonal/temperature-driven soil variability (moisture/freezing)	Soil resistivity (and hence wideband grounding impedance) can differ between wet/dry or frozen/unfrozen states, shifting predicted GPR/overvoltage levels across the year [77].	Time-invariant soil parameters; calibration from a single-season survey.	Limited seasonal field datasets for WT sites and limited use of time-varying soil parameterizations in transient models.	Report seasonal envelopes (wet/dry, frozen/unfrozen) and quantify sensitivity/uncertainty of key transient metrics under plausible seasonal soil states [77].
EMTP-type model limitations	System studies can be misleading if grounding is oversimplified	Lumped or resistive grounding without validity range	Reproducible wideband multi-port equivalent generation + verification	Use VF/state-space equivalents; define applicability boundaries [31,51,14]
Validation and benchmarking	Without independent validation, conclusions may be tool-dependent	Simulation cross-checks more common than measurements	Shared benchmark cases + consistent validation metrics	Benchmark-style reporting + measurement-linked validation [23,42]
Waveform variability	Different strokes/front-times can change the dominant stress mechanism	Single “representative” waveform cases	Joint sensitivity: waveform soil topology	Standard waveform set; report sensitivity of conclusions [47,65,9]
Full-wave computational limits	High-fidelity coupling/propagation is costly at farm scale	Reduced domains; limited cost/accuracy reporting	Scalable multi-turbine validation; transparent fit/bandwidth criteria	Use full-wave to derive validated reduced-order equivalents [12,9,7]
Wind-farm coupling/network effects	Transferred surges and redistribution cannot be captured by isolated models	Small farms or simplified interconnections	Integrated turbine+network modeling under consistent wideband assumptions	Multi-port equivalents + EMT network studies; validate transfers [52,57,9]

6.8. Prioritization of gaps (High/Medium/Low) and rationale

To guide future work, the extracted gaps are prioritized according to their expected impact on transient prediction accuracy and on practical wind-farm design decisions:

- High priority: (i) multilayer/heterogeneous soil representation, (ii) frequency-dependent soil parameters, (iii) wind-farm coupling and collector-network effects, and (iv) validation/benchmarking. These factors frequently dominate discrepancies in GPR/overvoltage predictions and directly influence design decisions [4,9,11,13,23].
- Medium priority: (i) EMTP-equivalent validity boundaries and reproducible wideband model extraction, and (ii) waveform-variability sensitivity when used to generalize conclusions. These are crucial for correct application of methods and for robust mitigation ranking, but they can be addressed once soil and coupling representations are under control [14,31,65].

Low priority (context-dependent): detailed nonlinear ionization modeling without site-calibrated evidence. Ionization can be important in specific scenarios, but parameter verification is often difficult; therefore, it should be treated as scenario-based unless supported by credible benchmarks [26,37,46].

6.9. Additional underexplored directions proposed by this review

Beyond the evidence-linked gaps above, the review suggests several design and modeling directions that appear underexplored and merit systematic study:

- Spatial variability of soil/grounding behavior across a wind-farm footprint and its impact on transient response.
- Non-standard grounding geometries and orientations (e.g., non-coplanar or inclined arrangements) and their effect on impulse behavior.
- Multi-ring or stacked ring configurations and the role of opposing/assisting magnetic coupling between rings.
- Inter-electrode spacing and angular placement strategies for horizontal/vertical electrodes under transient excitation.
- Multi-point observation/measurement perspectives during storms to relate local and transferred voltages.
- Comparative studies of alternative ring shapes (circular, rectangular, triangular, spiral, etc.) under the same soil/waveform assumptions.
- Systematic comparison of interconnection topologies (bridge, ring, partial mesh) across a range of soil conditions.
- Parallel interconnections: number of links vs. effective length and diminishing returns under high-resistivity soils.
- Transferred-voltage studies coupled to grounding configurations under different lightning conditions.
- Development of compact relations linking effective length, burial depth, number of conductors, and soil variability for design-stage screening.

These gaps motivate the practical engineering recommendations and the prioritized future-work roadmap summarized in the Conclusion.

7. Future research roadmap

To complement the challenges and research gaps identified, this section provides a forward-looking roadmap that is explicitly organized into three horizons. The intent is to translate the evidence synthesis of this review into concrete and reproducible next steps for (i) modeling fidelity and practicality, (ii) experimental validation and benchmarking, (iii) numerical acceleration and best practices, and (iv) industrial transfer and standardization alignment (e.g., IEC 61400-24) [3]. The roadmap also emphasizes wind-farm-scale coupling and seasonal/site variability (moisture/freezing) as cross-cutting issues that can amplify or mitigate lightning stresses [8,9,11,14].

7.1. Horizon 1 (1–2 years): consolidate reproducibility, best practices, and baseline validation

- (High) Reporting and reproducibility checklist for grounding-transient studies. Define a minimal reporting template for geometry, soil identification workflow, modeled bandwidth, waveform definition, and validation metric(s), to reduce ambiguity across studies and tools [6,23,42].
- (High) Wideband-ready grounding equivalents for EMT studies. When EMTP/ATP is used for lightning transients, prioritize validated wideband (multi-port where needed) grounding equivalents instead of purely resistive representations; document the frequency range and fitting adequacy of the broadband-to-time conversion (e.g., VF/state-space) [14,49,51,58].
- (High) Baseline field/lab benchmarking cases. Publish a small set of benchmark-style cases (site/geometry/waveform) with measurement-linked outputs (even if limited in scope) to enable cross-tool comparison and model calibration [20,22,23].
- (Medium) Sensitivity studies with multilayer and frequency-dependent soils. For representative WT grounding geometries, run controlled sensitivity sweeps that separate (i) multilayer soil profile effects and (ii) frequency-dependent soil parameter effects under consistent excitations [4,6,7,13].
- (Medium) Seasonal variability as an explicit axis. Where available, incorporate seasonal/site variability in soil parameters and evaluate the robustness of conclusions to that variability (scenario envelopes rather than single curves) [14,64].

(Low) Ionization modeling only with transparent assumptions. Use nonlinear ionization models as scenario studies unless parameters are supported by credible benchmarks; clearly state assumptions and intended applicability [26,37,46].

7.2. Horizon 2 (3–5 years): integrated wind-farm modeling, scalable validation, and acceleration workflows

- (High) Integrated wind-farm grounding + collector-network transient workflow. Develop and validate workflows that jointly include turbine grounding, inter-turbine links, and collector-network paths under consistent wideband assumptions, to capture transferred overvoltages and coupling-driven redistribution [8,9,52,57].
- (High) Scalable benchmark suite for coupling and multi-turbine behavior. Extend benchmark cases from single-turbine to small multi-turbine layouts with clear topology definitions (interconnection types/lengths) and comparable outputs (GPR, transferred voltage, key node waveforms) [9,11].
- (Medium) Reduced-order modeling (ROM) from full-wave to EMT. Use full-wave or wideband field/circuit formulations strategically to identify dominant mechanisms, then generate reduced-order, EMT-ready equivalents with explicit bandwidth and fit-quality reporting [7,9,12,14].
- (Medium) Numerical best practices and acceleration playbook. Document practical guidance for segmentation/meshing, time-step constraints, bandwidth sampling, and fit diagnostics; encourage sharing of scripts/workflows used for wideband fitting and verification [7,58].

(Medium) Waveform variability + soil uncertainty joint studies. Evaluate whether conclusions hold across a small, explicit waveform set (first/subsequent strokes and different front-times) jointly with soil-model uncertainty [4,47,48,65].

7.3. Horizon 3 (5+ years): industrial transfer, standardization-ready guidance, and robust design frameworks

- (High) Standardization-facing guidance derived from validated models. Translate validated findings on soil dispersion, multilayer effects, and wind-farm coupling into practitioner-oriented guidance aligned with IEC 61400-24 workflows (e.g., when wideband grounding equivalents are required vs. when simpler models are sufficient) [3].
- (High) Robust (uncertainty-aware) design envelopes for WT grounding under lightning. Move from single-scenario conclusions toward design envelopes that explicitly account for soil variability (including seasonal shifts) and waveform variability; this supports risk-informed engineering decisions without relying on a single “representative” case [64,65].
- (Medium) Wind-farm-scale mitigation co-design (grounding, bonding, SPDs, topology). Develop co-design studies that consider grounding/interconnection strategies together with surge protection and network layout, using validated multi-port equivalents and network-level EMT simulations [8,9,25].
- (Low) Data-driven acceleration for parametric design studies. Explore surrogate or data-driven models to accelerate parametric sweeps and optimization under uncertainty, while maintaining physics-based validation for lightning-relevant transients [17].

Table 8 provides the possible future trends.

Table 8. Future research roadmap horizons and concrete tasks suggested by the evidence synthesis in this review (no quantitative claims; tasks emphasize reproducibility, validation, acceleration, and wind-farm-scale realism).

Horizon	Topics	Concrete tasks	Expected impact
1--2y	Reproducibility, baseline validation, wideband EMT readiness, initial seasonal sensitivity	Reporting checklist; measurement-linked baseline benchmarks; wideband (VF/state-space) grounding equivalents with bandwidth/fit diagnostics; controlled sensitivity studies for multilayer and frequency-dependent soils; treat seasonal variability as an explicit axis	More comparable studies; reduced tool-dependent conclusions; clearer applicability boundaries for EMTP vs.\ wideband/full-wave approaches [23,14,6]
3--5y	Integrated wind-farm coupling + network effects; scalable validation; ROM and acceleration workflows	Joint turbine-grounding + interconnection + collector-network modeling under consistent wideband assumptions; multi-turbine benchmark suite; reduced-order equivalents derived from full-wave/wideband references; best-practices playbook for meshing/sampling/fitting	Validated farm-level predictions of transferred overvoltages and coupling; faster yet credible engineering workflows [9,57,7]
5y+	Industrial transfer and standardization; robust uncertainty-aware design; co-design mitigation	Standardization-facing guidance aligned with IEC 61400-24; uncertainty-aware design envelopes (soil + waveform + topology); co-design of grounding/bonding/SPDs and farm topology; careful use of data-driven acceleration only with physics validation	Improved industrial adoption and consistency; designs that remain robust to site variability and excitation uncertainty; clearer guidance for practitioners [3,64,65]

8. Limitations of this review

This review synthesizes published studies that differ substantially in assumptions, tools, modeled bandwidth, and reporting detail; therefore, many comparisons are necessarily qualitative and bounded by what is explicitly documented (e.g., soil characterization basis, topology/coupling paths included, and validation style). In parts of the literature, validation remains constrained by measurement availability, so evidence is sometimes based on simulation cross-checks rather than independent field/lab benchmarks. Finally, the scope of this paper is electrical grounding and lightning-transient modeling for WTs and wind farms; it does not attempt to standardize economic comparisons across tools or to provide site-specific prescriptions beyond the comparative indicators and sensitivity-oriented guidance synthesized herein.

9. Conclusion

This paper reviewed and synthesized the literature on lightning-related transient behavior of wind-turbine (WT) grounding systems, with an emphasis on time–frequency effects, soil representation (including dispersion and stratification), and system-level coupling paths in wind farms. The review was organized by method families (Section 3), formalized using an explicit classification framework (Section 4), and distilled into two cross-study matrices: a method-comparison matrix (Table 3) and a findings/takeaways matrix (Table 2). The extracted challenges and gaps (Section 6) and the prioritized roadmap (Section 7) translate this synthesis into actionable directions for both research and practice.

Distilled technical insights (cross-study). Based on the comparative synthesis (Section 5) and Tables 3-4, the following technical insights emerge:

1. Grounding performance under lightning is inherently wideband. Models that agree at DC or power frequency can diverge in predicted impulse behavior once inductive/capacitive storage, coupling, and propagation become influential; therefore, the modeled bandwidth must match the targeted failure/overvoltage mode (Section 4, Table 3).
2. Soil representation is a dominant driver of disagreement. Stratification (multilayer/heterogeneous soil) and frequency-dependent parameters change return-current distribution and wideband grounding impedance, which can materially alter GPR and overvoltage waveforms relative to homogeneous/constant-parameter assumptions (Table 2; Section 6).
3. Interconnection is a double-edged design variable at wind-farm scale. Bonding/interconnection can reduce local GPR by sharing injected current, but it also introduces transferred/redistributed stresses that must be assessed at the farm/network level rather than only at an isolated turbine (Table 2).
4. Collector-network and cable-sheath paths are part of the lightning problem. Overvoltage and stress allocation depend on coupled *structure* + *ground* + *network* paths; thus, grounding design and surge-protection placement should be coordinated with cable/sheath bonding and the collection network representation (Section 3; Table 2).
5. Circuit-based EMT studies are powerful, but grounding parametrization is the credibility bottleneck. EMTP/ATP-style studies are well-suited for system studies (e.g., SPD placement and topology comparisons), but they require validated wideband grounding equivalents (multi-port when needed) to remain credible for fast-front lightning behavior (Table 3).
6. Full-wave/distributed solvers are justified when propagation and coupling dominate. FDTD/TLM and thin-wire/full-wave (MoM/PEEC-type) approaches become necessary when wave propagation, reflections, and multi-conductor coupling control peak timing and stress distribution (Table 3).
7. Broadband-to-time conversion quality is itself a technical risk. Frequency-to-time workflows (e.g., wideband fitting/state-space equivalents) provide an essential bridge to EMT simulation, but their reliability depends on bandwidth selection, sampling adequacy, and fit diagnostics; otherwise, time-domain artifacts may bias conclusions (Section 4; Table 3).
8. Nonlinear soil ionization is scenario-dependent and difficult to calibrate. Ionization models can reshape transient response in some high-current scenarios, but without site-calibrated evidence or strong benchmarks, ionization-driven conclusions should be framed as scenario envelopes rather than universal design rules (Section 6; Table 6).

Methodological gaps and their implications (why results differ). The gaps extracted in Section 6 have direct implications for both prediction credibility and engineering decision-making:

- Validation scarcity: limited field/lab benchmarks force many studies to rely on cross-tool consistency rather than independent measurements, which can mask shared assumptions and reduce confidence in absolute waveform fidelity (Section 6).
- Incomplete system context: isolated-turbine studies can under-represent transferred/induced stresses that arise through wind-farm interconnections and collector networks, leading to incomplete mitigation ranking (Section 6).
- Unstated applicability boundaries: conclusions may not transfer across soils, waveforms, or topologies unless the modeled bandwidth, soil calibration basis, and interconnection assumptions are explicitly reported.

Practical engineering recommendations (actionable). Without prescribing site-specific numeric thresholds (outside the scope of this review), the following qualitative recommendations are supported by the synthesized evidence:

- Treat soil modeling as a first-order design axis: when lightning transients are the target, prefer a justified multilayer soil model and evaluate sensitivity to plausible soil profiles and seasonal variability rather than relying on a single “average” resistivity (Section 6).
- Use wideband grounding equivalents in EMT studies: if EMTP/ATP is used for fast-front lightning waveforms, embed grounding models that represent the intended wideband behavior (multi-port where required) and document the modeled

frequency range and conversion/fit adequacy (Section 7).

- Analyze wind farms as coupled systems: evaluate both struck and non-struck turbines, including interconnection topology and collector-network paths, before finalizing bonding strategies and SPD placement (Table 8).
- Prefer topology comparisons under consistent assumptions: when comparing grounding layouts or interconnections, keep waveform sets, bandwidth, soil representation, and validation targets consistent to avoid method-driven ranking artifacts (Section 4).
- Report reproducibility essentials: provide geometry description, soil identification workflow, waveform definition, modeled bandwidth, and validation style to make results portable across tools and sites.

Prioritized future work aligned with the roadmap. The roadmap in Section 7 is summarized here as prioritized tasks:

- High priority (near term): publish benchmark-style measurement-linked cases and adopt a reproducibility checklist (geometry, soil identification, bandwidth, waveform definition, validation metrics) to reduce tool-dependent conclusions.
- High priority (near-to-mid term): develop validated integrated workflows that jointly model turbine grounding, inter-turbine links, and the collector network under consistent wideband assumptions to quantify transferred/induced stresses at farm scale.
- Medium priority: derive reduced-order, EMT-ready wideband equivalents from full-wave references with explicit bandwidth and fit-quality reporting to balance fidelity and practicality.
- Context-dependent priority: treat nonlinear ionization modeling as scenario-based unless supported by site-calibrated evidence or credible experimental benchmarks.

Novelty and positioning relative to narrower reviews. Many review-style discussions in this domain are organized around a single axis (e.g., a specific solver family, a specific soil effect, or a specific component-level lightning protection topic) and therefore do not provide a unified basis for cross-method comparison. In contrast, the novelty of this manuscript is the *integration* of: (i) an explicit classification framework that links modeling assumptions to applicability boundaries (Section 4), (ii) a method-comparison matrix (Table 3) and a findings/takeaways matrix (Table 2) that make trade-offs and recurring patterns explicit without introducing unsupported numeric metrics, and (iii) a structured, evidence-linked gap taxonomy with a prioritized roadmap (Sections 6 and 7). This structure is intended to help readers move from paper-by-paper descriptions to defensible method selection, sensitivity-aware interpretation, and reproducible future studies.

For completeness, the conclusions above should be interpreted together with the scope and comparison limits stated in Section 8.

Based on the above synthesis, this review provides the following explicit recommendations for key stakeholders:

- Turbine Developers: should incorporate enhanced lightning protection in turbine designs (e.g., improved blade receptors and grounding systems) to improve reliability. Strengthening lightning defenses is expected to help extend component lifetimes and reduce failure rates, which in turn can boost turbine availability and keep O&M costs in check.
- Wind Farm Operators: should utilize real-time lightning monitoring and conduct regular LPS inspections (e.g., in line with IEC 61400-24 recommendations [78]) so that any strike damage is detected and repaired promptly. This proactive maintenance approach can minimize lightning-induced downtime and prevent costly component replacements [78].
- Grid Planners: should include lightning-related outage scenarios in grid reliability and integration studies. By planning for potential turbine downtime (e.g., ensuring backup generation or energy storage during severe thunderstorms), planners can maintain grid stability and supply security even when lightning temporarily reduces wind farm output.

Policymakers: should support lightning resilience by enforcing standards and incentivizing protective measures. For example, requiring compliance with lightning protection standards and providing incentives or research support for improved turbine LPS technologies can help reduce lightning-related losses and ultimately lower the cost of wind energy.

References

[1] P. H. Pretorius, "Lightning Ground Potential Rise - A Contributing Factor to Damage Associated with Wind Turbine Blades," *2022 36th International Conference on Lightning Protection (ICLP)*, pp. 697–704, 2022.

[2] S. A. Pastromas, I. A. Naxakis, S. I. Xerra, K. N. Koutras, and E. C. Pyrgioti, "Evaluation of Wind Turbine Earthing System," *Lecture Notes in Electrical Engineering*, pp. 316–328, 2019.

[3] *Wind Turbines – Part 24: Lightning Protection*, IEC 61400-24, International Electrotechnical Commission (IEC), 2010.

[4] R. Alipio, D. Conceição, et al., "A Comprehensive Analysis of the Effect of Frequency-Dependent Soil Electrical Parameters on the Lightning Response of Wind-Turbine Grounding Systems," *Electric Power Systems Research*, vol. 175, 105927, 2019.

[5] R. Alipio, M. T. Correia de Barros, M. A. O. Schroeder, and K. Yamamoto, "Analysis of the Lightning Impulse and Low-Frequency Performance of Wind Farm Grounding Systems," *Electric Power Systems Research*, vol. 180, 106068, 2020.

[6] M. Nazari, R. Moini, S. Fortin, F. P. Dawalibi, and F. Rachidi, "Impact of Frequency-Dependent Soil Models on Grounding System Performance for Direct and Indirect Lightning Strikes," *IEEE Transactions on Electromagnetic Compatibility*, vol. 63, no. 1, pp. 134–144, 2021.

[7] A. Mehri, R. Ghanizadeh, and M. Beiraghi, "Transient Analysis of Grounding Electrodes in a Two-Layer Soil Considering Frequency Dependence of Soil," *Electrical Engineering*, vol. 104, no. 2, pp. 1019–1028, 2021.

[8] A. A. Razi-Kazemi, and P. Eftekhari, "Investigation of the Impact of the Grounding of Wind Farms on the Distribution of Transient Over-Voltages Caused by Lightning Strikes," *Electric Power Systems Research*, vol. 220, 109362, 2023.

[9] W. C. da Silva, W. L. M. de Azevedo, A. R. J. de Araújo, and J. P. Filho, "Full-Wave Electromagnetic Analysis of Lightning Strikes to Wind Farm Connected to Medium-Voltage Distribution Lines," *Electric Power Systems Research*, vol. 223, 109597, 2023.

[10] R. Alipio, M. Guimarães, L. Passos, D. Conceição, and M. T. C. de Barros, "Ground Potential Rise in Wind Farms Due to Direct Lightning," *Electric Power Systems Research*, vol. 194, 107110, 2021.

[11] L. S. Passos, D. Conceição, R. Alípio, M. Guimarães, and M. T. C. de Barros, "Assessing the Effect of the Interconnecting Electrode Length on the Ground Potential Rise of Wind Turbines Subject to Representative Currents of First and Subsequent Strokes," *Journal of Control, Automation and Electrical Systems*, vol. 32, no. 6, pp. 1728–1734, 2021.

[12] H. Chen, Y. Zhang, Y. Du, and Q. S. Cheng, "Comprehensive Transient Analysis for Low-Voltage System in a Wind Turbine Under Direct Lightning," *International Journal of Electrical Power & Energy Systems*, vol. 121, 106131, 2020.

[13] Z. Li, Y. Yin, and K. Wang, "Lightning Response of a Grounding System Buried in Multilayered Earth Based on the Galerkin's Boundary Element and Quasi-Static Complex Image Methods," *IEEE Transactions on Electromagnetic Compatibility*, vol. 63, no. 4, pp. 1118–1127, 2021.
[14] J. Gholinezhad, and R. Shariatinasab, "Time-Domain Modeling of Tower-Footing Grounding Systems Based on Impedance Matrix," *IEEE Transactions on Power Delivery*, vol. 34, no. 3, pp. 910–918, 2019.
[15] N. A. Sabiha and N. I. Elkalashy, "Evaluation of grounding system design for wind farm using COMSOL," *International Journal of Applied Engineering Research*, vol. 13, no. 6, pp. 4124–4132, 2018.
[16] A. O. Ganongo, M. Gogom, Nianga-Apila, L. L. A. Obita, and G. Ganga, "Optimisation of Lightning Current Discharge to the Ground in Electrical Networks: Introduction of the Proportionality Coefficient (K)," *Electric Power Systems Research*, vol. 231, 110348, 2024.
[17] Z. Jiang, H. Li, et al., "Review of Artificial Intelligence-Based Design Optimization of Wind Power Systems," *Wind*, vol. 5, no. 3, 18, 2025.
[18] North American Clean Energy, "New study reveals lightning risks and damage potential for over 1,500 U.S. wind farms," *North American Clean Energy*, 2024.
[19] D. Budisetyawan, F. N. Fauzi, et al., "Wind Turbine Reliability Forecast: A Technical Review on the Research Milestone and Assessment of the Energy Cost Using Monte Carlo Simulation," *Engineered Science*, 2025.
[20] A. Zalhaf, M. Abdel-Salam, D. A. Mansour, M. Ahmed, and S. Ookawara, "An Experimental Study of Lightning Overvoltages on a Small-Scale Wind Turbine Model," *Energy Procedia*, vol. 156, pp. 442–446, 2019.
[21] Y. Hu, Z. Liu, et al., "A New Grounding Resistance Reduction Method for Wind Turbines by Grounding Grid Connection in Limited Areas," *Frontiers in Energy Research*, vol. 10, 2022.
[22] G. P. Kondylis, K. D. Damianaki, V. P. Androvitsaneas, and I. F. Gonos, "Simplified Formulae Method for Estimating Wind Turbine Generators Ground Resistance," *IEEE Transactions on Power Delivery*, vol. 33, no. 6, pp. 2829–2836, 2018.
[23] D. S. Gazzana, A. Smorgonskiy, et al., "An Experimental Field Study of the Grounding System Response of Tall Wind Turbines to Impulse Surges," *Electric Power Systems Research*, vol. 160, pp. 219–225, 2018.
[24] Y. M. Hernández, T. Tsovilis, et al., "A Simulation Approach on Rotor Blade Electrostatic Charging and Its Effect on the Lightning Overvoltages in Wind Parks," *Electric Power Systems Research*, vol. 139, pp. 22–31, 2016.
[25] A. A. Razi-Kazemi, and A. RajabiNezhad, "Protection of Wind Electrical Power Energy Systems Against Indirect Lightning Strike Surge," *2016 24th Iranian Conference on Electrical Engineering (ICEE)*, pp. 1388–1393, 2016.
[26] S. Pastromas, I. Naxakis, and E. Pyrgioti, "Typical Lightning Protection System for Wind Turbines," *Engineering and Industry*, 2016.
[27] S. Hajeforosh, Z. Pooranian, A. Shabani, and M. Conti, "Evaluating the High Frequency Behavior of the Modified Grounding Scheme in Wind Farms," *Applied Sciences*, vol. 7, no. 12, 1323, 2017.
[28] K. Pyo, K. Kim, J. Woo, and T. Kim, "Comparison and Analysis of Lightning Overvoltage by Grounding; Methods Between Wind Turbines," *2019 11th Asia-Pacific International Conference on Lightning (APL)*, pp. 1–4, 2019.
[29] Z. Qibin, Y. Hongxiang, W. Zhenxing, B. Xiaoyan, and Y. Ximei, "Research and Protection of Overvoltage Caused by Lightning Stroke on Wind Farm Collector Lines," *2019 11th Asia-Pacific International Conference on Lightning (APL)*, pp. 1–5, 2019.
[30] N. A. Sabiha, M. Alsharef, et al., "Assessment of Grounding Grid for Enhancing Wind Turbine Service Sustainability," *Ain Shams Engineering Journal*, vol. 12, no. 1, pp. 577–589, 2021.
[31] A. S. Zalhaf, M. Ahmed, S. Ookawara, and M. Abdel-Salam, "A Simplified Model of Wind Turbine for Lightning Transient Analysis as Influenced by Structure of Grounding System," *2018 5th International Conference on Electric Power and Energy Conversion Systems (EPECS)*, pp. 1–6, 2018.
[32] D. Poljak, and D. Čavka, "Electromagnetic Compatibility Aspects of Wind Turbine Analysis and Design," *Advanced Structured Materials*, pp. 345–369, 2016.
[33] M. Talaat, M. Farahat, and M. Osman, "Assessment of Earthing System Location for Wind Turbines Using Finite Element Method," *Renewable Energy*, vol. 93, pp. 412–423, 2016.
[34] S. Pastromas, I. Naxakis, G. Peppas, and E. Pyrgioti, "Effectiveness Investigation of Wind Farm Earthing System," *2016 IEEE International Conference on High Voltage Engineering and Application (ICHVE)*, pp. 1–4, 2016.
[35] S. A. Pastromas, K. Maimaris, I. K. Stasinos, I. A. Naxakis, and E. C. Pyrgioti, "Assessment of Wind Turbine Grounding System," *2018 IEEE International Conference on High Voltage Engineering and Application (ICHVE)*, pp. 1–4, 2018.
[36] X. Zhang, Y. Zhang, and X. Xiao, "An Improved Approach for Modeling Lightning Transients of Wind Turbines," *International Journal of Electrical Power & Energy Systems*, vol. 101, pp. 429–438, 2018.
[37] M. Fakhraei, M. Mahmoudian, and E. Manuel Godinho Rodrigues, "Grounding System Modeling and Evaluation Using Integrated Circuit Based Fast Relaxed Vector Fitting Approach, Considering Soil Ionization," *Applied Sciences*, vol. 10, no. 16, 5632, 2020.
[38] O. Kherif, S. Chiheb, M. Teguar, and A. Mekhaldi, "On the Analysis of Lightning Response of Interconnected Wind Turbine Grounding Systems," *2017 5th International Conference on Electrical Engineering - Boumerdes (ICEE-B)*, pp. 1–4, 2017.
[39] O. Kherif, S. Chiheb, M. Teguar, A. Mekhaldi, and N. Harid, "Time-Domain Modeling of Grounding Systems' Impulse Response Incorporating Nonlinear and Frequency-Dependent Aspects," *IEEE Transactions on Electromagnetic Compatibility*, vol. 60, no. 4, pp. 907–916, 2018.
[40] H. Chen, Y. Zhang, and Y. Du, "A Study on the Cable Grounding Condition in Wind Turbines Under Direct Lightning," *2019 11th Asia-Pacific International Conference on Lightning (APL)*, pp. 1–6, 2019.
[41] M. E. M. Rizk, F. Mahmood, M. Lehtonen, E. A. Badran, and M. H. Abdel-Rahman, "Investigation of Lightning Electromagnetic Fields on Underground Cables in Wind Farms," *IEEE Transactions on Electromagnetic Compatibility*, vol. 58, no. 1, pp. 143–152, 2016.
[42] K. Yamamoto, Y. Kubo, and S. Sumi, "Transient Grounding Characteristic of Wind Turbines Affecting Back-Flow Lightning Current into Distribution System," *2016 33rd International Conference on Lightning Protection (ICLP)*, pp. 1–5, 2016.
[43] A. Yamanaka, A. Hori, H. Murakami, and N. Nagaoka, "A Vertical Conductor Circuit Model Including Up- and Down-Ward Traveling Waves," *Electric Power Systems Research*, vol. 162, pp. 50–56, 2018.
[44] M. Kose, S. Tanaka, et al., "Effective Length of Counterpoises Connected to Wind Turbine Foundation," *IEEE Transactions on Power Delivery*, vol. 36, no. 6, pp. 3956–3963, 2021.
[45] A. Djaborebbi, "Modeling the Transient Response of Lightning Current on Grounding Systems Wind Turbines," *Przegląd Elektrotechniczny*, vol. 1, no. 2, pp. 161–166, 2021.
[46] A. Djaborebbi, B. Zegnini, T. Seghier, and D. Mahi, "Transient analysis of wind turbine grounding system buried in uniform and stratified soil," in *Advances in Communication Technology, Computing and Engineering*. RGN Publications, 2021, pp. 757–768.
[47] R. Alipio, D. Conceicao, R. N. Dias, S. Visacro, and K. Yamamoto, "The Effect of Frequency Dependence of Soil Electrical Parameters on the Lightning Performance of Typical Wind-Turbine Grounding Systems," *2017 International Symposium on Lightning Protection (XIV SIPDA)*, pp. 353–358, 2017.
[48] R. Alipio, M. T. C. de Barros, M. A. O. Schroeder, and K. Yamamoto, "Lightning and Low-Frequency Performance of Interconnected Grounding Systems of Wind Turbines," *2018 34th International Conference on Lightning Protection (ICLP)*, pp. 1–6, 2018.
[49] D. Mestriner, R. A. Ribeiro de Moura, R. Procopio, and M. A. de Oliveira Schroeder, "Impact of Grounding Modeling on Lightning-Induced Voltages Evaluation in Distribution Lines," *Applied Sciences*, vol. 11, no. 7, 2931, 2021.
[50] R. Araneo, and S. Celozzi, "Transient Behavior of Wind Towers Grounding Systems Under Lightning Strikes," *International Journal of Energy and Environmental Engineering*, vol. 7, no. 2, pp. 235–247, 2015.
[51] R. Shariatinasab, B. Kermani, and J. Gholinezhad, "Transient Modeling of the Wind Farms in Order to Analysis the Lightning Related Overvoltages," *Renewable Energy*, vol. 132, pp. 1151–1166, 2019.
[52] R. Araneo, G. Lovat, S. Celozzi, and P. Burghignoli, "Numerical Analysis of Mutual Transient Voltages in Grounding Systems of Offshore Wind Farms," *2018 International Applied Computational Electromagnetics Society Symposium (ACES)*, pp. 1–2, 2018.
[53] A. Sunjerga, Q. Li, D. Poljak, M. Rubinstein, and F. Rachidi, "Transient Impedance of Interconnected Wind Turbine Grounding Systems," *2018 26th International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*, pp. 1–4, 2018.
[54] A. Sunjerga, Q. Li, D. Poljak, M. Rubinstein, and F. Rachidi, "Isolated Vs. Interconnected Wind Turbine Grounding Systems: Effect on the Harmonic Grounding Impedance, Ground Potential Rise and Step Voltage," *Electric Power Systems Research*, vol. 173, pp. 230–239, 2019.
[55] P. Tete, F. S. Hasnaoui, and S. Georges, "Analysis of the Lightning Transient Response of the Grounding System of Large Wind Farms," *2020 5th International Conference*

on Renewable Energies for Developing Countries (REDEC), 2020.
[56] W. Li, N. Xiang, et al., "Transient Characteristics of Wind Turbine Grounding System in High Soil Resistivity Area Due to Lightning Strike," *2020 IEEE International Conference on High Voltage Engineering and Application (ICHVE)*, pp. 1–4, 2020.
[57] R. Alipio, A. De Conti, N. Duarte, and M. T. Correia de Barros, "Bare Versus Insulated Conductors for Improving the Lightning Response of Interconnected Wind Turbine Grounding Systems," *Electric Power Systems Research*, vol. 197, 107320, 2021.
[58] B. Gustavsen, and A. Semlyen, "Rational Approximation of Frequency Domain Responses by Vector Fitting," *IEEE Transactions on Power Delivery*, vol. 14, no. 3, pp. 1052–1061, 1999.
[59] N. Xiang, J. Ni, et al., "Research on Broadband Modeling of Transmission Line Tower Based on Vector Matching Method," *2023 IEEE 6th International Electrical and Energy Conference (CIEEC)*, pp. 3890–3895, 2023.
[60] F. Grange, S. Journet, R. Moini, and F. P. Dawalibi, "Safety of Wind Farm Grounding Systems Under Fault and Lightning Currents," *2016 33rd International Conference on Lightning Protection (ICLP)*, pp. 1–7, 2016.
[61] R. D. Goud, T. Auditore, R. Rayudu, C. P. Moore, and E. Sturov, "A New Method for Calculating Earth Electrode Length for a Wind Turbine Generator Grounding System Based on a Two-Layer Soil Structure," *2018 International Conference on Power System Technology (POWERCON)*, pp. 1270–1276, 2018.
[62] R. D. Goud, T. Auditore, R. Rayudu, and C. P. Moore, "Analysis of Earth Electrodes of Wind Turbine Generator Grounding System Under Lightning Discharge Currents," *2018 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, pp. 502–507, 2018.
[63] R. G. Deshagoni, T. Auditore, R. Rayudu, and C. P. Moore, "Factors Determining the Effectiveness of a Wind Turbine Generator Lightning Protection System," *IEEE Transactions on Industry Applications*, vol. 55, no. 6, pp. 6585–6592, 2019.
[64] R. D. Goud, T. Auditore, R. Rayudu, and C. P. Moore, "Frequency Domain Analysis of a Wind Turbine Generator Earthing System for Lightning Discharge Currents," *IEEE Access*, vol. 7, pp. 60501–60512, 2019.
[65] Q. Ma, Y. Xu, et al., "Study on the Influence of Lightning Current Waveform on the Impulse Characteristics of Grounding Grid," *2023 IEEE 4th International Conference on Electrical Materials and Power Equipment (ICEMPE)*, pp. 1–4, 2023.
[66] N. A. F. Mohd Nasir, M. S. Mohd Nasir, et al., "Impact of Lightning on Tower Footing Design of 500 kV Transmission Line," *2023 12th Asia-Pacific International Conference on Lightning (APL)*, pp. 1–6, 2023.
[67] T. Yang, X. Yang, Y. Liu, Z. Zhu, Y. Xie, and X. Zhou, "Application of three-dimensional interleaved short conductors in transmission tower grounding device," *Journal of Electric Power Science and Technology*, vol. 38, no. 6, pp. 259–266, 2024.
[68] A. Mousa, "The Soil Ionization Gradient Associated with Discharge of High Currents into Concentrated Electrodes," *IEEE Transactions on Power Delivery*, vol. 9, no. 3, pp. 1669–1677, 1994.
[69] I. Gonos, and I. Stathopulos, "Soil Ionisation Under Lightning Impulse Voltages," *IEE Proceedings - Science, Measurement and Technology*, vol. 151, no. 5, pp. 343–346, 2004.
[70] N. Ramezani, and A. Shabani, "High Frequency Behavior Evaluation of Grounding System in Wind Farms," *2024 9th International Conference on Technology and Energy Management (ICTEM)*, pp. 1–7, 2024.
[71] R. P. Tshubwana, T. Shongwe, and M. Hove, "Effects of Fulgurites on the Earthing System," *2017 IEEE AFRICON*, pp. 1131–1136, 2017.
[72] *IEEE Guide for Measurement of Impedance and Safety Characteristics of Large, Extended or Interconnected Grounding Systems*, IEEE Std 81.2-1991, Institute of Electrical and Electronics Engineers (IEEE), 1991.
[73] Y. Mendez, J. Birkl, et al., "The 2018 Revision of the Standard IEC 61400-24: Lightning Protection of Wind Turbines," *2018 34th International Conference on Lightning Protection (ICLP)*, pp. 1–6, 2018.
[74] N. Hatziargvriou, "Wind Farm Earthing," *IEE Half-day Colloquium on Lightning Protection of Wind Turbines*, vol. 1997, pp. 6–6, 1997.
[75] LinkedIn, "Permissible touch vs. step voltage standards," *LinkedIn*.
[76] N. Hatziargvriou, "Wind Farm Earthing," *IEE Half-day Colloquium on Lightning Protection of Wind Turbines*, vol. 1997, pp. 6–6, 1997.
[77] *IEEE Guide for Measuring Earth Resistivity, Ground Impedance, and Earth Surface Potentials of a Grounding System*, IEEE Std 81-2012, Institute of Electrical and Electronics Engineers (IEEE), 2012.
[78] Wind Systems Magazine, "Wind systems magazine: Article from 03/2025 PDF (0325-IF2)," *Wind Systems Magazine*, Mar. 2025.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

Bibliography



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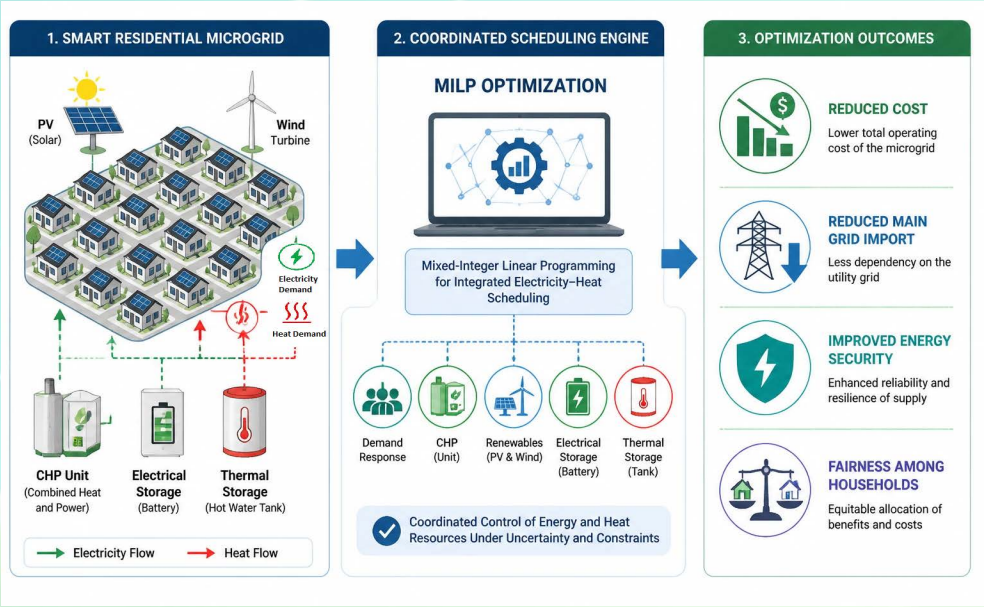
Integrated Analysis of Electrical and Thermal Energy Distribution in Smart Homes Connected to Microgrids with CHP Sources

Arash Karami, Fardad Rastgou, Saman Hosseini-Hemati, Saeed Kharrazi, Maryam Shirzadian Gilan

Highlights

- **Comprehensive analysis of electrical and thermal energy in smart homes.**
- **Developed a MILP model for scheduling appliances and load shifting.**
- **Increasing CHP capacity significantly enhances energy distribution efficiency.**
- **Integrated approach reduces costs and strengthens supply security in microgrids.**

Graphical Abstract



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Integrated Analysis of Electrical and Thermal Energy Distribution in Smart Homes Connected to Microgrids with CHP Sources

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A B S T R A C T

This paper presents a comprehensive analysis of the joint distribution of electrical and thermal energy in a smart home connected to a microgrid integrating renewable resources, combined heat and power (CHP) units, and storage systems. While most existing studies have primarily focused on generation planning and storage management, fewer works have examined the simultaneous optimization of electricity and heat flows in residential environments. To address this gap, a mixed-integer linear programming (MILP) model is developed to schedule household appliances and manage load shifting according to time-varying electricity prices, heating demand, and demand profiles, and the optimization is solved using MATLAB tools. The proposed framework is applied to a residential complex of 10 and 20 households under different CHP capacities and demand scenarios. Simulation results reveal that increasing CHP capacity from 5 kW to 20 kW significantly improves the coordination of electrical and thermal distribution, reduces reliance on the main grid, and lowers boiler operation, thereby enhancing overall efficiency. Additional analyses with different numbers of households confirm the scalability of the model, ensuring stable performance under varying load levels. A comparative scenario without microgrid integration further highlights the substantial benefits of the proposed system in reducing operational costs and improving resilience. To address this gap, a unified MILP jointly schedules electrical–thermal resources (CHP, renewables, and dual electrical/thermal storage) and employs a price–energy iterative scheme with explicit fairness constraints, ensuring no household is worse off than in non-cooperative operation. These results demonstrate that the coordinated consideration of both power and heat flows provides a more holistic strategy for smart home energy management than electricity-only approaches. In 24-h studies, increasing installed CHP capacity from 5 to 100 kW reduced total operating cost from \$379.68 to \$191.52 (≈49.6%). By integrating demand response (DR) programs with CHP and renewable resources, the proposed method reduces energy costs, strengthens supply security, and contributes to the sustainability of residential microgrids.

1. Introduction

The rapid growth in energy consumption, together with the global transition toward renewable energy sources and sustainable energy infrastructures, has significantly promoted the development of MGs and SHs as essential components of modern power systems. In contrast to conventional centralized generation frameworks, MGs are capable of integrating various distributed energy resources (DERs), including photovoltaic (PV) systems, wind turbine (WT) units, combined heat and power (CHP) technologies, and energy storage devices [1]. These localized energy networks can operate in both grid connected and islanded modes, thereby enhancing system reliability, operational flexibility, and economic efficiency. At the same time, smart homes, residential units equipped with advanced monitoring, control, and communication technologies, have become important platforms for implementing intelligent energy management schemes [2].

Through bidirectional information exchange between consumers and utility operators, SHs allow users to actively engage in energy management and market participation, improve the efficiency of electricity consumption, and contribute to maintaining overall grid stability. Despite these advancements, the integration of renewable energy introduces significant uncertainties due to the intermittent nature of wind and solar power. This intermittency challenges the stability of microgrids and underscores the importance of flexible demand-side management strategies [3]. To mitigate these challenges, researchers have explored various mechanisms, including storage technologies such as batteries and hydrogen-based systems [4], and distributed generation resources like CHP units, which provide simultaneous electricity and thermal energy with higher overall efficiency compared to conventional generation [5]. CHP not only reduces operating costs and emissions but also contributes to local energy autonomy. Nevertheless, the effective utilization of these resources relies heavily on advanced optimization techniques capable of handling multi-objective and multi-constraint environments.

Within this context, Demand Response (DR) has emerged as a cornerstone of modern energy management. DR programs aim to reshape the load profile by incentivizing consumers to shift or curtail their consumption in response to dynamic electricity pricing, grid signals, or other incentive mechanisms [6]. By adjusting demand rather than solely focusing on supply, DR introduces greater flexibility, improves grid stability, and supports renewable energy integration. Studies have shown that DR can reduce operating costs [7], flatten load curves [8], and improve the reliability of both standalone microgrids and interconnected systems [9].

Although considerable research has been conducted on general energy management of smart homes and microgrids, relatively fewer studies have provided an in-depth economic and operational assessment of DR programs specifically in the context of residential microgrids integrating CHP, renewables, and storage systems. Many existing works focus primarily on optimization models for cost minimization [10], heuristic algorithms for appliance scheduling [11], or the integration of storage technologies [12]. While valuable, these contributions often treat DR as an auxiliary element rather than as the central focus of analysis.

Previous studies have examined various approaches to improve the efficiency and management of modern distributed energy systems. Reference [13] analyzes the role of DR within a peer-to-peer (P2P) electricity trading framework applied to a residential smart home. The considered system includes several controllable household appliances, an electric vehicle, a battery energy storage system (BESS), and renewable-based distributed generation units such as solar photovoltaic and wind sources. The results indicate that coordinated interaction between DR programs and local energy trading mechanisms can enhance operational flexibility and improve the overall energy management of residential environments.

Paper [14] used a practical microgrid test platform to investigate system monitoring and performance assessment. The experimental setup consists of a hybrid wind–solar generation system supplying a number of domestic electrical loads. The study demonstrates that inexpensive power meters integrated with IoT communication capabilities can effectively collect detailed information about power quality indices and energy consumption patterns. Such data provide valuable insights for monitoring system behavior and can support advanced control strategies to optimize microgrid operation.

Reference [15] focuses on the economic and regulatory aspects of emerging distributed generation technologies. In this work, several policy mechanisms and incentive programs are proposed to encourage the deployment of renewable resources, CHP systems, and fuel cell units. Four different pricing frameworks for electricity generated by these technologies are developed and analyzed. Based on these scenarios, the potential tariff structures and expected financial support for electricity produced by fuel cells are determined, allowing an evaluation of their economic feasibility under different policy conditions.

A different perspective is presented in [16], which investigates the integration of solar energy with combined heat and power systems as an effective pathway for producing clean electricity while simultaneously meeting thermal energy demands. The proposed integration configuration enables the utilization of higher-temperature solar heat with minimal thermal degradation. To evaluate its effectiveness, the method is modeled and compared with three alternative integration schemes. The comparison is performed using indicators such as solar energy conversion efficiency, annual system performance, and levelized energy cost. Simulation results from the case study reveal that the proposed configuration delivers the best performance, achieving a solar heat-to-electricity efficiency of 37.1% with an integrated solar heat capacity of 54.45 MW. In addition, it provides the highest annual solar-to-electricity efficiency (21.5%) and the lowest electricity generation cost among the investigated strategies.

Under these conditions, the annual solar-generated electricity increased by 33.28 GW. In [17], various types of renewable energy sources, electric vehicles, smart homes, and IoT are considered. In addition, energy storage systems, microgrids, and the distribution network are installed to control the negative effects of the resulting operational uncertainties and load demand.

In the proposed approach, microgrids prepare their market participation bids using a fuzzy-based decision framework derived from the optimal scheduling results, with the primary objective of minimizing operational expenditures. The mathematical formulation of the model is expressed in a linear structure and evaluated on a modified IEEE 33-bus distribution system that includes three interconnected microgrids. Simulation outcomes indicate that the integration of an IoT communication infrastructure facilitates more efficient participation of microgrids in the electricity market, leading to a cost reduction of approximately 9.13%. Moreover, the results reveal that providing vehicle-to-grid related services, when coordinated through optimal scheduling, can significantly influence market dynamics; specifically, electricity prices during peak demand periods decrease by nearly 25%, while overall daily operational performance is also improved.

Reference [18] investigates the integration and optimization of energy systems using CHP technology. The study emphasizes efficient energy utilization, appropriate management of energy flows, and systematic optimization of the overall operational process in order to achieve multiple engineering objectives simultaneously. In addition to proposing an integrated framework, the work highlights several unresolved challenges in CHP research and outlines potential directions for future investigations.

In [19], a mixed-integer linear programming (MILP) model is developed to study the operational scheduling of CHP units. The research analyzes how different hydrogen blending ratios influence both energy consumption patterns and environmental performance indicators. Based on this analysis, an optimal energy exchange strategy is formulated. The findings show that electricity trading plays a dominant role in the revenue structure, mainly due to electricity sales income, generation subsidies, and carbon trading mechanisms. According to the obtained results, the proposed strategy can reduce system costs by up to 60%.

Reference [20] proposes a real-time energy management framework that integrates neural networks with an advanced control strategy. The main objective of the control mechanism is to mitigate the impact of forecasting errors while enabling real-time operational decision-making using actual generation and demand data. Simulation studies demonstrate that the proposed approach effectively prevents unnecessary power export to the upstream grid and achieves an operating cost reduction of approximately 8.75% compared with conventional offline scheduling techniques.

In paper [21], the daily energy management problem of a CHP-based microgrid is examined, where multiple types of CHP technologies are employed to simultaneously supply electrical and thermal demands. A distinctive feature of this study is the incorporation of a detailed heat-transfer loss model within the optimization framework. Furthermore, different CHP configurations are comparatively analyzed with respect to their operational characteristics. The simulation results indicate that accurate modeling of thermal losses significantly affects the optimal scheduling decisions and the total operational cost of the microgrid.

In references [22,23], a multi-objective particle swarm optimization (MOPSO) technique is applied to evaluate three renewable-based microgrid configurations designed for the climatic conditions of Shiraz, Iran. The analyzed configurations include WT, PV systems, and CHP units. The microgrid is assumed to be connected to both electricity and natural gas networks, and surplus electrical generation can be exported to the main grid. The optimization problem considers two main objective functions: the loss of power supply probability (LPSP) and the unit energy cost. The obtained results indicate that relying solely on wind turbines considerably increases dependency on the main grid. However, due to the region's high solar irradiation levels, incorporating PV units into the configuration significantly reduces the portion of electricity that must be supplied by the grid.

Reference [24] focuses on demand-side management within smart homes. In this work, household electrical loads are dynamically adjusted according to demand response signals in order to mitigate peak demand and lower consumer electricity expenses. To support this process, multidimensional data aggregation techniques are used to gather detailed power consumption information. These data enable the control center to design more effective and responsive demand response programs.

In [25], the integration of CHP units with distributed energy resources is investigated within the context of multi-carrier microgrids. The study employs a scenario-based stochastic modeling approach to represent uncertainties associated with electricity market prices. Consequently, a hybrid stochastic optimization framework is formulated for optimal energy management in the multi-carrier microgrid. Unlike conventional demand-response models that focus solely on electricity, the proposed improvement introduces a unified MILP formulation that simultaneously optimizes both electrical and thermal energy flows, determines internal energy trading mechanisms, and ensures fairness among participating households.

In this paper, an integrated framework is proposed for the joint distribution of electrical and thermal energy in smart residential microgrids, addressing a research gap where most previous studies have primarily focused on electricity management. The novelty of this study lies in the simultaneous optimization of power and heat flows through the coordinated use of DR, CHP units, renewable resources, and storage systems. A MILP model is formulated to capture the interactions between the electrical and thermal domains while accounting for household demand variability and time-varying energy prices. The framework is evaluated on a residential complex of 30 households under different CHP capacities and demand scenarios. Results demonstrate the scalability and robustness of the model and confirm its effectiveness in reducing operational costs, minimizing reliance on the main grid, and enhancing energy security. By incorporating both power and heat distributions, this work provides a more comprehensive and practical strategy for smart home energy management compared to electricity-only approaches.

The main contributions of this work are as follows:

- An integrated MILP for joint electricity–heat scheduling in residential microgrids with CHP, renewables, demand response, and dual electrical/thermal storage.
- An intra-microgrid trading mechanism based on a simple price–energy iterative procedure with a quantitative stopping criterion, resolving bilinear coupling between traded energy and internal price.
- Explicit household-level cost-fairness constraints ensuring no participant is worse off than in non-cooperative operation.
- Case studies with 10 and 20 households and multiple CHP capacities, including a no-microgrid benchmark, demonstrating reductions in total cost, grid imports, and boiler runtime.
- Reproducibility enhancements through unified notation, clarified constraints, and organized data/parameter tables.

Table 1 summarizes the main characteristics of the reviewed studies and compares them with the proposed method in this paper. The comparison is performed based on several important aspects, including the consideration of ESS, demand response capability, smart building implementation, MG integration, the use of CHP units, and the applied optimization method.

As shown in the table, previous works have investigated some of these components individually or in limited combinations. However, most of the existing studies do not simultaneously consider all key elements such as ESS, demand response, smart building environments, MG structure, and CHP units within a unified optimization framework. In contrast, the proposed method integrates all these features together and employs a MILP optimization approach, providing a more comprehensive framework for energy management and system optimization.

Table 1. Comparison of research from the last few years and current research.

Ref	Optimization Method	CHP	Microgrid	Smart Building	Demand Response	ESS
[13]	BDA	-	+	+	+	+
[14]	ILP	-	+	+	-	-
[15]	ILP	+	+	-	+	+
[17]	FUZZY	+	+	+	+	-
[19]	MILP	+	-	-	+	-
[20]	MILP	+	-	-	+	+
[21]	ICA	+	+	-	+	-
[22]	ILP	+	+	-	+	+
[23]	MOO	+	+	-	+	+
[24]	MILP	+	+	-	+	-
Proposed Method	MILP	+	+	+	+	+

2. Objective function

Renewable energy plants are being established as modern infrastructures that are simultaneously encountering two major trends: the continuous growth in electricity demand and the reduction in energy prices. Drawing on the practices of developed nations provides a valuable pathway for promoting the application of renewable energies in developing countries. This is particularly evident in two primary areas, one of which is wind energy systems. The assumed specifications for the wind turbine [26], solar panel [27], and load demand [28] are given in the references mentioned.

The problem of power consumption scheduling in a smart home is expressed as a MILP framework. In this formulation, daily operational activities are planned within specific time windows, defined by the earliest possible start and the latest permissible end time of each task. The primary objective is to minimize the overall daily energy cost while simultaneously lowering the peak load drawn from the grid. To achieve this, the time horizon is divided into discrete intervals of equal duration. The principal decision variables of the model include appliance operating states, scheduling of task initiation, and load deployment strategies. These variables must satisfy multiple constraints, such as device capacity limitations, demand requirements, thermal and electrical storage restrictions, and operational time boundaries, all while ensuring the minimization of daily costs. In optimization theory, the obtained solution can be interpreted in several ways. Typically, the goal is to determine the global optimal solution; however, in practice, a local optimum is sometimes acceptable depending on the problem complexity. For many real-world challenges (such as solving nonlinear systems, differential equations, and large-scale optimization) numerical methods serve as the most viable tools. These methods rely on an initial approximation and iteratively refine it through successive calculations until convergence toward a feasible solution is reached. More formally, numerical techniques generate a sequence, initiated from a starting guess, which gradually approaches the problem's solution. The objective function used in this study, derived from [29-31], and given in Equation (1), considers the total operational costs within a 24-hour horizon. It is composed of three main components: the cost of purchasing electricity, the cost of natural gas, and the environmental cost associated with emissions, as given in Equations (2)-(4).

$$f = \sum_{s\in S} \rho(s) \times \sum_{t\in T} \left[C_{pe}(t) + C_{pg}(t) + C_{oe}(t)\right] \tag{1}$$

$$C_{pe}(t) = \rho_e(t) \times P^{GRD}(t) \times \Delta t \quad \forall t \in T \tag{2}$$

$$C_{pg}(t) = \rho_g(t) \times \left[P_{gas}^{PGU}(t) + P_{gas}^{AB}(t) + P_{gas}^{CAES}(t)\right] \times \Delta t = \rho_g(t) \times \left[\frac{P_e^{PGU}(t)}{\eta_e^{PGU}} + \frac{H^{HRU}(t)}{\eta_h^{PGU}} + \frac{H^{AB}(t)}{\eta_h^{AB}} + \frac{P_{CAES}^{dis}(t)}{\eta_{CAES}^{dis}}\right] \times \Delta t \,, \forall t \in T \tag{3}$$

$$C_{oe}(t) = \theta \times \left[\varphi_{in} \times P^{GRD}(t) + \varphi_g \times \left(\frac{P_e^{PGU}(t)}{\eta_e^{PGU}} + \frac{H^{HRU}(t)}{\eta_h^{PGU}} + \frac{H^{AB}(t)}{\eta_h^{AB}} + \frac{P_{CAES}^{dis}(t)}{\eta_{CAES}^{dis}}\right)\right] \times \Delta t \;\; \forall t T \tag{4}$$

Here, $C_{pe}(t)$ denotes the electricity purchase cost from the grid at time t (in $); $C_{oe}(t)$ represents the natural gas purchase cost at time t (in $); and $C_{oe}(t)$ corresponds to the carbon emission cost at time t (in $). The electricity price at time t is given by $\rho_g(t)$ in units of $/kWh, while $\rho_g(t)$ indicates the gas price at time t in the same units. The parameter θ represents the cost associated with carbon dioxide emissions in $/kg. Furthermore, φ_{in} and φ_g denote the equivalent emission coefficients of electricity and natural gas, respectively, measured in kg/kWh. Finally, Δt specifies the length of each time interval, assumed to be one hour. On this basis, the total daily cost minimization is expressed through the following objective function [32]:

$$\eta^{HRU} \times H^{HRU}(t) + H^{AB}(t) + P^{dis}_{TESS}(t) = H^{L}(t) + H^{AC}(t) + P^{ch}_{TESS}(t) \quad \forall t \in T \tag{5}$$

In this model, $H^{HRU}(t)$ represents the thermal output generated by the Heat Recovery Unit (HRU), while η^{HRU} denotes the efficiency of this unit, which is determined by its technical characteristics. Similarly, $H^{AB}(t)$ ndicates the heat supplied by the auxiliary boiler. The term $P^{dis}_{TESS}(t)$ corresponds to the power discharged from the Thermal Energy Storage System (TESS), whereas $P^{ch}_{TESS}(t)$ refers to the power stored within the TESS. In addition, $H^{L}(t)$ expresses the thermal demand response at time t, and $H^{AC}(t)$ defines the required heating load associated with the absorption chiller (refer to Equation (6)).

$$\mathrm{P^{ELE}}(t) + \mathrm{P^{PV}}(t) + \mathrm{P^{WT}}(t) + \mathrm{P_e^{PGU}}(t) = P^{L}(t,s) + P^{ISC}(t) \quad \forall t \in T \tag{6}$$

In the given formulation, $P^{PV}(t)$ denotes the electrical output generated by photovoltaic panels, while $P^{WT}(t)$ corresponds to the power produced by wind turbine units. The term $P_e^{PGU}(t)$ represents the electricity supplied by gas turbine generators. Likewise, $P^{dis}_{CAES}(t)$ refers to the discharged power from the Compressed Air Energy Storage (CAES) system, $P^{L}(t)$ indicates the electrical demand response at time t, and $P^{ISC}(t)$ expresses the amount of stored electrical energy, as presented in Equations (7)-(12).

$$0 \le P^{ch}_{ESS}(t) \le P^{ch-max}_{ESS} \times U^{Ch}_{ESS}(t) \quad \forall t \in T \tag{7}$$

$$0 \le P^{dis}_{ESS}(t) \le P^{dis-max}_{ESS} \times U^{dis}_{ESS}(t) \quad \forall t \in T \tag{8}$$

$$U^{dis}_{ESS}(t) + U^{Ch}_{ESS}(t) \le 1 \quad \forall t \in T \tag{9}$$

$$\mathrm{E_{ESS}}(\mathrm{t,s}) = \mathrm{E_{ESS}}(\mathrm{t}-1) - \mathrm{P^{dis}_{ESS}}(\mathrm{t}) \times \eta^{\mathrm{dis}}_{\mathrm{ESS}} + \left(\frac{P^{ch}_{ESS}(t)}{\eta^{ch}_{ESS}}\right) \quad \forall t \in T, t > 1 \tag{10}$$

$$E^{min}_{ESS} \le E_{ESS}(t) \le E^{max}_{ESS} \quad \forall t \in T \tag{11}$$

$$E_{ESS}(0) = E_{ESS} \tag{12}$$

In the ESS model, $P^{ch}_{ESS}(t)$denotes the charging power of the storage unit at time t, whereas $P^{dis}_{ESS}(t)$represents the discharged power at the same time interval. The charging process is limited by the maximum allowable charging rate P^{ch-max}_{ESS}, while the discharging capability cannot exceed $P^{dis-max}_{ESS}$. To represent the operational state of the storage device, two binary decision variables are defined: $U^{ch}_{ESS}(t)$and $U^{dis}_{ESS}(t)$, which indicate whether the ESS is in charging or discharging mode at time t, respectively. In addition, $E_{ESS}(t)$describes the energy stored in the ESS at a given time step and reflects the state of charge of the system. The parameters $\eta^{ch}_{ESS}$and η^{dis}_{ESS}correspond to the charging and discharging efficiencies, which account for energy losses occurring during the storage and retrieval processes. Incorporating these parameters into the optimization framework allows a more realistic representation of ESS operation and ensures that the energy balance and operational constraints of the storage system are accurately maintained.

For load management, a time-based DR program is implemented, as illustrated in Figure 1. This program aims to reshape the load profile by transferring a portion of electricity consumption from peak demand periods to off-peak or medium-load intervals. Such load shifting helps reduce stress on the power system, improves the utilization of available generation resources, and contributes to lowering operational costs. Furthermore, the implementation of this strategy can enhance system flexibility and support more efficient integration of distributed energy resources within the overall energy management framework.

The mathematical model is shown in Equations (13) and (14):

$$Load(t) = (1 - DR(t)) * load(t)^{\cdot} + ldr(t) \tag{13}$$

$$load(t)^{\cdot} - Load(t) = DR(t) * load(t)^{\cdot} - idr(t) \tag{14}$$

Where:

$Load(t)$: Load considering the load demand program

$DR(t)$: Load reduction rate

$load(t)^{\cdot}$: Predicted load

ldr: Load increase rate

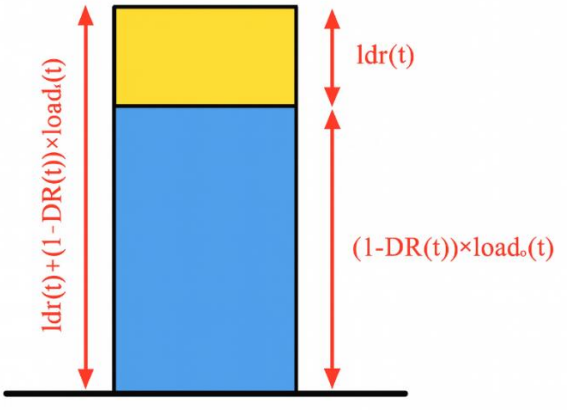


Figure 1. Load model considering load response.

Also, the load-responsive constraints can be expressed according to Equation (15):

$$\sum_{t=1}^{T} ldr(t) = \sum_{t=1}^{T} DR(t).load(t) \quad (15)$$

This equation reflects the fact that the load does not decrease or increase, but rather shifts from peak periods to medium or low load periods, in other words, the decreasing load is equal to the increasing load during the operation period. The technical limitations of the load response can also be stated as Equations (16)-(18):

$$load(t)^{inc} \leq inc(t).load(t) \quad (16)$$

$$DR(t) \leq DRmax \quad (17)$$

$$inc(t) \leq inc\ max \quad (18)$$

Where:

$load(t)^{inc}$: Maximum load that can be increased

$inc(t)$: Increaseable load percentage

$DRmax$: Maximum load percentage that can be reduced

This constraint states that the percentage of load decrease or increase must be less than a certain value.

Finally, our final objective function is written as Equation (19):

$$\emptyset = \sum_{t} \delta \mathrm{nu}_t / \propto + \sum_{t} \delta \mathrm{m}^{\mathrm{p}} p_t + \sum_{t} \delta \mathrm{m}^{\mathrm{w}} \mathrm{w}_t + \frac{\sum_t \delta \mathrm{nx}_t}{\eta_t} + \sum_{t} \delta \mathrm{m}^{\mathrm{E}} \mathrm{y}_t + \sum_{t} \delta \mathrm{m}^{\mathrm{T}} f_t + \sum_{t} \delta \mathrm{b}_t I_t + \sum_t (c^{dis}(d_t^- + d_t^+) + c^{reb}.reb_t - \pi_t^{DR}.r_t) - \sum_{t} \delta \mathrm{qR}_t \quad (19)$$

Which are, respectively, the operating costs of CHP, photovoltaic, wind turbine, boiler, electrical storage, thermal storage, electricity purchase from the grid, load response program, and revenue from selling electricity to the grid.

2.1. Optimization model

This section examines the problem of optimizing integrated residential energy costs in the smart grid. We begin with a simple model that incorporates household appliance characteristics, user preferences, and utility energy prices, leading to a MILP formulation. The model is then gradually expanded to include storage systems, renewable energy sources, and microgrids. In the context of microgrids, energy trading requires the model to determine both the optimal amount of energy and the optimal trading price. These aspects are represented using nonlinear expressions, which are transformed into a MILP problem. However, energy trading introduces a challenge of cost fairness among participating households. While the model minimizes the total energy purchase cost for the entire microgrid, it does not directly address cost optimization at the household level. A key issue arises when the model, relying on a single objective function (minimizing the sum of energy and non-use costs across all households), reduces costs for some households at the expense of increasing them for others. This unfair cost distribution diminishes the model's appeal to participants. To overcome this limitation, the model is extended to a multi-objective optimization framework that explicitly accounts for individual household costs. In this setting, optimality must ensure that no household experiences higher costs as a consequence of reducing costs for others. Overall, this section builds the integrated cost optimization model step by step, incorporating new components and their features. First, a complete cost optimization model is developed, capturing load and resource responsiveness as well as appliance preferences. Next, the model is extended to guarantee fairness and optimality among households participating in the microgrid.

2.2. Problem-Solving Flowchart

Consider several households within a microgrid equipped with a two-way distribution network that enables energy exchange among participants. Each household maintains access to the main power grid. When local generation within the microgrid is insufficient to meet a household's demand, additional energy is purchased from the power grid. Energy prices are announced by the utility, which may be determined based on time, demand, or any pricing scheme intended to manage consumption. Households differ in electricity consumption and generation profiles. Some may be equipped with renewable energy generation units, whose output varies with weather conditions. Appliances within each household have diverse power requirements and priority levels, while energy storage units may provide additional flexibility by shifting usage over time. Energy can also be exchanged among households within the microgrid to reduce costs or generate revenue. The objective is the minimization of total energy cost across all participating households. More specifically, given a set of appliances that must operate within a specified time horizon, the aim is to determine the optimal scheduling of consumption and resource utilization to minimize overall costs. It should be noted that this objective differs from load balancing or demand peak reduction, which are generally priorities for the utility.

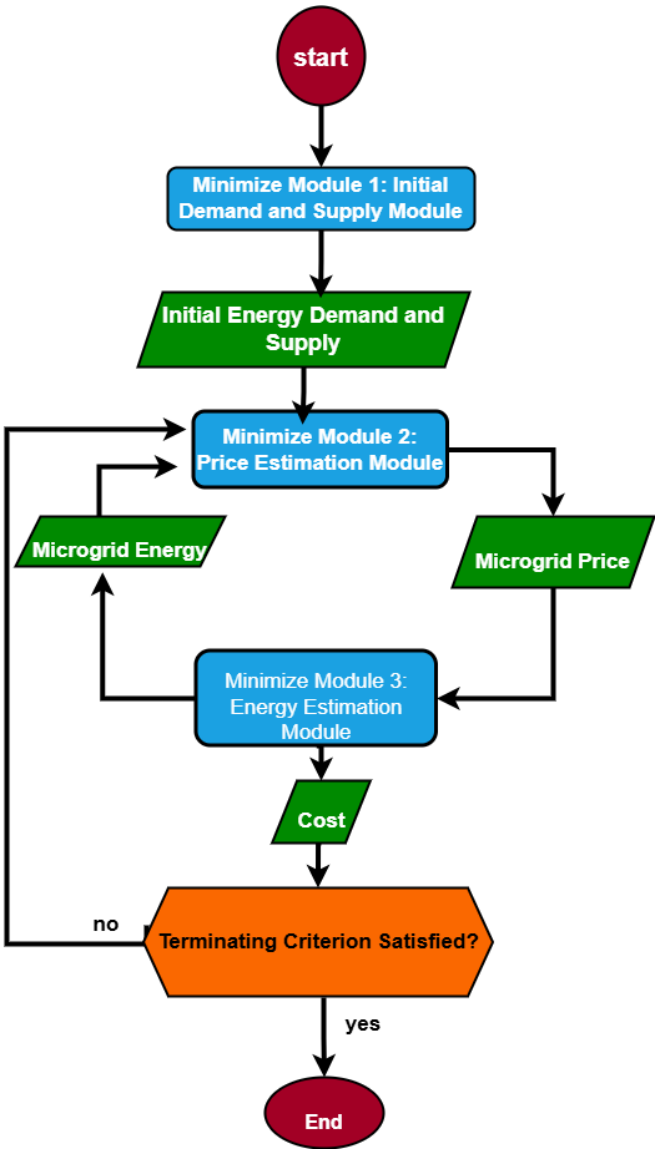


Figure 2. Problem solving flowchart.

To address the problem, a MILP model is developed. The notations required to define the input parameters and decision variables are introduced as follows. In the proposed framework, each MILP mode addresses a partial problem, while a bilinear model iteratively approximates the overall solution. Figure 2 illustrates the interaction between modes. Mode 1 generates initial estimates of energy demand and supply, which are then provided to Mode 2. Mode 2, treating these values as constants, determines the microgrid energy price. Mode 3, using the microgrid price as a constant, computes the amount of energy that can be traded. The resulting traded energy value is then passed back to Mode 2. Through this iterative process, the bilinear model updates both the microgrid energy price (Mode 2) and traded energy (Mode 3) until the stopping criterion is satisfied. The heuristic is employed solely for resolving the price–energy coupling in intra-microgrid trading; each iteration solves a structured MILP, and the core scheduling model itself is never handled by a metaheuristic. If the total cost does not improve by more than 0.1% during the final iterations, the procedure terminates. Once the termination condition is met, Mode 3 provides the final solution.

3. Simulation Results

The microgrid load is shown in Figure 3. Figures 4 and 5 show the amount of power generated from the solar system and wind turbine for the system under study. Figure 6 shows the boiler power changes. As can be seen, the amount of boiler power has also increased during times when the microgrid load has a high peak.

For the evaluation of a smart building consisting of 30 houses, the energy resources are allocated according to the total energy demand, and their capacities are determined based on this demand while considering the technical parameters and associated costs. It is assumed that the power capacity of the CHP unit can vary between 5 and 100 kW; however, in this study, the cases of 5 kW and 20 kW are specifically analyzed to illustrate the results.

For 24-hour system management, the optimal dispatch of the available resources is scheduled over a 48-hour horizon. The results of the electrical energy distribution are presented in Figure 7, while the corresponding heat distribution is illustrated in Figure 8. Furthermore, when the CHP capacity is set to 20 kW, the electrical distribution results are shown in Figure 9 and the heat distribution results are provided in Figure 10.

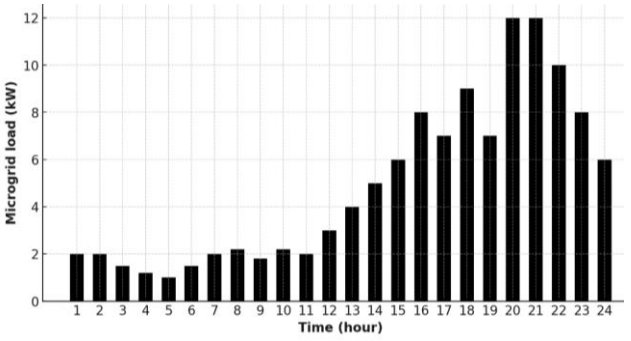


Figure 3. Microgrid load.

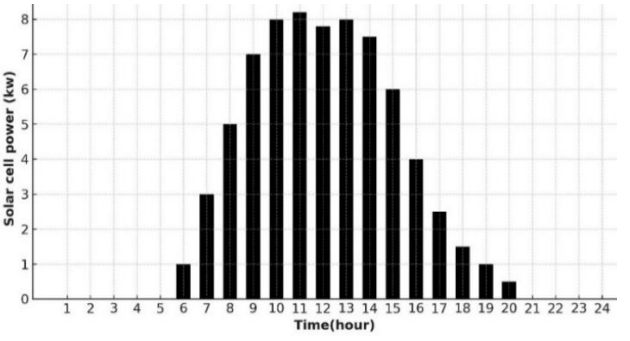


Figure 4. Solar cell output power.

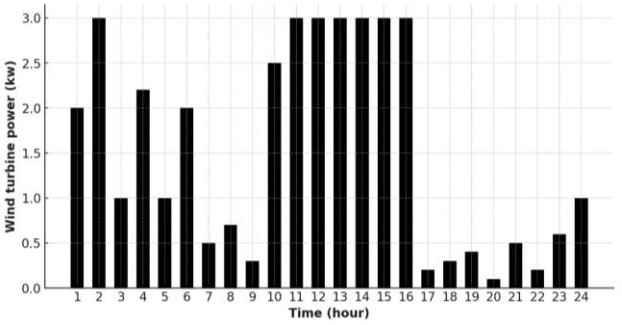


Figure 5. Wind turbine output power.

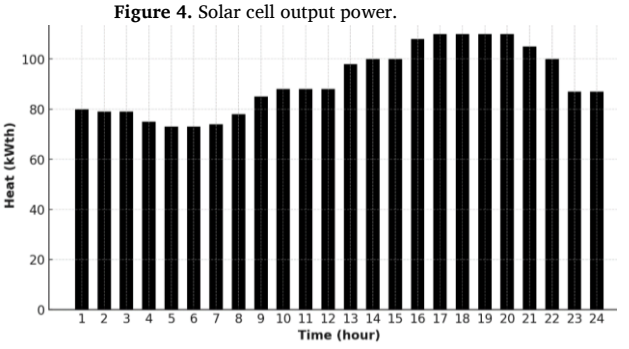


Figure 6. Boiler changes.

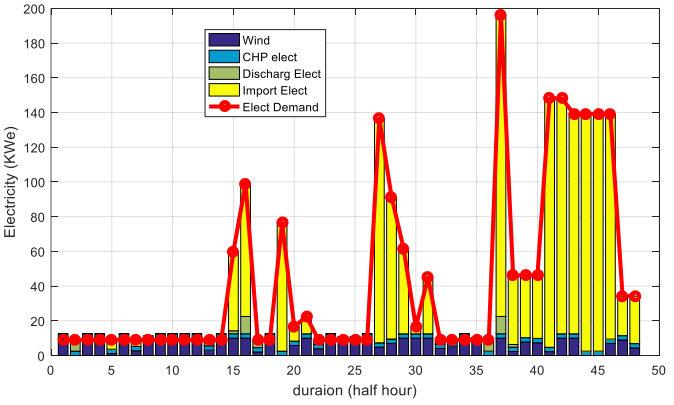


Figure 7. Electrical distribution of the studied system with CHP power and capacity of 5 kW.

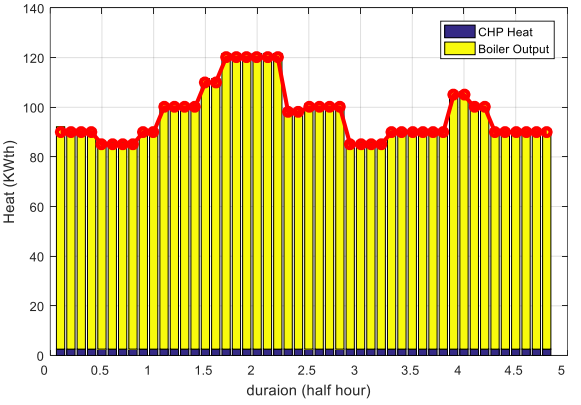


Figure 8. Heating distribution of the studied system with CHP power and capacity of 5 kW.

Figures 11 and 12 show the simulation results for 10 and 20 households, respectively

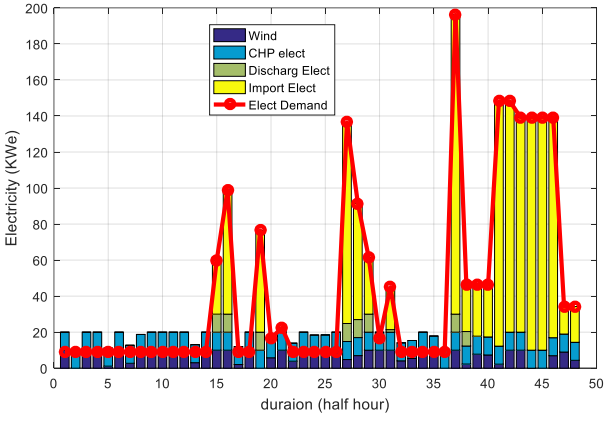


Figure 9. Electrical distribution of the studied system with CHP power and capacity of 20 kW.

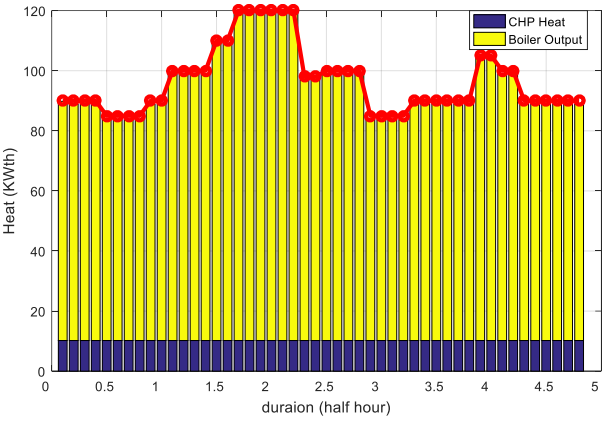


Figure 10. Heating distribution of the studied system with CHP power and capacity of 20 kW.

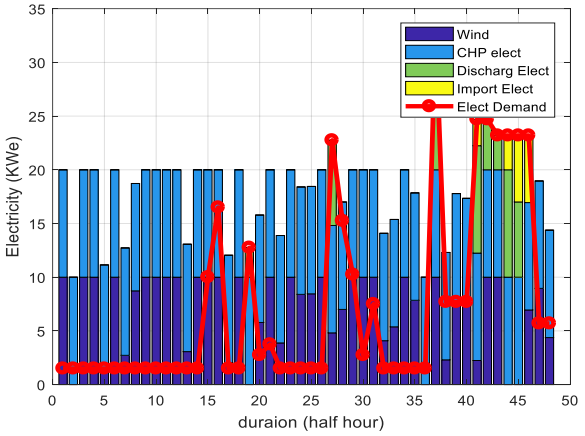


Figure 11. Electrical distribution system for 10 households.

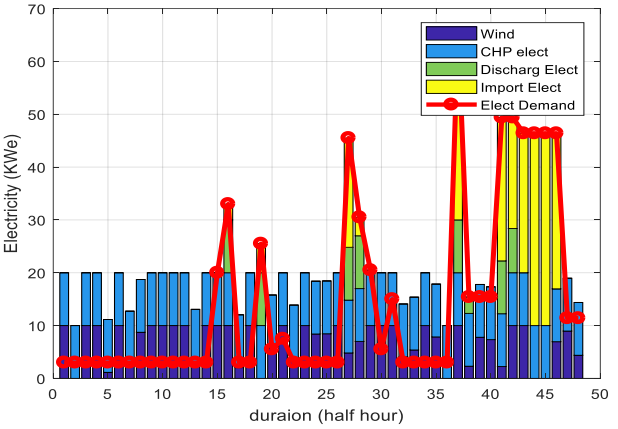


Figure 12. Electrical distribution system for 20 households.

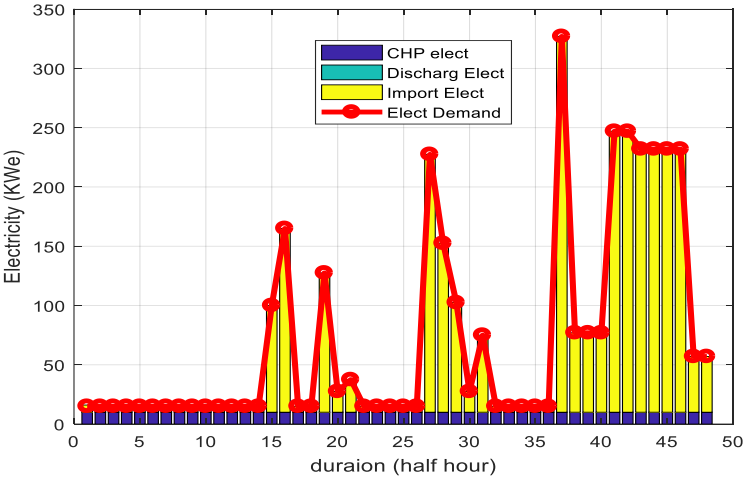


Figure 13. Electrical distribution system without the presence of a microgrid.

The electrical power distribution of the system in the absence of a MG is illustrated in Figure 13. As observed in this figure, the level of energy demand increases when the MG is not present. In addition, Table 2 presents the calculated costs for the smart house as the CHP capacity is gradually varied from 5 kW to 100 kW.

4. Results and Discussion

The simulation results provide a comprehensive overview of how different DERs and CHP capacities affect the performance of a smart home microgrid. The figures presented in the previous section illustrate the variations in load demand, renewable generation, and the corresponding behavior of the electrical and thermal distribution under different conditions.

4.1. Microgrid load and renewable generation

As shown in Figures 3-5, the electrical demand of the microgrid fluctuates significantly over time, reflecting the dynamic nature of residential consumption. Solar PV and wind turbine generation exhibit their well-known intermittency patterns, with PV output highly dependent on daylight hours and wind generation influenced by wind speed variations. These fluctuations highlight the necessity of complementary resources such as CHP and boiler units to ensure continuous supply.

The boiler output (Figure 6) shows a clear increase during peak load periods, compensating for the mismatch between renewable supply and demand. This confirms the critical role of thermal units in stabilizing the system when renewable generation is insufficient.

4.2. Effect of CHP capacity on energy distribution

The results of CHP operation at different capacities reveal a strong influence on both electrical and thermal distributions. For a small CHP unit of 5 kW (Figures 7 and 8), the system relies heavily on external resources and the boiler to meet demand. The electrical distribution shows more stress on the grid, while thermal supply requires frequent boiler adjustments. This leads to less efficient operation and higher overall costs.

In contrast, increasing the CHP capacity to 20 kW (Figures 9 and 10) substantially improves system performance. The electrical distribution becomes more balanced, with fewer fluctuations and less reliance on external supply. Similarly, the thermal distribution demonstrates smoother variations, reducing the boiler's operational burden. These results suggest that scaling up CHP capacity enhances both energy efficiency and cost-effectiveness, supporting the integration of distributed resources in smart homes.

4.3. Impact of household numbers on distribution

The simulation further evaluates the effect of varying the number of households. Figures 11 and 12 present the results for 10 and 20 households, respectively. As expected, increasing the number of consumers raises the total load and shifts the distribution profile. However, the system demonstrates scalability, with CHP and renewable sources adapting to the higher demand. Importantly, the distribution patterns remain stable, indicating that the proposed framework is robust to variations in residential scale.

4.4. Comparison with non-microgrid operation

Figure 13 depicts the distribution when the system operates without a microgrid. The demand increases significantly, and the reliance on external supply becomes dominant. This scenario clearly shows the benefits of microgrid integration, which not only reduces dependence on the main grid but also enhances the resilience and sustainability of the energy system.

4.5. Discussion of findings

The obtained results emphasize the crucial role of CHP capacity, renewable generation, and microgrid integration in achieving efficient energy management for smart homes. Increasing the CHP size leads to a more balanced distribution of both electrical and thermal energy, thereby reducing fluctuations and minimizing reliance on auxiliary resources such as the boiler or external supply.

Table 2. Obtained costs for CHP changes.

CHP capacity (kW)	Cost ($)
5	379.6838
10	379.6838
20	352.099
40	307.353
50	292.960
80	226.390
100	191.521

This indicates that higher-capacity CHP units not only improve overall efficiency but also enhance cost-effectiveness by lowering operational expenditures. Moreover, the inherent intermittency of renewable sources, including solar PV and wind turbines, highlights the necessity of stable backup systems. In this regard, CHP and boiler units act as reliable stabilizers, ensuring that the demand is continuously met despite the variability of renewable outputs.

Another key finding is the scalability of the proposed framework. The results for different household numbers confirm that the system maintains its stability and performance even as the load increases. This demonstrates the flexibility of the model, which can be effectively adapted to residential complexes of varying sizes without fundamental modifications. Finally, the comparison with non-microgrid operation clearly shows the advantages of microgrid integration. By reducing dependence on the main grid, the system enhances energy security, decreases costs, and improves sustainability.

Overall, the simultaneous analysis of electrical and thermal distributions offers a more comprehensive perspective compared to studies that focus solely on electricity. This dual consideration provides a holistic approach to residential energy management, ensuring that both power and heat demands are optimized in a coordinated manner. Consequently, the findings confirm that integrating CHP with renewable resources in microgrids represents a promising solution for the future of smart homes, combining economic, technical, and environmental benefits.

5. Conclusion

This study proposed an integrated framework for optimizing the joint distribution of electrical and thermal energy in smart homes connected to a microgrid equipped with renewable resources, CHP units, and storage systems. The developed MILP-based model coordinated power and heat flows under time-varying electricity prices and household demand profiles. Simulation results demonstrated that increasing CHP capacity from 5 kW to 20 kW improved the balance of energy distribution, reduced boiler operation, and minimized reliance on the external grid. Additional scenarios with 10 and 20 households confirmed the scalability of the framework, ensuring stable and efficient operation across different residential scales. Furthermore, comparison with a non-microgrid configuration highlighted the benefits of microgrid integration in lowering costs and enhancing resilience. Overall, the findings show that simultaneous consideration of electrical and thermal domains provides a more comprehensive strategy for residential energy optimization, and that combining demand response, CHP, and renewable resources within a unified structure enhances cost-effectiveness, strengthens energy security, and contributes to the sustainability of smart homes. Quantitatively, expanding CHP capacity from 5 kW to 100 kW reduces the 24-h operating cost from \$379.68 to \$191.52 ($\approx$ 49.6%). The most pronounced stepwise gains are observed at 20→40 kW ($\approx$ 12.7%) and 50→80 kW ($\approx$ 22.7%), highlighting where capacity additions deliver the largest marginal benefits before diminishing returns. Future research could extend this framework to larger-scale community microgrids, incorporate uncertainty modeling for renewable variability and demand fluctuations, and explore real-time control strategies to complement the optimization-based scheduling approach.

References

[1] R. H. Lasseter, "Smart Distribution: Coupled Microgrids," *Proceedings of the IEEE*, vol. 99, no. 6, pp. 1074–1082, 2011.

[2] F. Mohammadi, B. Mohammadi-Ivatloo, et al., "Robust Control Strategies for Microgrids: A Review," *IEEE Systems Journal*, vol. 16, no. 2, pp. 2401–2412, 2022.

[3] J. Han, C. Choi, W. Park, I. Lee, and S. Kim, "Smart Home Energy Management System Including Renewable Energy Based on ZigBee and PLC," *IEEE Transactions on Consumer Electronics*, vol. 60, no. 2, pp. 198–202, 2014.

[4] H. A. S. Al-Khalaf, R. Aazami, and M. Shirkhani, "Economic Evaluation of Energy Reduction in Smart Buildings Using Wireless Sensor Networks," *2025 6th International Conference on Optimizing Electrical Energy Consumption (OEEC)*, pp. 1–5, 2025.

[5] R. Aazami, M. Moradi, et al., "Technical Analysis of Comfort and Energy Consumption in Smart Buildings With Three Levels of Automation: Scheduling, Smart Sensors, and IoT," *IEEE Access*, vol. 13, pp. 8310–8326, 2025.

[6] D. E. Olivares, A. Mehrizi-Sani, et al., "Trends in Microgrid Control," *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1905–1919, 2014.

[7] M. Beaudin, H. Zareipour, A. Schellenberglabe, and W. Rosehart, "Energy storage for mitigating the variability of renewable electricity sources," *Energy for Sustainable Development*, vol. 14, no. 4, pp. 302–314, 2010.

[8] K. Owebor, E. Diemuodeke, T. Briggs, and M. Imran, "Power Situation and Renewable Energy Potentials in Nigeria – A Case for Integrated Multi-Generation Technology," *Renewable Energy*, vol. 177, pp. 773–796, 2021.

[9] L. Xu, G. Hou, et al., "Modeling and Assessment of a Novel Solar-Biomass Based Distributed Multi-Generation System," *Journal of Renewable and Sustainable Energy*, vol. 14, no. 3, 2022.

[10] F. Alfaverh, M. Denai, and Y. Sun, "A Dynamic Peer-To-Peer Electricity Market Model for a Community Microgrid With Price-Based Demand Response," *IEEE Transactions on Smart Grid*, vol. 14, no. 5, pp. 3976–3991, 2023.

[11] D. Stanelyte, N. Radziukyniene, and V. Radziukynas, "Overview of Demand-Response Services: A Review," *Energies*, vol. 15, no. 5, 1659, 2022.

[12] P. Siano, "Demand Response and Smart grids—A Survey," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461–478, 2014.

[13] X. Li, T. Li, et al., "Operation Optimization for Integrated Energy System Based on Hybrid CSP-CHP Considering Power-To-Gas Technology and Carbon Capture System," *Journal of Cleaner Production*, vol. 391, 136119, 2023.

[14] V. Isanbaev, R. Baños, F. Martínez, A. Alcayde, and C. Gil, "Monitoring Energy and Power Quality of the Loads in a Microgrid Laboratory Using Smart Meters," *Energies*, vol. 17, no. 5, 1251, 2024.

[15] S. Bozorgmehri, H. Heidary, and M. Salimi, "Market Diffusion Strategies for the PEM Fuel Cell-Based Micro-CHP Systems in the Residential Sector: Scenario Analysis," *International Journal of Hydrogen Energy*, vol. 48, no. 9, pp. 3287–3298, 2023.

[16] J. Wu, and Y. Han, "Integration Strategy Optimization of Solar-Aided Combined Heat and Power (CHP) System," *Energy*, vol. 263, 125875, 2023.

[17] S. Fatemi, A. Ketabi, and S. A. Mansouri, "A Multi-Level Multi-Objective Strategy for Eco-Environmental Management of Electricity Market Among Micro-Grids Under High Penetration of Smart Homes, Plug-In Electric Vehicles and Energy Storage Devices," *Journal of Energy Storage*, vol. 67, 107632, 2023.

[18] W. Ma, W. Han, Q. Liu, and G. Xu, "A review of combined heat and power (CHP)," *Preprints*, 2023.

[19] C. He, Z. Liang, et al., "Multi-Objective Optimization for Hydrogen-Mixed Combined Heat and Power (CHP) Plants Considering Economic and Environmental Factors Based on MILP," *Electric Power Systems Research*, vol. 221, 109442, 2023.

[20] M. B. Sigalo, S. Das, A. C. Pillai, and M. Abusara, "Real-Time Economic Dispatch of CHP Systems with Battery Energy Storage for Behind-The-Meter Applications," *Energies*, vol. 16, no. 3, 1274, 2023.

[21] P. Ahmadi, and H. Rastegar, "Optimal Energy Management of CHP-based Microgrid Examining Different Types of District Heating Networks," *IET Renewable Power*

Generation, vol. 17, no. 9, pp. 2174–2194, 2023.
[22] M. Parvin, H. Yousefi, and Y. Noorollahi, "Techno-Economic Optimization of a Renewable Micro Grid Using Multi-Objective Particle Swarm Optimization Algorithm," *Energy Conversion and Management*, vol. 277, 116639, 2023.
[23] B. Liu, "Optimal Scheduling of Combined Cooling, Heating, and Power System-Based Microgrid Coupled with Carbon Capture Storage System," *Journal of Energy Storage*, vol. 61, 106746, 2023.
[24] S. Zhang, J. Chang, and B. Wang, "A Multidimensional Data Aggregation Scheme of Smart Home in Microgrid With Fault Tolerance and Billing for Demand Response," *IEEE Systems Journal*, vol. 17, no. 3, pp. 4639–4649, 2023.
[25] M. Komeili, P. Nazarian, A. Safari, and M. Moradlou, "Robust Optimal Scheduling of CHP-Based Microgrids in Presence of Wind and Photovoltaic Generation Units: An IGDT Approach," *Sustainable Cities and Society*, vol. 78, 103566, 2022.
[26] P. Megantoro, S. A. Halim, et al., "Optimizing Reactive Power Dispatch with Metaheuristic Algorithms: A Review of Renewable Distributed Generation Integration with Intermittency Considerations," *Energy Reports*, vol. 13, pp. 397–423, 2025.
[27] A. H. Azad, and H. Shateri, "A Novel Control Strategy for On-Grid Photovoltaic Systems Based on Adaptive PI Control," *2019 Iranian Conference on Renewable Energy & Distributed Generation (ICREDG)*, pp. 1–6, 2019.
[28] A. Zakariazadeh, S. Jadid, and P. Siano, "Economic-Environmental Energy and Reserve Scheduling of Smart Distribution Systems: A Multiobjective Mathematical Programming Approach," *Energy Conversion and Management*, vol. 78, pp. 151–164, 2014.
[29] N. Mohammadkhani, M. Sedighizadeh, and M. Esmaili, "Energy and Emission Management of CCHPs with Electric and Thermal Energy Storage and Electric Vehicle," *Thermal Science and Engineering Progress*, vol. 8, pp. 494–508, 2018.
[30] H. Eskandari, M. Kiani, M. Zadehbagheri, and T. Niknam, "Optimal Scheduling of Storage Device, Renewable Resources and Hydrogen Storage in Combined Heat and Power Microgrids in the Presence Plug-In Hybrid Electric Vehicles and Their Charging Demand," *Journal of Energy Storage*, vol. 50, 104558, 2022.
[31] R. Doosti, M. Sedighizadeh, D. Sedighizadeh, and A. Sheikhi Fini, "Robust Stochastic Optimal Operation of an Industrial Building Including Plug in Electric Vehicle, Solar-powered Compressed Air Energy Storage and Ice Storage Conditioner: A Case Study in the City of Kaveh, Iran," *IET Smart Cities*, vol. 4, no. 1, pp. 56–77, 2022.
[32] D. Zhang, N. Shah, and L. G. Papageorgiou, "Efficient Energy Consumption and Operation Management in a Smart Building with Microgrid," *Energy Conversion and Management*, vol. 74, pp. 209–222, 2013.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

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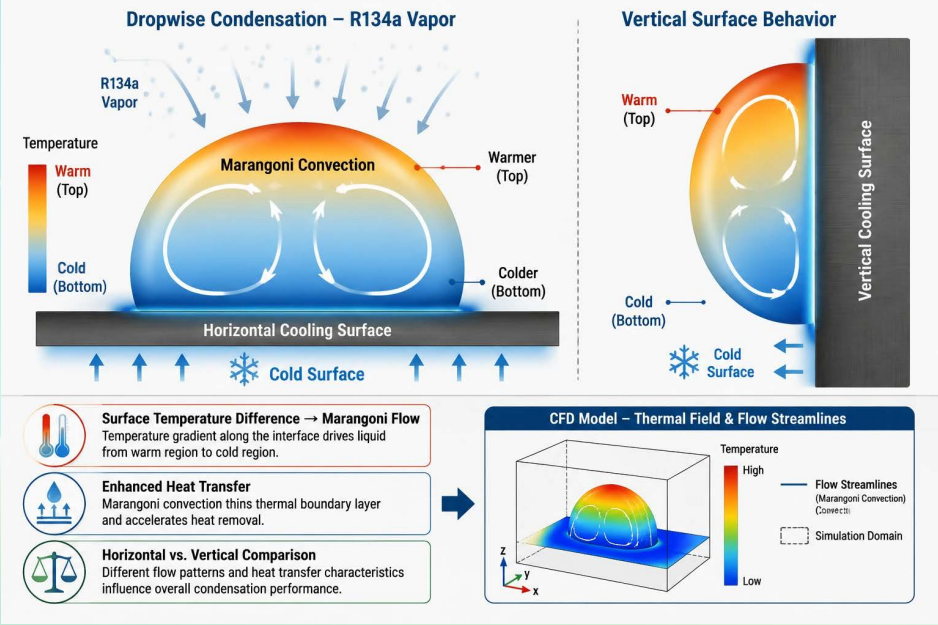
Thermal Behavior of R134a Droplet in Dropwise Condensation Considering Marangoni Convection Flow on Horizontal and Vertical Surfaces for Refrigeration Systems

Loghman Mohammadpour, Hesam Moghadasi

Highlights

- **The impacts of Marangoni convection, contact angle and surface orientation in refrigerant R134a droplet on DWC utilizing CFD tools are evaluated.**
- **The influences of Ma number on temperature distribution and average heat flux across horizontal and vertical surfaces are assessed.**
- **The vertical surface delivers about 4.5% greater average heat flux than the horizontal one at $Ma = 11020$ and $\theta = 110°$.**
- **The findings offer refrigeration focused insights that can help reduce energy consumption.**

Graphical Abstract



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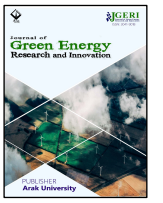
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Thermal Behavior of R134a Droplet in Dropwise Condensation Considering Marangoni Convection Flow on Horizontal and Vertical Surfaces for Refrigeration Systems

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A B S T R A C T

Dropwise condensation (DWC) increases phase change heat transfer efficiency, enabling more energy efficient thermal processes that directly support greener energy technologies and help lower overall carbon emissions. Correspondingly, this research work presents a numerical assessment of isolated R134a droplet during DWC on solid surfaces, focusing on the coupled impacts of Marangoni convection, contact angle across horizontal ($\beta = 0°$) and vertical ($\beta = 90°$) surfaces to investigate their impact on heat transfer during DWC. In this regard, droplet geometry was modeled utilizing Surface Evolver, while computational fluid dynamics (CFD) simulations were performed in ANSYS FLUENT with a pressure-based solver and Semi-Implicit Method for Pressure-Linked Equations (SIMPLE) algorithm. The simulation outcomes were validated through comparison with established theoretical models and previously published experimental measurements. Regarding the results, greater Marangoni numbers (Ma) enhance internal circulation, leading to more uniform temperature distributions and increased heat transfer coefficients. Also, contact angle was found to positively influence average heat flux (AHF) by reducing liquid–solid contact area, while vertical surfaces consistently exhibited higher AHF because of smaller droplet footprints. The results indicate that at $Ma = 11020$ and $\theta = 110°$, the vertical surface yields an AHF that is nearly 4.5% superior than that of the horizontal surface. Furthermore, unlike previous studies, which primarily examined these phenomena in general condensation contexts, this work specifically addresses their implications for refrigeration systems. By investigating R134a droplets, the findings provide novel insights into droplet scale condensation mechanisms that can contribute to reducing energy consumption in refrigerators.

1. Introduction

Condensation refers to the phase transition process in which vapor transforms into liquid when it comes into contact with a solid surface whose temperature is lower than that of the surrounding vapor environment [1-3]. When the surface temperature falls below the saturation temperature corresponding to the vapor pressure, vapor molecules lose energy and begin to accumulate on the surface in liquid form. This physical phenomenon is widely encountered in both natural environments and engineered systems and represents one of the most important mechanisms of phase-change heat transfer. Because condensation involves the release of latent heat, it plays a crucial role in thermal transport processes and significantly influences the efficiency of many energy conversion and thermal management technologies. From a large-scale engineering perspective, condensation processes are fundamental in several industrial sectors. In power generation systems, particularly in steam power plants, condensation is a key stage of the thermodynamic cycle where exhaust steam from turbines is condensed in condensers to recover water and maintain low turbine back pressure, thereby improving cycle efficiency [4].

Similarly, condensation mechanisms are central to water desalination technologies such as thermal distillation, where vaporized seawater must condense efficiently to produce fresh water [5]. In addition, many thermal control and heat recovery systems rely on condensation to remove heat effectively from working fluids [6]. At smaller technological scales, condensation is also essential in devices used in everyday life. Refrigeration systems and air-conditioning units operate based on vapor compression cycles in which the working refrigerant condenses after releasing heat to the surroundings [7,8]. The effectiveness of the condensation stage directly influences the overall performance and energy efficiency of these systems. Condensation on solid surfaces generally occurs in two primary modes: dropwise condensation (DWC) and filmwise condensation (FWC) [9,10]. These two modes differ significantly in terms of liquid distribution and heat transfer characteristics. In the dropwise condensation regime, vapor condenses into numerous discrete droplets that form and grow on the surface [11]. The droplets remain separated from one another and periodically detach or slide away, allowing new droplets to form on freshly exposed surface areas. This continuous renewal of the condensing surface minimizes the thermal resistance between the vapor and the solid substrate. As a result, DWC is widely recognized as a highly efficient mode of phase-change heat transfer. Enhanced heat transfer performance during DWC can significantly improve the efficiency of thermal systems, which is particularly important in the context of sustainable energy technologies and efforts aimed at reducing global carbon emissions. As condensation proceeds, individual droplets gradually increase in size due to direct condensation and droplet coalescence. When neighboring droplets merge, they can form larger droplets that eventually create a continuous liquid layer covering the surface. This transition marks the onset of filmwise condensation. In the FWC mode, a stable liquid film develops on the surface, which acts as a thermal barrier between the vapor and the solid wall. Because heat must then be conducted through this liquid layer, the overall heat transfer resistance increases substantially. Numerous experimental and theoretical investigations have demonstrated that heat transfer coefficients during DWC can be several times higher than those observed in FWC, making dropwise condensation the preferred mode for many heat transfer applications [12]. Given the significant thermal advantages of DWC, considerable research efforts have been directed toward increasing the probability of maintaining this mode on condensing surfaces. One widely adopted approach involves modifying the surface properties of the substrate in order to reduce its surface energy, thereby encouraging droplet nucleation and preventing the formation of continuous liquid films [13,14]. This objective can be achieved through the application of promoter layers or ultrathin coatings that alter the wettability characteristics of the surface. Such coatings are typically extremely thin and introduce minimal additional thermal resistance, which is why their influence on heat conduction through the surface is often considered negligible [15,16]. The heat transfer performance associated with dropwise condensation is influenced by a variety of physical and geometric parameters. Among the most important factors are the contact angle between the liquid droplet and the solid surface, which determines droplet shape and wettability behavior [17], the inclination angle of the surface relative to gravity [18], the micro- and nano-scale texture of the surface [19], and the thermophysical properties of the condensing liquid such as viscosity, surface tension, and thermal conductivity [20]. Each of these parameters affects droplet dynamics, including nucleation, growth, coalescence, and departure from the surface. The role of surface inclination in condensation heat transfer has been examined in several experimental studies. For example, Tancon et al. [21] conducted a comparative investigation of condensation on horizontal and vertical surfaces. Their experimental findings indicated that vertical surfaces exhibited approximately 40% higher heat transfer rates compared with horizontal configurations, and about a 10% improvement relative to surfaces inclined at $\beta = 45^{\circ}$. The enhanced performance observed on vertical surfaces was mainly attributed to more efficient droplet removal due to gravitational forces. In another study, Baghel et al. [22] analyzed the heat transfer characteristics of individual droplets beneath surfaces with different thermal resistances. Their results showed that the overall heat transfer rate remained nearly identical for droplets with a deformed geometry and those exhibiting an ideal spherical cap shape. Inclined surfaces frequently appear in practical thermal systems. A common example can be observed in domestic refrigeration units, where condensation often takes place on both horizontal and vertical internal walls. Improving condensation heat transfer in such systems can lead to noticeable gains in energy efficiency and operational performance. Some investigations [23] have reported that increasing the inclination angle can enhance the heat transfer rate for water droplets because gravity assists droplet movement and removal. However, this improvement becomes less significant for relatively small droplets ($V < 20$ μL) and for inclination angles below approximately 45°, where gravitational effects are comparatively weak. Another important mechanism affecting heat transfer during dropwise condensation is Marangoni convection [24]. In a stationary droplet attached to a solid surface, a temperature difference typically exists between the liquid–vapor interface and the substrate. This temperature difference generates a thermal gradient along the droplet surface. Since surface tension is a temperature-dependent property, variations in temperature along the interface lead to spatial variations in surface tension. These gradients induce tangential stresses along the interface that drive fluid motion within the droplet, creating internal circulation patterns commonly referred to as Marangoni flow. This internal flow mechanism can influence heat transfer in two competing ways: it may introduce additional thermal resistance by redistributing temperature fields, or it may enhance convective heat transport inside the droplet, thereby improving the overall heat transfer rate [25]. The intensity of Marangoni convection is typically characterized using the Marangoni number (Ma), a dimensionless parameter that represents the relative importance of surface tension–driven convection compared with diffusive transport mechanisms. The Marangoni number is defined according to Equation (1) and provides a useful metric for evaluating the influence of interfacial temperature gradients on droplet dynamics and heat transfer behavior during dropwise condensation [26].

$$Ma = -\frac{d\sigma}{dT}\frac{\Delta T\, C_P\, L\, \rho}{k\, \mu} \tag{1}$$

In Equation (1), the parameter dσ/dT represents the variation of surface tension with respect to temperature, commonly referred to as the surface tension gradient. The term ΔT indicates the temperature difference established between the vapor phase and the condensation surface, which acts as a driving force for the condensation process. Additionally, several thermophysical properties of the liquid droplet are incorporated into the formulation.

Specifically, L denotes the height of the droplet formed on the condensing surface, while ρ corresponds to the liquid density. The parameter μ represents the dynamic viscosity of the liquid, reflecting the internal resistance of the fluid to flow, and k indicates the thermal conductivity of the liquid, which characterizes its ability to conduct heat. Together, these parameters describe the physical and thermal characteristics of the droplet that influence the condensation behavior represented in Equation (1). Furthermore, the internal flow within the droplet is directed from regions of lower surface tension gradient (corresponding to higher temperatures) toward regions of greater surface tension gradient (lower temperatures). This behavior is characteristic of Marangoni convection. Figure 1 illustrates the resulting flow pattern inside a liquid droplet resting on a solid surface.

In a numerical study, Phadnis and Rykaczewski [1] assessed the impact of Marangoni convection on heat transfer. Their findings indicated that this convection mechanism enhances heat transfer, although the impact is noteworthy only for droplets with radii below 100 μm. A review of the literature reveals extensive research on the effects of inclination angle and Marangoni convection on heat transfer during DWC. However, few studies have specifically addressed these phenomena in the context of refrigeration systems. To bridge this gap, the present research numerically examines R134a, one of the most commonly utilized refrigerants, with the aim of contributing to energy efficiency improvements in refrigerators. In this study, numerical simulations were conducted for an isolated liquid droplet on both horizontal ($\beta = 0°$) and vertical ($\beta = 90°$) surfaces. Surface Evolver was utilized to model the droplet geometry on the inclined surfaces, while ANSYS FLUENT was employed to perform the computational fluid dynamics (CFD) simulations and attain the thermal outcomes. Besides, the effects of contact angle and Marangoni convection were systematically analyzed.

2. Physical Model

2.1. Arrangement

To initiate examination of single droplets on solid surfaces process, an accurate simulation of droplet behavior on the surface is essential. Two primary approaches are commonly utilized to model droplet shapes: the two-circle approximation [2] and the Surface Evolver [3] method. The former requires manual geometric construction based on analytical calculations, whereas the latter now more extensively adopted relies on computational modeling. Surface Evolver is an interactive software tool designed to simulate the geometry and energy of surfaces influenced by surface tension and other forces. It iteratively evolves the surface toward a minimal energy configuration, typically minimizing surface area under given constraints. In this work, a liquid R134a droplet on a solid surface was simulated at inclination angles of 0° and 90°, with contact angles of 100° and 110°. Figure 2 depicts the droplet configuration for $\beta = 0°$ and $\theta = 110°$. To promote DWC, the solid surface was coated with a boosted promoter layer. The thermo-physical features of the R134a droplet as well as, solid substrate, and promoter layer are reported in Tables 1 and 2, respectively.

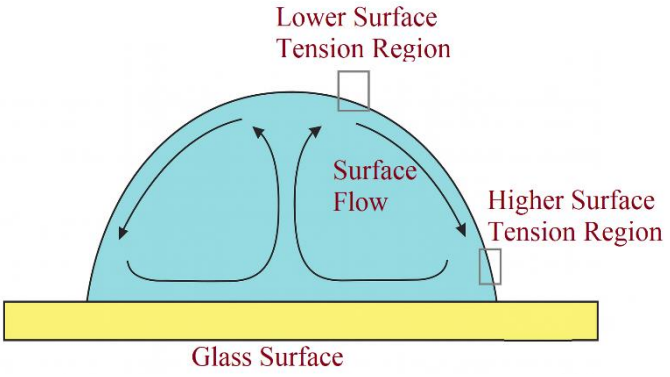


Figure 1. Marangoni flow inside a liquid droplet.

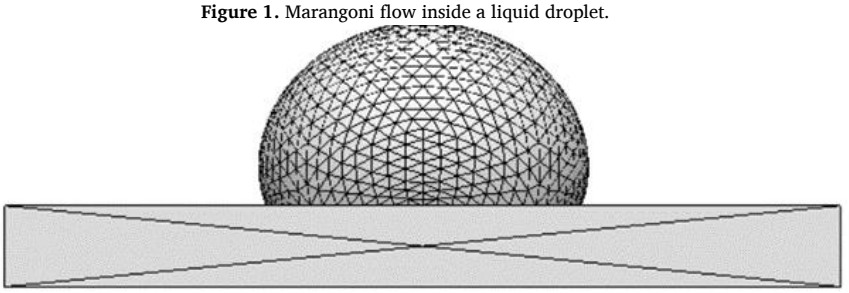


Figure 2. Schematic of a simulated liquid droplet on a solid surface in Surface Evolver with θ = 110°; β = 0°; V = 20μl and ρ_l = 1207 kg/m^3.

Table 1. Thermo-physical properties of R134a droplet [4,5].

Properties	Value	Unit
Pr	2.94	-
C_P	837	$J/kg\ K$
T_{sat}	280	K
T_w	270	K
ρ_l	1207	kg/m^3
ρ_v	31.2	kg/m^3
h_{lv}	134.8	kJ/kg
σ	0.0046	N/m
k	0.082	$W/m\ K$
M	102.03	$kg/kmol$
μ	0.198	$gr/cm\ s$
$\hat{\sigma}$	0.01	-

Table 2. Thermo-physical features of the condensing surface and drop promoter layer [6].

Sub-Domain	Material	Density (kg/m3)	Specific Heat (J/kg K)	Thermal Conductivity (W/m K)	Thickness (μm)
Surface	Al	2702	879.04	180	1000
Promoter Layer	Long Chain Hydrocarbon Coating	764.64	3100	0.05	0.1

2.2. Mathematical Framework

In the present work, the fluid within the droplet is assumed to behave as an incompressible medium, meaning that its density remains constant throughout the flow field. Additionally, the influence of viscous dissipation on the thermal energy balance is considered negligible and therefore omitted from the governing equations. Under these assumptions, the transport phenomena occurring within the droplet are described using the three fundamental conservation laws of fluid mechanics: conservation of mass, conservation of momentum, and conservation of energy. These governing relations are formulated in the Cartesian coordinate system to facilitate numerical implementation. The equations are discretized and solved using the Finite Volume Method (FVM), which is widely employed in computational fluid dynamics due to its strong conservation properties and robustness in handling complex geometries and boundary conditions. The simplified mathematical expressions corresponding to the continuity, momentum, and energy equations are presented in Equations (2) to (4). Equation (2) represents the continuity equation, which enforces mass conservation within the fluid domain. This relation indicates that, for an incompressible fluid, the divergence of the velocity field must be zero, ensuring that the mass flow entering any control volume is equal to the mass flow leaving it. Equation (3) describes the momentum conservation equation derived from the Navier–Stokes equations. This equation accounts for the temporal variation of momentum, the convective transport of momentum, the pressure gradient forces acting within the fluid, viscous diffusion effects, and the influence of body forces such as gravity. Equation (4) corresponds to the energy conservation equation, which governs the temperature distribution within the droplet. This equation represents the balance between transient heat storage, convective heat transport caused by fluid motion, and thermal diffusion due to temperature gradients.

$$\frac{\partial u_i}{\partial x_i} = 0 \tag{2}$$

$$\frac{\partial u_i}{\partial t} + \frac{\partial u_j u_i}{\partial x_i} = -\frac{1}{\rho}\frac{\partial P}{\partial x_i} + \frac{\mu}{\rho}\frac{\partial u_i}{\partial x_i^2} + g_i \tag{3}$$

$$\frac{\partial T}{\partial t} + \frac{\partial u_i T}{\partial x_i} = \alpha \frac{\partial^2 T}{\partial x_i^2} \tag{4}$$

Moreover, in order to find the exact magnitude of the capillary temperature (T_{cap}), Equation (5) can be utilized:

$$T_{cap} = T_{sat}\left(1 - \frac{2\sigma}{r h_{lv} \rho}\right) \tag{5}$$

where T_{sat} represents the saturation temperature of the working fluid, σ denotes the surface tension at the liquid–vapor interface, and r corresponds to the radius of the condensed droplet. In addition, h_{lv} refers to the latent heat of vaporization, which characterizes the amount of energy required for the phase change process, while ρ indicates the density of the liquid phase. These parameters collectively describe the thermophysical properties that govern droplet formation and heat transfer behavior during condensation.

Furthermore, in order to determine the heat transfer coefficient at the droplet interface, denoted by h_i, the formulation provided in Equation (6) is utilized, as reported in [7]. This expression enables a more accurate evaluation of interfacial heat transfer by accounting for the relevant fluid properties and interfacial conditions.

$$h_i = \left(\frac{2\hat{\sigma}}{2-\hat{\sigma}}\right)\left(\frac{h_{lv}^2 \Delta\rho}{T_{sat}}\right)\left(\frac{M}{2\pi \bar{R}\, T_{sat}}\right)^{0.5}\left(1-\frac{P_v}{\Delta\rho 2 h_{lv}}\right) \quad (6)$$

In Equation (6), $\hat{\sigma}$ represents the condensation coefficient, which characterizes the effectiveness of the phase change process occurring at the liquid–vapor interface. The term P_v corresponds to the vapor pressure evaluated at the dew point temperature, reflecting the thermodynamic state of the vapor during condensation. Furthermore, the parameter $\Delta\rho$ indicates the density difference between the liquid and vapor phases, a quantity that significantly influences condensation dynamics and droplet behavior. In addition, M denotes the molecular weight of the vapor, while $\bar{R}$ represents the universal gas constant. These thermophysical parameters are incorporated into Equation (6) to properly characterize the interfacial heat and mass transfer processes associated with vapor condensation.

2.3. Numerical Solution and Boundary Conditions

In this study, the transient three-dimensional Navier–Stokes equations together with the energy conservation equation are solved simultaneously in a coupled framework in order to accurately capture the fluid flow and heat transfer processes occurring within the system. Considering the unsteady nature of droplet behavior and thermal interactions, the governing equations are treated in their time-dependent form, allowing the evolution of velocity, pressure, and temperature fields to be properly represented throughout the computational domain.

For the thermal boundary conditions, a Dirichlet condition is prescribed on the solid surface, where the wall temperature is fixed and expressed as $T = T_W$. This assumption implies that the temperature of the inclined substrate remains constant during the condensation process, thereby providing a controlled thermal environment for droplet formation and heat transfer.

At the interface between the liquid droplet and the surrounding medium, a mixed boundary condition is imposed to represent the heat exchange between the droplet and its environment. Specifically, a Robin boundary condition is applied in which the heat transfer coefficient is defined as $HTC = h_i$. In addition to this convective heat transfer formulation, a temperature constraint is enforced at the interface, expressed as $T = T_{cap}$, which represents the characteristic temperature at the droplet cap. These boundary conditions collectively describe the thermal interaction between the droplet surface and the ambient vapor phase.

The overall configuration of these boundary conditions for a liquid droplet resting on an inclined surface is illustrated in Figure 3. This figure provides a schematic representation of the computational domain and clearly identifies the locations where the specified thermal constraints and interfacial conditions are applied. Such a boundary specification enables a more realistic simulation of the droplet heat transfer and fluid dynamics on inclined surfaces.

To numerically solve the governing equations, a pressure-based computational fluid dynamics solver available in ANSYS FLUENT was utilized. Within this framework, the spatial discretization of the convective terms was carried out using a second-order upwind scheme. The use of this higher-order discretization approach improves the accuracy of the numerical solution by reducing numerical diffusion and providing a more precise representation of gradients in velocity, pressure, and temperature fields throughout the computational domain. In addition, the coupling between the pressure and velocity fields was handled using the Semi-Implicit Method for Pressure-Linked Equations (SIMPLE) algorithm. This algorithm is widely applied in pressure-based solvers to iteratively enforce mass conservation while updating the pressure and velocity distributions. Through this procedure, the pressure correction equation is solved to adjust the velocity field, ensuring that the continuity equation is satisfied at each iteration. The combined use of the second-order upwind discretization scheme and the SIMPLE pressure–velocity coupling approach enhances the stability and reliability of the numerical solution for the fluid flow and heat transfer processes considered in this study.

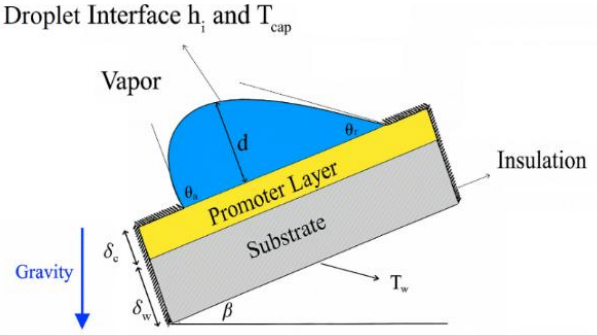


Figure 3. Applied boundary conditions on the studied domain for a droplet on an inclined surface.

2.4. Grid Independence Evaluation

Mesh generation plays a critical role in computational accuracy and efficiency, as it directly affects both simulation time and the quality of outcomes. In this examination, ANSYS ICEM CFD, a commercial meshing software, was employed to generate an optimal mesh for the computational domain. Also, Figure 4 exhibits the resulting grids for the liquid droplet on an inclined solid surface, viewed from diverse angles. It is crucial to mention that, the meshes are unstructured and composed of tetrahedral elements.

As illustrated in Figure 5, a mesh independence study was carried out to ensure that the numerical results are not influenced by the discretization of the computational domain. In this evaluation, the temperature distribution inside the liquid droplet was examined along the droplet height while it was positioned on an inclined solid surface. By comparing the temperature profiles obtained from several mesh configurations with different element densities, the sensitivity of the solution to grid refinement was carefully investigated. The analysis showed that further refinement beyond a certain grid resolution produced negligible changes in the predicted temperature distribution. Based on this comparison, a computational mesh containing approximately 1.2 million elements was selected for the remaining simulations. This grid density was found to provide sufficiently accurate results while maintaining a reasonable computational time. Consequently, the chosen mesh offers an appropriate compromise between numerical accuracy and computational efficiency, ensuring reliable simulation outcomes without imposing unnecessary computational cost.

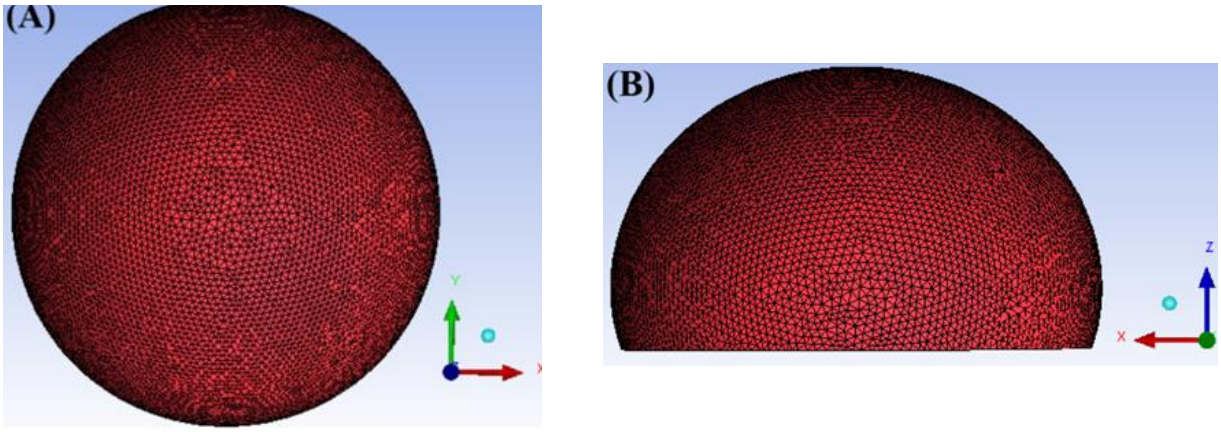


Figure 4. The generated grid for a liquid droplet on an inclined surface with β = 0° at different perspectives, (A) X-Y plane (Z = 0) (B) X-Z plane (Y = 0).

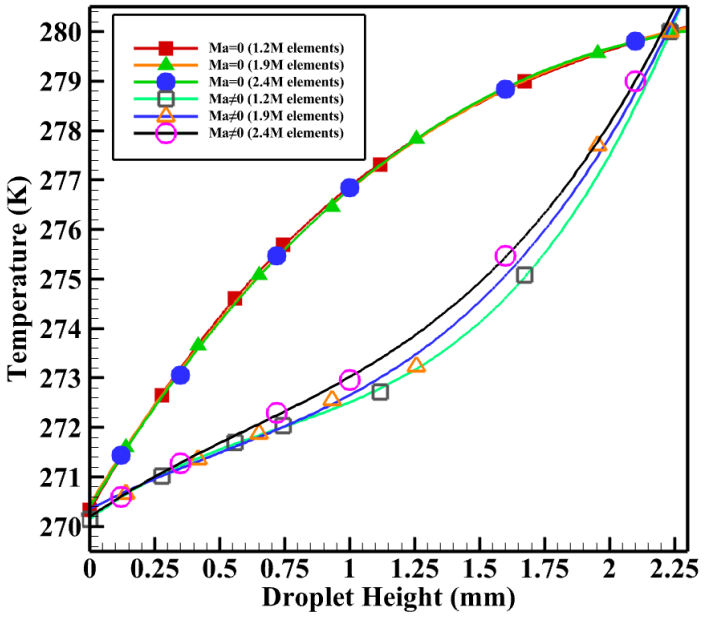


Figure 5. Temperature profile at midline of droplet (X-Y plane, Z = 0) versus droplet height for various grid sizes ranging from 1.2 to 2.4 million element. Considering, contact angle (θ) = 110°, V = 20 µl, T_{sat} = 280 K, ΔT = 10 K, $\hat{\sigma}$ = 0.01, δ_w = 1 mm, δ_c = 10 µm, K_c = 0.2W/m K and K_w = 180W/m K.

2.5. Validation

The validation of this study was carried out through two complementary approaches. First, the droplet shape generated considering Surface Evolver was compared with experimental observations reported by Annapragada et al. [8]. As demonstrated in Figure 6, the simulated droplet profile closely matches the experimental data, representing strong agreement and confirming the reliability of the Surface Evolver based modeling. Second, the findings attained from the CFD simulations were validated against both theoretical predictions and experimental findings from the literature. This dual validation approach reinforces the credibility of the numerical framework employed in this research.

To evaluate the average heat flux (AHF) associated with a single droplet, Baghel et al. [22] performed a theoretical investigation in which a liquid droplet with a volume of V = 3.59 μl was analyzed at different contact angles. In the present study, an identical droplet configuration was reproduced using Surface Evolver under the same physical conditions to ensure a consistent comparison. The obtained droplet geometry and associated characteristics were then compared with the results reported by Baghel et al. As illustrated in Figure 7(a), the comparison indicates a strong level of agreement between the two studies, confirming that the implemented approach can accurately capture the droplet shape and its geometric characteristics. In addition to this validation step, further verification of the numerical model was carried out by comparing the CFD predictions with available experimental data reported by Rajkumar et al. [33]. In their experimental work, the authors investigated the influence of subcooling on the heat transfer coefficient associated with an individual droplet during the condensation process. Their observations demonstrated that the heat transfer coefficient gradually decreases as the degree of subcooling increases, highlighting the sensitivity of droplet heat transfer performance to thermal conditions. To ensure a meaningful comparison, the same droplet configuration and operating conditions considered in the experimental study were replicated in the present simulations. The resulting numerical predictions for the heat transfer coefficient were then compared with the corresponding experimental measurements reported by Rajkumar et al. As depicted in Figure 7(b), the comparison reveals a satisfactory level of agreement between the CFD results and the experimental data. This consistency between numerical and experimental findings provides additional confidence in the validity and reliability of the adopted numerical methodology and confirms that the implemented modeling framework is capable of accurately predicting the thermal behavior of individual droplets under varying subcooling conditions.

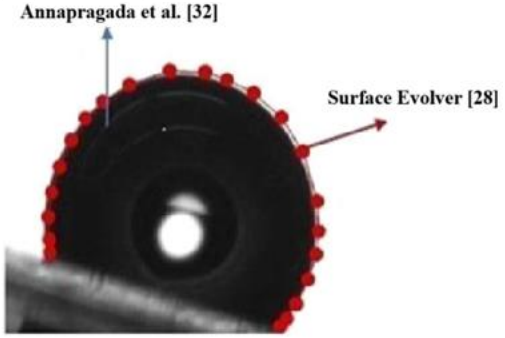


Figure 6. The comparison of the obtained simulated droplet shape from Surface Evolver with an experimental work for a liquid water droplet with $\beta = 15°$, $V = 10\ \mu l$ and $T_{sat} = 313\ K$.

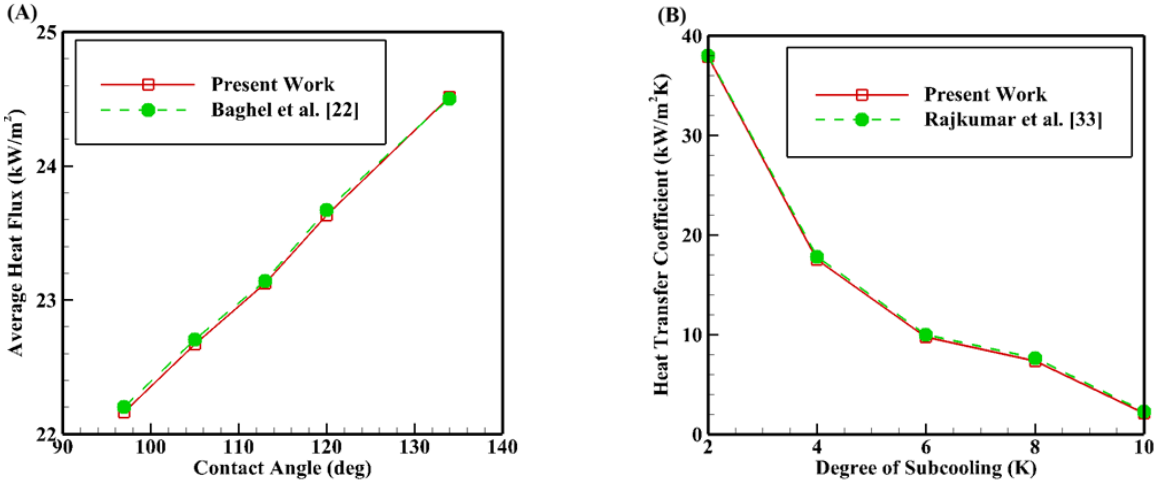


Figure 7. Validation of the current solution with the data of (a) Baghel et al. [9] at $V = 3.59\ \mu l$, $T_{sat} = 313K$, $\Delta T = 10\ K$, $\hat{\sigma} = 0.04$ and $\beta = 0°$ (b) Rajkumar et al. [10] at $V = 10\ \mu l$ and $\beta = 0°$.

3. Result and Discussion

The present research scrutinizes the combined impacts of the Ma number and contact angle on heat transfer rate and internal temperature distribution within an individual liquid droplet. In addition, simulations were executed for droplets on both horizontal ($\beta = 0°$) and vertical ($\beta = 90°$) surfaces to capture the influence of surface orientation.

3.1. The Impacts of Ma Number on AHF for an Individual Droplet across Horizontal and Vertical Surfaces

As mentioned previously, Marangoni convection plays an important role in influencing the heat transfer characteristics during DWC. This phenomenon arises due to gradients in surface tension along the liquid–vapor interface, which are typically induced by temperature differences across the droplet surface. Such variations generate tangential stresses that drive fluid motion within the droplet, leading to internal circulation patterns that can enhance the transport of heat and mass. To quantify the relative significance of this effect, the Marangoni number (Ma) is commonly employed as a dimensionless parameter. This number represents the ratio between the transport mechanisms associated with surface tension–driven convection and those governed by diffusive processes. In other words, the Ma number compares the rate of momentum and energy transport induced by Marangoni flows with the rate of transport resulting from molecular diffusion. Consequently, larger values of the Marangoni number indicate stronger surface tension–driven convection and a more pronounced influence of Marangoni effects on the overall heat transfer behavior during DWC. Figure 8 displays the change in AHF against contact angle for three diverse Ma numbers on a horizontal ($\beta = 0°$) and vertical ($\beta = 90°$) surface. As it can be seen in Figure 8, when there is no Marangoni convection ($Ma = 0$) inside the R134a liquid droplet, the growth in contact angle does not lead to an increase in AHF. In the absence of Marangoni convection, heat transfer during DWC is governed primarily by conduction through the liquid droplets, while vapor-side diffusion controls the condensation rate. Under these conditions, the contact angle influences only the droplet geometry, redistributing the liquid volume between droplet height and footprint area without significantly altering the overall thermal resistance. Although variations in contact angle modify the local conduction path length within individual droplets, these effects are geometrically compensating when averaged over the droplet population. Consequently, the effective liquid-phase thermal resistance remains nearly invariant with respect to contact angle, rendering the average heat flux insensitive to wettability in the conduction-limited regime. Only when interfacial-driven convection is present does the contact angle play a direct role in heat transfer by altering internal flow structures and advective transport. However, when $Ma = 2204$ and $\beta = 0°$, the increase in contact angle from $\theta = 100°$ to $\theta = 110°$ results in 5.5% increase in AHF. Moreover, for the case of $Ma = 11020$ and $\beta = 0°$, the value attains 21.5%. A greater Ma number results in a superior surface tension gradient and consequently a higher temperature gradient which can lead to having an increase in heat transfer coefficient and that explains why AHF at elevated Ma numbers is more compared to lower Ma numbers. As for the contact angle, when it increases the AHF increases as well since a higher contact angle results in a lower liquid-solid contact which in turn ameliorates the AHF. For the vertical surface, AHF increase by 0%, 7.1% and 25% when $Ma = 0$, $Ma = 2204$ and $Ma = 11020$, respectively. It is evident that inclination angle has a direct influence on AHF. Also, when $Ma = 11020$ and $\theta = 110°$, AHF is greater by approximately 4.5% on a vertical surface compared to a horizontal one. The droplet's footprint on a solid surface when $\beta = 90°$ is smaller than when $\beta = 0°$. To be more specific, if an equal amount of heat is going to transfer through two surfaces, the AHF for the surface with less area is undoubtedly higher. This illustrates why AHF increase with inclination angle.

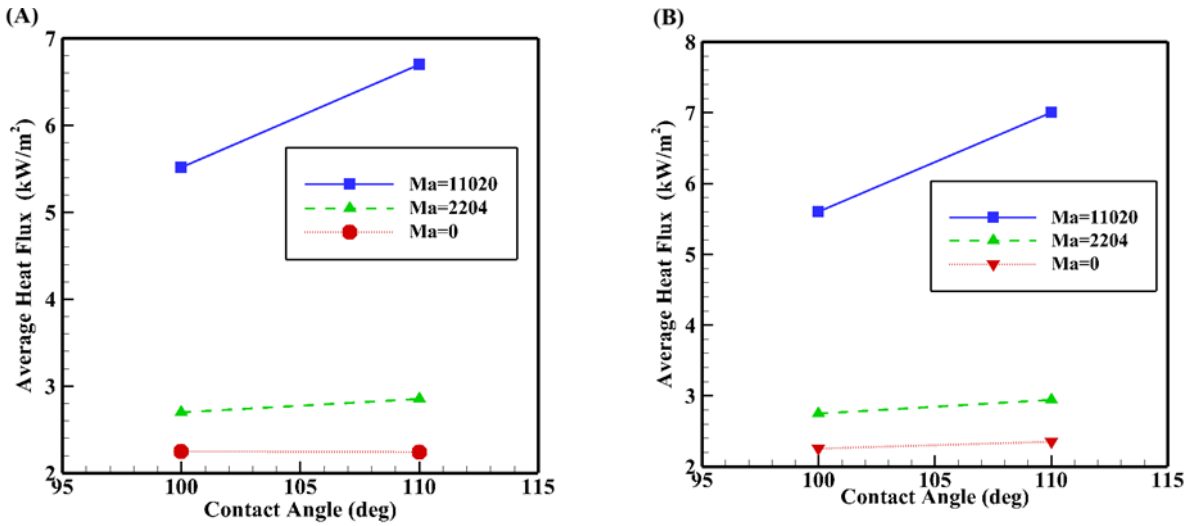


Figure 8. AHF against contact angle at diverse Ma numbers while V = 20 µl, $\hat{\sigma} = 0.01$, $\delta_w = 1$ mm, $\delta_c = 10$ µm, $K_c = 0.2$ W/m K, $K_w = 180$W/m K and $T_{sat} = 280$ K (A) $\beta = 0°$ (B) $\beta = 90°$.

3.2. The Impacts of Ma Number on Temperature Distribution across Horizontal and Vertical Surfaces

Figure 9 points out the temperature distribution inside an R134a droplet with $\theta = 110°$ on both horizontal and vertical surfaces at diverse Ma numbers. As observed, increasing the Ma number leads to a more uniform temperature distribution within the droplet. As the Marangoni number increases, surface-tension gradients along the liquid–vapor interface intensify, generating stronger interfacial shear stresses that drive internal circulation within the droplet. This Marangoni-induced flow enhances advective transport of thermal energy, which rapidly redistributes heat compared to pure conduction. When advection dominates diffusion (high Ma), temperature differences are continuously mixed by the internal flow, suppressing local thermal gradients and leading to a more spatially uniform temperature field. In contrast, at low Marangoni numbers, weak interfacial stresses result in negligible internal motion, and heat transfer remains diffusion-dominated, allowing pronounced temperature gradients to persist. Thus, increasing the Marangoni number effectively homogenizes the droplet temperature by reducing the relative importance of conductive thermal resistance. This uniformity promotes the development of internal circulating flow, which enhances the temperature gradient at the droplet vapor interface. The resulting stronger gradients contribute to an enlarged heat transfer rate. Furthermore, the temperature distribution on the vertical surface appears more uniform compared to the horizontal surface. This observation is consistent with earlier findings that demonstrated superior AHF for droplets on vertical surfaces, thus reinforcing the role of inclination angle in ameliorating heat transfer performance.

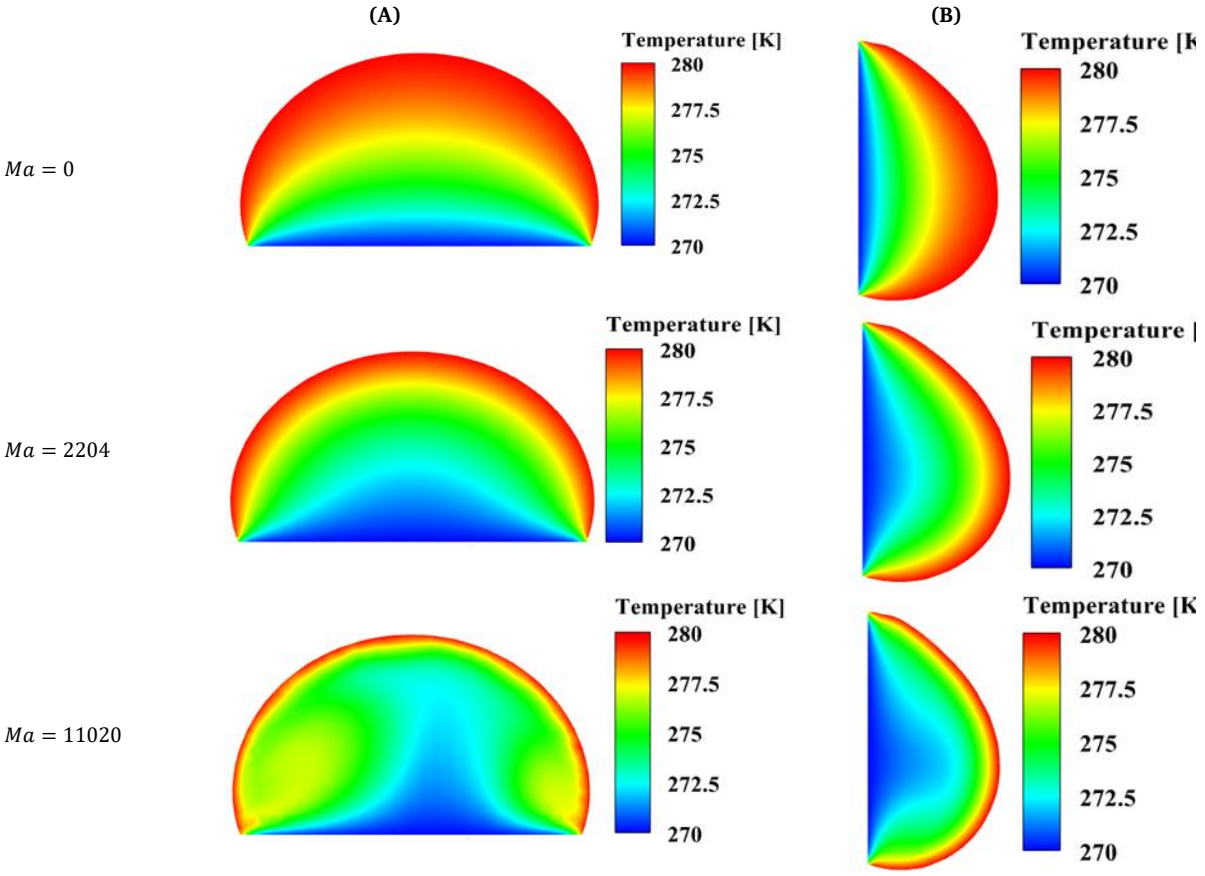


Figure 9. Temperature contours at Z-Y plane (X = 0) inside an individual R134a droplet while V = 20 µl, θ = 110°, ΔT = 10 K, T_{sat} = 280 K at three diverse Ma numbers for (A) β = 0° (B) β = 90°.

4. Conclusion

The findings of the present study demonstrate that Marangoni convection, contact angle, and surface inclination jointly exert a significant influence on the heat transfer characteristics during DWC of R134a droplets. These parameters interact to determine the internal flow structure of the droplet, the effective heat transfer area, and ultimately the overall condensation performance. An increase in the Marangoni number (Ma) strengthens thermocapillary forces generated by surface tension gradients along the liquid–vapor interface. As a consequence, stronger internal circulation develops inside the droplet, which promotes enhanced mixing and reduces temperature gradients within the liquid phase. This intensified fluid motion leads to a more uniform temperature distribution and facilitates more efficient heat transport from the vapor–liquid interface toward the solid surface, thereby increasing the overall heat transfer rate. The contact angle (θ) also plays a crucial role in determining condensation performance. Larger contact angles produce droplets with a more spherical geometry and a smaller liquid–solid contact area. Although the footprint of the droplet decreases, the associated reduction in thermal resistance and modification of heat flow paths can enhance the AHF through the droplet. The numerical results confirm that increasing the contact angle systematically improves the heat transfer capability of the droplet under the investigated conditions. For a horizontal surface configuration ($\beta = 0^{\circ}$) at Ma = 2204, increasing the contact angle from $\theta = 100^{\circ}$ to $\theta = 110^{\circ}$ results in approximately 5.5% enhancement in the AHF. When the thermocapillary effects become stronger and the Marangoni number increases to Ma = 11020, the sensitivity of heat transfer to the contact angle becomes considerably more significant, leading to an AHF improvement of about 21.5% over the same contact-angle range. A different trend is observed for the vertical surface configuration ($\beta = 90^{\circ}$). Under this orientation, the increases in AHF corresponding to the same change in contact angle are 0%, 7.1%, and 25% for Ma = 0, Ma = 2204, and Ma = 11020, respectively. These results clearly indicate that the influence of contact-angle variation on heat transfer intensifies as Marangoni convection becomes stronger, highlighting the strong coupling between thermocapillary-driven flow and droplet geometry. Furthermore, a comparison between surface orientations reveals that vertical surfaces consistently exhibit superior heat transfer performance compared with horizontal surfaces. This improvement can be attributed to the reduced droplet footprint on vertical surfaces, which leads to a more concentrated heat transfer region and a more favorable droplet geometry for thermal transport. Quantitatively, at Ma = 11020 and $\theta = 110^{\circ}$, the vertical surface provides approximately 4.5% higher AHF than the horizontal configuration. To ensure the reliability of the computational approach, the numerical model was validated against both theoretical predictions and experimental measurements reported in previous studies. The strong agreement obtained in these comparisons confirms the robustness and accuracy of the developed numerical framework. Overall, the analysis highlights that microscale droplet dynamics play a critical role in determining macroscopic condensation performance. By carefully controlling parameters such as Marangoni convection intensity, surface wettability, and surface orientation, it is possible to significantly enhance heat transfer during dropwise condensation. These insights are particularly valuable for thermal management systems and refrigeration technologies, where improved droplet-level heat transfer can contribute to higher refrigeration efficiency and reduced energy consumption.

Nomenclature

Symbols

$d\sigma/dT$	Surface Tension Gradient (N/mK)
$\left(\frac{\partial T}{\partial x_i}\right)_c$	Temperature Gradient Vector at The Condensing Surface (K/m)
g	Gravity Acceleration (m/s^2)
h_i	Interfacial Heat Transfer Coefficient $(W/m^2\,K)$
h_{lv}	Latent Heat of Vaporization (J/kg)
k	Thermal Conductivity (W/mK)
L	Droplet Height (m)
M	Vapor Molecular Weight (kg/mol)
P_v	Vapor Pressure (Pa)
q	Average Heat Flux (W/m^2)
$\bar{R}$	Universal Constant of Gases $(J/mol\,K)$
T	Temperature (K)
T_{cap}	Temperature Near Droplet Interface (K)
u	Fluid Velocity in X-Direction (m/s)
v	Fluid Velocity in Y-Direction (m/s)
w	Fluid Velocity in Z-Direction (m/s)
V	Volume of Droplet (μl)
x, y, z	Cartesian Coordinate

Greek symbols

α	Thermal Diffusivity (m^2/s)
β	Surface Inclination Angle (deg)
ρ	Condensate Density (kg/m^3)
θ	Contact Angle (deg)
μ	Dynamic viscosity $(kg/m\,s)$
σ	Surface Tension (N/m)
$\hat{\sigma}$	Condensation Coefficient
δ	Thickness (m)

Subscripts

sat	Saturation Condition

Abbreviations

CFD	Computational Fluid Dynamics
DWC	Dropwise Condensation
FWC	Filmwise Condensation
FVM	Finite Volume Method
Ma	Marangoni Number

References

[1] O. M. E. S. Khayal, et al., "Condensation Heat Transfer: Principles, Mechanisms, and Mathematical Modeling," *Excellence Journal for Engineering Sciences*, vol. 2, no. 1, 2025.

[2] L. Mohammadpour, E. Aminian, and H. Saffari, "Investigating the Effect of Marangoni Phenomenon on Single Drop Density on Wenzel and Cassie Structures," *Journal of Solid and Fluid Mechanics*, vol. 10, no. 4, pp. 387–398, 2020.

[3] D. Schurk, "The Fundamentals of Condensation," *ASHRAE Journal*, vol. 67, no. 2, 2025.

[4] Q. Peng, L. Jia, et al., "Analysis of Droplet Dynamic Behavior and Condensation Heat Transfer Characteristics on Rectangular Microgrooved Surface with CuO Nanostructures," *International Journal of Heat and Mass Transfer*, vol. 130, pp. 1096–1107, 2019.

[5] A. M. Al-Tajer, W. H. Alawee, H. A. Dhahad, K. A. Hammoodi, and Z. M. Omara, "Assessing the Environmental Impact of Innovative Hybrid Desalination and Atmospheric Water Harvesting Technologies," *Journal of Thermal Analysis and Calorimetry*, vol. 150, no. 20, pp. 16735–16752, 2025.

[6] Z. Wang, T. Horseman, et al., "Pathways and Challenges for Efficient Solar-Thermal Desalination," *Science Advances*, vol. 5, no. 7, 2019.

[7] V. P. Carey, *Liquid-Vapor Phase-Change Phenomena: An Introduction to the Thermophysics of Vaporization and Condensation Processes in Heat Transfer Equipment*, CRC Press, 2020.

[8] W. Ji, G. Chong, C. Zhao, H. Zhang, and W. Tao, "Condensation Heat Transfer of R134a, R1234ze(E) and R290 on Horizontal Plain and Enhanced Titanium Tubes," *International Journal of Refrigeration*, vol. 93, pp. 259–268, 2018.

[9] P. Dehghani, S. M. Hosseinalipour, and H. Akbari, "Investigating the Effect of Environmental Conditions and Surface Type on Condensation Heat Transfer Coefficient and Droplet Departure Time," *International Journal of Thermal Sciences*, vol. 208, 109466, 2025.

[10] M. Afshari, H. Moghadasi, and L. Mohammadpour, "Assessing Parameters Impact in Dropwise Condensation Heat Transfer for an Individual Droplet on Inclined/Grooved Surfaces: a Sobol Sensitivity Analysis," *Scientific Reports*, vol. 15, no. 1, 2025.

[11] H. Chen, C. Shi, et al., "Investigation of the Droplet Dynamics and Thermal Performance During Dropwise Condensation in the Wickless Heat Pipe Condenser," *International Communications in Heat and Mass Transfer*, vol. 161, 108487, 2025.

[12] E. Schmidt, W. Schurig, and W. Sellschopp, "Versuche Über Die Kondensation Von Wasserdampf in Film- Und Tropfenform," *Technische Mechanik und Thermodynamik*, vol. 1, no. 2, pp. 53–63, 1930.

[13] L. Mohammadpour, H. Moghadasi, and H. Saffari, "Computational Fluid Dynamics Investigation of Dropwise Condensation Heat Transfer Through a Single Droplet on Wenzel Structures," *International Communications in Heat and Mass Transfer*, vol. 145, 106853, 2023.

[14] L. Mohammadpour, H. Moghadasi, and A. Moosavi, "The Influence of Nusselt Number on Dropwise Condensation Heat Transfer for a Single Droplet on Inclined and Grooved Surfaces," *Scientific Reports*, vol. 15, no. 1, 2025.

[15] P. Varshney, S. Mohapatra, and A. Kumar, "Fabrication of Mechanically Stable Superhydrophobic Aluminium Surface with Excellent Self-Cleaning and Anti-Fogging Properties," *Biomimetics*, vol. 2, no. 1, 2, 2017.

[16] Y. Huang, D. Sarkar, and X. Chen, "A One-Step Process to Engineer Superhydrophobic Copper Surfaces," *Materials Letters*, vol. 64, no. 24, pp. 2722–2724, 2010.

[17] S. Abedinnezhad, M. Ashouri, C. Chhokar, and M. Bahrami, "Natural Dropwise Condensation of Humid Air on Engineered Flat Surfaces: An Experimental Study," *Energy*, vol. 316, 134412, 2025.

[18] K. Chen, P. Gao, et al., "Theoretical Analysis of Condensation Heat Transfer Enhancement on Dot-Matrix Hydrophilic-Hydrophobic Composite Surfaces: Hydrophobic Shapes and Surface Inclination Effect," *International Communications in Heat and Mass Transfer*, vol. 169, 109568, 2025.

[19] C. Chu, X. Zhou, et al., "How Can Dropwise Condensation Be Achieved on Superhydrophobic Nanocones?," *Soft Matter*, vol. 21, no. 33, pp. 6584–6595, 2025.

[20] V. K. Dhir, and G. Son, "Film and Dropwise Condensation," *Phase Change Heat Transfer*, pp. 216–242, 2025.

[21] M. Tancon, A. Abbatecola, et al., "Investigation of Surface Inclination Effect During Dropwise Condensation of Flowing Saturated Steam," *International Journal of Thermal Sciences*, vol. 196, 108738, 2024.

[22] V. Baghel, B. S. Sikarwar, and K. Muralidhar, "Modeling of Heat Transfer Through a Liquid Droplet," *Heat and Mass Transfer*, vol. 55, no. 5, pp. 1371–1385, 2018.

[23] L. Mohammadpour, H. Moghadasi, and H. Saffari, "Numerical Scrutinization of Dropwise Condensation Heat Transfer on an Inclined Surface," *Heat Transfer*, vol. 51, no. 5, pp. 4667–4687, 2022.

[24] A. Obeidat, and H. M. Ali, "Marangoni Condensation of Steam-Ethanol Mixture on Wire-Wrapped Tube: Effect of Wire Pitch on Heat Transfer Augmentation," *International Journal of Thermal Sciences*, vol. 214, 109912, 2025.

[25] A. Phadnis, and K. Rykaczewski, "The Effect of Marangoni Convection on Heat Transfer During Dropwise Condensation on Hydrophobic and Omniphobic Surfaces," *International Journal of Heat and Mass Transfer*, vol. 115, pp. 148–158, 2017.

[26] J. Guadarrama-Cetina, et al., "Droplet Pattern and Condensation Gradient around a Humidity Sink," *Physical Review E*, vol. 89, no. 1, p. 012402, 2014.

[27] B. S. Sikarwar, K. Muralidhar, and S. Khandekar, "Effect of Drop Shape on Heat Transfer During Dropwise Condensation Underneath Inclined Surfaces," *Interfacial Phenomena and Heat Transfer*, vol. 1, no. 4, pp. 339–356, 2013.

[28] K. A. Brakke, "The Surface Evolver," *Experimental Mathematics*, vol. 1, no. 2, pp. 141–165, 1992.

[29] B. Chen, J. Tian, R. Wang, and Z. Zhou, "Theoretical Study of Cryogen Spray Cooling with R134a, R404A and R1234yf: Comparison and Clinical Potential Application," *Applied Thermal Engineering*, vol. 148, pp. 1058–1067, 2019.

[30] J. Tian, L. Kong, et al., "Experimental Investigation on Heat Transfer Performance During Electrospray Cooling with Ethanol–R141b Mixture," *Applied Thermal Engineering*, vol. 230, 120879, 2023.

[31] J. J. Valencia, and P. N. Quested, "Thermophysical Properties," *Metals Process Simulation*, pp. 18–32, 2010.

[32] S. Ravi Annapragada, J. Y. Murthy, and S. V. Garimella, "Droplet Retention on an Incline," *International Journal of Heat and Mass Transfer*, vol. 55, no. 5-6, pp. 1457–1465, 2012.

[33] M. R. Rajkumar, A. Praveen, R. Arun Krishnan, L. G. Asirvatham, and S. Wongwises, "Experimental Study of Condensation Heat Transfer on Hydrophobic Vertical Tube," *International Journal of Heat and Mass Transfer*, vol. 120, pp. 305–315, 2018.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

Bibliography



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Contribution Statement: Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Writing-review & editing.