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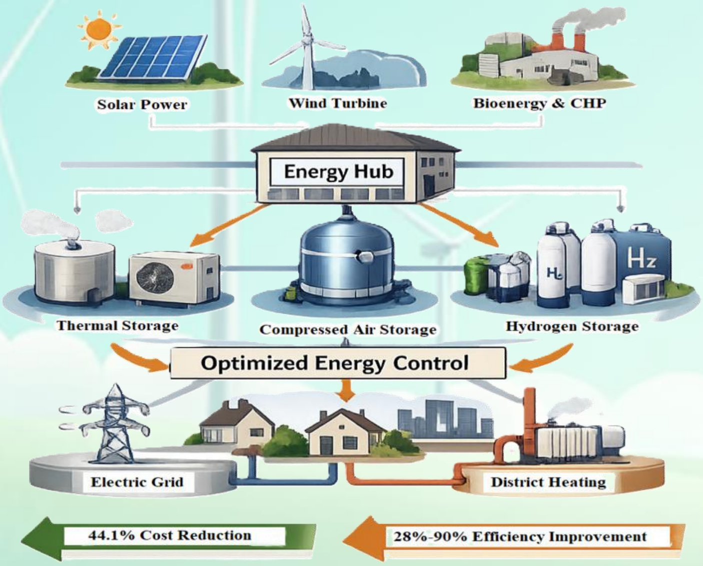
Highlights

- The study optimizes a unified energy hub framework integrating solar, wind, and bio-waste sources with compressed air, thermal, and hydrogen storage.
- Advanced management of interdependencies between heat pumps, CHP systems, and storage units reduced energy procurement costs by approximately 44.1%.
- Operational efficiency improvements ranged from 28% to 90%, significantly outperforming traditional load flow methodologies.
- The proposed multi-criteria strategy successfully balances economic performance and technical reliability for modern electricity and heat grid operators.

Graphical Abstract



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Optimized Energy Management in Grid-Connected Renewable Energy Hubs Incorporating Thermal, Compressed Air, and Hydrogen Storage Systems with Heat Pumps

Ehsan Akbari [1], Sasan Pirouzi [2,*], Abdolreza Behvandi [3]

[1] *Department of Electrical Engineering, Mazandaran University of Science and Technology, Babol, Iran.*

[2] *Department of Engineering, Sem.C., Islamic Azad University, Semmirom, Iran.*

[3] *Department of Electrical Engineering, Ramh.C., Islamic Azad University, Ramhormoz, Iran.*

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* ***Corresponding authors***
E-mail address
s.pirouzi@sutech.ac.ir (S. Pirouzi)

A B S T R A C T

This study explores the effective energy management strategies employed by electricity and heat grids hubs, emphasizing multi-criteria objectives that balance economic performance and operational efficiency for network operators. The primary objective of this study is to optimize the integration of multiple renewable energy sources, namely solar energy, bio-waste units, and wind turbines, within a unified management framework. The system employs advanced energy storage technologies, including compressed air, thermal, and hydrogen storage units. Thermal energy production is achieved through electrically powered heat pumps, while combined heat and power (CHP) systems are utilized to enhance the performance of both bio-waste and hydrogen storage subsystems. The proposed approach seeks to optimize energy procurement costs across these networks, aligning with their operational models. A key challenge tackled involves efficiently managing the interdependencies of energy sources and storage systems within the conceptual framework of an energy hub. By addressing these complexities, the strategy demonstrates measurable improvements in both technical and financial outcomes for electricity and heat grids. The numerical analysis highlights the efficacy of the proposed approach, demonstrating significant improvements in both economic viability and operational efficiency. Specifically, the integration of renewable energy hubs, storage, and heat pump systems, has achieved an approximate 44.1% enhancement in economic conditions and operational improvements ranging from 28% to 90%. These gains signify a clear advantage over traditional load flow methodologies, reaffirming the potential of advanced hub energy management in modern networks.

1. Introduction

Energy Hubs (EHs) play a pivotal role in advancing energy network operations, and their functionality has been thoroughly explored across various research studies. In [1], EH unit commitment (UC) models, as outlined in earlier research, incorporate critical components such as hydrogen vehicle (HV) parking lots, electric heat pumps (HP), absorption chillers (AC), photovoltaic (PV) arrays, boilers, hydrogen electrolyzers (HELs), and a broad array of storage systems, including electric, thermal, cooling, and hydrogen facilities. These integrated systems transform inputs like natural gas, electricity, and heat into outputs satisfying demand for hydrogen, heating, cooling, natural gas, and electrical power. In [2], EHs collaborate with demand response aggregators to enable day-ahead scheduling, guided by existing methodologies. Renewable energy incorporation into EHs has been a notable focus area in past studies, with technologies such as PV panels, wind turbines (WTs), biomass systems, hydrogen ELs, combined heat and power (CHP) units, solar heaters, boilers, and associated storage systems receiving substantial attention. In [3], Beyond tapping into the gas and electricity grids, EHs leverage demand response aggregators for electricity procurement. To navigate uncertainties, such as fluctuating solar heat availability, electricity prices, variable PV and wind power outputs, and dynamic energy demands, a risk-aware framework called Information Gap Decision Theory (IGDT) has been employed.

In [4], optimizing EH operations to minimize costs and environmental impact has also been a core research objective. One study addresses optimal power flow for an EH equipped with components including electric vehicles (EVs), gas boilers, PV panels, CHP units, WTs, and heat storage systems. In [5], Future uncertainties in electricity pricing are managed using a grasshopper search algorithm alongside Monte Carlo simulation (MCS) to account for EV-related unpredictability. Further, the model integrates comprehensive thermal and electrical demand response strategies to enhance operational efficiency. Another approach leverages robust optimization to tackle uncertainties in power pricing and renewable energy availability. By analyzing EV charging behaviors through coordinated and uncoordinated charging loads with MCS methods, a clearer picture of charging dynamics emerges. Simultaneously, Smart Hub modeling frameworks have been developed to evaluate EH technical and economic feasibility. In [6], A simulation-based study investigates parameters like driver preferences, price inflation rates, PV module degradation, EV adoption trends, energy losses, and charging station variability. These factors are incorporated into simplified mathematical models capable of realistic day-ahead and real-time market assessments. For electricity market operations linked to EHs, researchers have proposed a two-stage stochastic modeling strategy aimed at handling demand uncertainties, renewable power fluctuations, and variable real-time pricing schemes. In [7], employing value-at-risk as a metric mitigates costs under adverse conditions while optimizing operational parameters for EH components and natural gas-electricity interactions. A multi-objective optimization methodology balances cost-effectiveness against risk resilience in complex EH designs. Innovative applications for EHs include their thermal integration within industrial settings like thermomechanical pulp mills. One study highlights how equipment such as electric boilers and steam generator HPs can be configured to meet the heating demands of paper machines while simultaneously supporting pulp mill operations. In [8], Advanced load forecasting techniques combined with reliability analyses and thermo-economic evaluations inform an efficient yet sophisticated EH design approach tailored to industrial processing needs. Finally, a multi-tier optimization strategy introduces stochastic-probabilistic models to enhance primary-level planning and secondary-level operations for EHs. This dual approach addresses challenging uncertainties linked to dynamic demand patterns and renewable energy generation variability while prioritizing resource efficiency and operational resilience. In [9], energy management strategies for heat and electricity generation grids in the context of renewable energy sources (RESs) focus on enhancing network flexibility through dynamic pricing services. These strategies revolve around EHs, which are composed of RESs, bio-waste units (BUs), responsive loads, and storage systems. Notably, bio-waste systems contribute to both electrical energy and heat generation simultaneously. The proposed methodology addresses gaps between network energy costs and hub-flexibility revenue by optimizing resource allocation. It incorporates flexibility models for hubs, advanced power-flow equations, and operational frameworks for managing resources, storage systems, and responsive loads. Reference [10] discusses how flexible EHs equipped with technologies such as compressed air systems, thermal and hydrogen storage (HS) devices, BUs, and wind farms (WFs) can be effectively integrated into energy markets through market-clearing price models. These hubs, operating within both electricity and heat grids, employ integrated heat and power technologies to produce heat and electricity concurrently through BUs. Ref. [11] proposed an innovative energy management framework that integrates Unified Plug-In Electric Vehicle (PEV)-based demand response strategies with energy storage systems through a hybrid coordination approach. Reference [12] presents a two-layer optimization model that enables coordinated energy exchange between two interconnected energy hubs (EHs). Operating collectively as a virtual energy hub (VEH), the system addresses heat, water, and electricity demands while engaging in the thermal energy market and adjusting to the upstream distribution network's hosting capacity to efficiently accommodate supplementary loads. Reference [13] proposes an innovative solution to address multifaceted challenges associated with EHs, particularly focusing on energy generation and transmission complexities across gas and electricity grids. A multi-carrier EH capable of generating and distributing electricity, heating, and cooling from diverse sources, including wind, solar, fuel cells (FCs), batteries, and compressed air, is featured in [14]. This hub incorporates intelligent functionalities to support participation in both electrical and thermal demand response programs, easing peak demand periods and enhancing overall system efficiency. Lastly, [15] examines stochastic energy management strategies within microgrid environments, considering renewable sources such as solar, wind, and tidal power alongside demand response initiatives and comprehensive energy storage systems.

Hubs generally rely on renewable sources such as wind and solar energy, but another valuable renewable option is the bio-waste system. This system generates gas by processing waste and, when paired with a CHP unit, can simultaneously produce heat and electricity. However, the utilization of bio-waste systems integrated with CHP has been examined in only a handful of studies. The majority of research efforts have focused on battery technology due to its high efficiency, although batteries are limited by a short lifespan and elevated installation costs. Consequently, storage devices like hydrogen and compressed air emerge as suitable alternatives, offering commendable efficiency and extended service life. Despite this potential, their integration has also seen limited exploration in scholarly works. This study develops an energy management strategy specifically designed for hubs that are integrated with both thermal and electrical networks. It aims to balance operational efficiency with financial optimization from the perspective of network operators. These hubs are equipped with RESs, including wind, solar, and BUs, complemented by storage systems for hydrogen, compressed air, and thermal energy. In addition, BU and FC are enhanced with CHP systems to boost energy efficiency, while HP convert electricity into thermal energy for broader use. The electrical output of these hubs primarily comes from WT, PV, and supplementary backup units.

$$P_{Sb,t} + \sum_i C_{Ei,b} P_{EHi,t} + \sum_j A_{Ej,b} P_{Lb,j,t} = P_{Db,t} \ \forall b,t \tag{1}$$

$$Q_{Sb,t} + \sum_j A_{Ej,t} Q_{Lb,j,t} = Q_{Db,t} \ \forall b,t \tag{2}$$

$$H_{Sn,t} + \sum_i C_{Hi,n} H_{EHi,t} + \sum_j A_{Hj,n} H_{Ln,j,t} = H_{Dn,t} \forall n,t \tag{3}$$

$$P_{Lb,j,t} = G_{Lb,j}\left(V_{b,t}\right)^2 - V_{b,t}V_{j,t}\begin{Bmatrix} G_{Lb,j}\cos\left(\varphi_{b,t} - \varphi_{j,t}\right) + \\ B_{Lb,j}\sin\left(\varphi_{b,t} - \varphi_{j,t}\right) \end{Bmatrix} \forall b,j,t \quad (4)$$

$$Q_{Lb,j,t} = -B_{Lb,j}\left(V_{b,t}\right)^2 + V_{b,t}V_{j,t}\begin{Bmatrix} B_{Lb,j}\cos\left(\varphi_{b,t} - \varphi_{j,t}\right) \\ -G_{Lb,j}\sin\left(\varphi_{b,t} - \varphi_{j,t}\right) \end{Bmatrix} \forall b,j,t \quad (5)$$

$$H_{Ln,j,t} = C_{Ln,j}\left(T_{n,t} - T_{j,t}\right) \forall n,j,t \quad (6)$$

$$V_{\min} \le V_{b,t} \le V_{\max} \forall b,t \quad (7)$$

$$T_{\min} \le T_{n,t} \le T_{\max} \forall n,t \quad (8)$$

$$\left(P_{Lb,j,t}\right)^2 + \left(Q_{Lb,j,t}\right)^2 \le \bar{S}_{Lb,j} \forall b,j,t \quad (9)$$

$$\left|H_{Ln,j,t}\right| \le \bar{H}_{Ln,j} \forall n,j,t \quad (10)$$

$$\left(P_{Sb,t}\right)^2 + \left(Q_{Sb,t}\right)^2 \le \bar{S}_{Sb} \forall b,t \quad (11)$$

$$\left|H_{Sn,t}\right| \le \bar{H}_{Sn} \forall n,t \quad (12)$$

$$P_{EHi,t} = P_{Wi,t} + P_{Vi,t} + P_{Bi,t} + \left(P_{Fi,t} - P_{Ei,t}\right) + \left(P_{Gi,t} - P_{Mi,t}\right) - P_{HPi,t} - P_{Di,t} \forall i,t \quad (13)$$

$$H_{EHi,t} = H_{Bi,t} + H_{HPi,t} + H_{Fi,t} + \left(H_{DISi,t} - H_{CHi,t}\right) - H_{Di,t} \forall i,t \quad (14)$$

$$H_{Bi,t} = \frac{(1-\eta_B)\eta_H}{\eta_B} P_{Bi,t} \forall i,t \quad (15)$$

$$H_{HP_{i,t}} = \eta_{HP} P_{HPi,t} \forall i,t \quad (16)$$

$$0 \le H_{HP_{i,t}} \le n_{HP}\bar{H}_{HPi} \forall i,t \quad (17)$$

$$0 \le P_{Fi,t} \le n_{HS}\bar{P}_{Fi} \forall i,t \quad (18)$$

$$0 \le P_{Ei,t} \le n_{HS}\bar{P}_{Ei} \forall i,t \quad (19)$$

$$P_{Fi,t}P_{Ei,t} = 0 \forall i,t \quad (20)$$

$$n_{HS}E_{HTi} \le n_{HS}\hat{E}_{HTi} + \sum_{h=1}^{t}\left(\eta_E P_{Ei,t} - \frac{1}{\eta_F}P_{Fi,t}\right) \le n_{HS}\bar{E}_{HTi} \forall i,t \quad (21)$$

$$H_{Fi,t} = \frac{(1-\eta_F)\eta_H}{\eta_F} P_{Fi,t} \forall i,t \quad (22)$$

$$0 \le P_{Gi,t} \le n_{CA}\bar{P}_{Gi} \forall i,t \quad (23)$$

$$0 \le P_{Mi,t} \le n_{CA}\bar{P}_{Mi} \forall i,t \quad (24)$$

$$P_{Gi,t}P_{Mi,t} = 0 \forall i,t \quad (25)$$

$$n_{CA}E_{CATi} \le n_{CA}\hat{E}_{CATi} + \sum_{h=1}^{t}\left(\eta_M P_{Mi,t} - \frac{1}{\eta_G}P_{Gi,t}\right) \le n_{CA}\bar{E}_{CATi} \forall i,t \quad (26)$$

$$0 \le H_{DISi,t} \le n_T\bar{H}_{DISi} \forall i,t \quad (27)$$

$$0 \le H_{CHi,t} \le n_T\bar{H}_{CHi} \forall i,t \quad (28)$$

$$H_{DISi,t}H_{CHi,t} = 0 \forall i,t \quad (29)$$

$$n_T\underline{E}_{TESi} \le n_T\hat{E}_{TESi} + \sum_{h=1}^{t}\left(\eta_{CH}H_{CHi,t} - \frac{1}{\eta_{DIS}}H_{DISi,t}\right) \le n_T\bar{E}_{TESi} \forall i,t \quad (30)$$

Meanwhile, thermal energy is generated via FCs, HPs, and backup units as well. To ensure reliable energy storage, hydrogen and compressed air systems are dedicated to the electrical section, while thermal storage systems support the thermal side. The proposed energy management scheme represents the primary innovation introduced by this paper. It is structured as a deterministic optimization model aimed at minimizing total expected operating costs across electricity and heat generation networks. The formulation incorporates a series of constraints, including equations for optimal power distribution alongside operational models for RESs, storage units, and HPs, all interconnected to function seamlessly within the EH framework. Due to its non-linear nature, the optimization model is addressed by adopting the Interior Point OPTimizer (IPOPT) algorithm implemented in the General Algebraic Modeling System (GAMS). The core contributions of this scheme are twofold: first, it focuses on the optimal operation of a bio-waste energy unit within the hub to enhance overall energy efficiency. Second, it introduces robust energy management strategies for hydrogen and compressed air storage systems to improve the network's both economic and operational metrics.

Section 2 provides a comprehensive analysis of energy management strategies formulated for network-connected energy hubs. Section 3 focuses on a detailed case study, followed by Section 4, which presents and interprets the numerical results obtained from multiple simulation scenarios. Finally, Section 5 concludes the paper by summarizing the principal findings and outlining key insights.

2. Formulation of the Proposed Plan

This segment explores the energy management approaches utilized by renewable EHs, which incorporate diverse resources such as compressed air, hydrogen, and thermal storage. These hubs are designed with interconnected electric and thermal grids to maximize operational efficiency and minimize costs. The presented framework outlines the functional behavior of renewable and adaptable energy sources within the EH system, while also formulating critical equations to achieve optimal power allocation across network infrastructures. Consequently, the methodology is systematically expressed through mathematical definitions as described in Equations (1)-(31).

$$\min Cost = \sum_{b,t} \lambda_{Et} P_{Sb,t} + \sum_{n,t} \lambda_{Ht} H_{Sn,t} \tag{31}$$

Subject to:

To minimize the anticipated operating costs (Cost) within the electrical and thermal grids, this approach focuses on the objective function, given in Equation (1). Here, the energy procurement cost from the upstream network is expressed as the sum of two components, corresponding respectively to the electricity grid (first term) and the heat grid (second term) [9]. The cost is calculated by multiplying the energy price by the quantity of energy transmitted through the distribution points. Equations (2) to (13) outline the equations needed for optimal power flow across these networks. Equations (2) to (7) specifically detail the interactions involved in distributing power within these systems. Specifically, Equations (2) and (4) define the distribution of active and reactive power across electrical buses and the allocation of heat power within thermal nodes, respectively [9–10]. Furthermore, Equations (5)–(7) describe the flow of active and reactive power through the electrical distribution lines and the transfer of thermal energy through the pipeline network [16].

Equations (8) to (13) specify the boundaries within the heat and electricity grids. Equations (8) and (9) address the limits on voltage magnitude at electrical buses and temperature at thermal nodes, respectively. The limits on apparent power flowing through electrical distribution lines and heat power through pipelines are outlined in limitations (10) and (11). Additionally, Equations (12) and (13) take into account these limitations for electricity and heat distribution posts. Equations (14) to (31) define the operational parameters for Environmental Hubs that utilize flexible and RESs. Specifically, Equations (14) and (15) describe the balance between thermal and active power within these hubs. The model for RESs includes WF, PV Farms (PVF), and Battery Unit Farms (BUF). The findings indicate that the battery unit (BU) is integrated with combined heat and power (CHP) technology, allowing simultaneous generation of electrical and thermal energy. The heat power output of the BU is defined in Equation (16) as a coefficient corresponding to its active power [9]. The operational behavior of heat pumps (HPs) is described in Equations (17) and (18). The HP unit converts electrical energy into thermal energy [17], effectively acting as an active power consumer while producing thermal output. Equation (17) outlines the correlation between heat power and active HPs [17]. Equation (18) addresses the capacity limitations for power generation at the HPs' output. Equations (19) to (23) define the operational model for the HS [18,19], which includes the FC, electrolyzer (EL), and hydrogen tank (HT). Equation (19)-(20) specify the capacity limits for the FC and EL, respectively. To prevent simultaneous operation of HS in charge and discharge modes, Equation (21) ensures that the EL and FC do not operate at the same time. Equation (22) sets the maximum allowable hydrogen energy storage in the HT. The CHP model for FCs is described by Equation (23), stating that an FC's output heat power is proportional to its active power [18]. Equations (24) to (27) define the CAES operational model [20], which consists of a compressed air tank (CAT), a generator, and a motor. Equations (24) and (25) address the capacity restrictions of the generator and motor. Equation (26) prohibits their simultaneous operation, and restriction (27) sets the maximum energy capacity for compressed air storage in the CAT [20]. The TES operational model is defined in Equations (28) to (31). These include charge and discharge rate limitations in Equations (28) and (29). Relation (30) prevents simultaneous charging and discharging of TES, while Equation (31) sets limitations on the energy stored within TES [16].

3. Case Study

Figure 1 illustrates the integration of the EMS described in this section across the IEEE 33-bus electrical network [21] and the 14-node Madumvej heat network [22]. To obtain the time-varying load profile, the load factor curve is multiplied by the corresponding maximum load at each time interval. The projected daily load factor curve for the electrical network, established in previous studies [9-10], serves as the basis for calculations. During off-peak hours, from 01:00 to 07:00, the cost of electricity is set at 17.6 \$/MWh. This price elevates to 33 \$/MWh during peak hours from 17:00 to 22:00, and stabilizes at 26.4 \$/MWh throughout mid-load periods at remaining intervals [9]. On the thermal energy side, pricing remains constant at 22 \$/MWh during both peak hours (05:00–15:00) and off-peak periods (01:00–04:00 and 16:00–24:00) [9]. As depicted in Figure 1, the system is distributed across six operational hubs. Locations and attributes of each hub, including sources, storage units, and installed HP configurations, align with details provided in Table 1. Specifically, hubs 1 and 2 deliver thermal energy via BUF technology, whereas hubs 4 and 5 utilize localized HPs for thermal energy distribution. Electrical storage within hubs 1, 4, and 5 relies on CAES systems, while the remaining hubs are equipped with HS-type storage solutions. Comprehensive technical specifications for sources, storage units, and HPs are elaborated in supplementary references [23-24]. Each hub's load assignment corresponds directly to its strategic role within the network framework. Additional data regarding wind speed profiles, BU gas consumption trends, and solar radiation patterns are detailed in the referenced studies. It is noteworthy that the proposed scheme has no limitations for implementation on various types of energy networks, resources, and storage devices.

4. Numerical Reports and Discussions

This section presents the simulation studies carried out using the GAMS optimization environment, in which the IPOPT algorithm was employed as the primary solution strategy [25]. Owing to the inherently nonlinear and continuous characteristics of the proposed mathematical formulation, advanced nonlinear solvers such as IPOPT, BARON, BONMIN, and similar algorithms are particularly appropriate for achieving reliable and accurate solutions. To ensure robustness and computational efficiency, an extensive iterative trial-and-error procedure was conducted, during which multiple solvers and configurations were systematically evaluated and compared. The outcomes of this comparative analysis demonstrated that IPOPT consistently provided superior performance in terms of convergence stability, solution accuracy, and computational time, making it the most suitable solver for the problem under investigation. Consequently, IPOPT was selected for all subsequent simulations. The comprehensive quantitative findings obtained from these simulation studies are presented and discussed in detail in the following section.

A) Performance Assessment of Renewable Energy Hubs Incorporating Storage Units and Heat Pumps: The anticipated daily output patterns of active and heat power generated by sources, storage units, HPs, and EHs are illustrated in Figures 2 and 3. Figure 2 focuses on the daily production profiles of WT, PV, and biomass energy sources (BESs), providing a numerical correspondence to the variations in wind speed, solar radiation, and biogas rates presented in prior research [21]. The active power output of RESs is affected by these environmental conditions.

Per Figure 2's analysis, WFs, biogas utilization facilities (BUFs), and photovoltaic farms (PVFs) demonstrate peak performance at 1.8 MW, 2.4 MW, and 1.08 MW of active power generation, respectively. Regarding storage systems like heat storage units (HSs), Figure 2 reveals that during off-peak hours (1:00 to 7:00), they remain inactive due to lower electricity prices. In mid-load periods (8:00 to 16:00), HSs enter a charge mode where active power from RESs is transferred to them via ELs within the hubs. This operational strategy arises from substantial active power production by RESs during these hours, which could potentially overburden the electrical network with excess voltage.

Redirecting energy into HSs mitigates such risks. Furthermore, HSs consume power solely from RESs during this timeframe, thereby eliminating the need for supplementary energy costs from upstream networks. Later, between 17:00 and 22:00, HSs remain in charge mode, while FCs supply power to the electrical grid during peak hours from 23:00 to 24:00. HS operation at these times reduces energy expenses, as electricity prices are comparatively higher. Compressed air energy storage systems (CAESs) generally perform similarly to HSs but contribute additional active power to the grid during peak hours. Unlike ELs and FCs, CAES systems exhibit nearly equivalent motor and generator efficiency levels, whereas FC efficiency is notably lower than generator efficiency. Consequently, HS systems experience greater energy losses compared to CAESs, resulting in diminished discharge-mode power output relative to CAESs.

Both HSs and CAESs cease operation during off-peak hours due to the insufficient active power output from RESs during these periods, as illustrated in Figure 2. Operating energy storage systems under such conditions would necessitate additional power procurement from the main electrical grid, which would lead to increased operational expenditures while failing to achieve optimal cost efficiency. As a result, the strategic shutdown of HSs and CAESs during off-peak hours is economically justified and aligned with overall system optimization objectives.

In contrast, the performance of EHs enables sustained and reliable active power generation throughout the entire operational horizon. Consequently, EHs continuously inject electricity into the grid, providing a stable and uninterrupted energy supply despite fluctuations in RES production. The operational performance of HPs is intrinsically linked to EH functionality. Supplied primarily by energy generated within EHs, HPs remain operational during the periods of 1:00–7:00 and 17:00–24:00. Notably, during low-demand hours between 1:00 and 7:00, WF operations within Hub 4 produce approximately 1 MW of active power, which is sufficient to support the stable operation of HPs in this hub using energy derived exclusively from renewable energy sources.

In contrast, Hub 5 depends on solar energy production during low-load periods based on Figure 2's data; because solar output is minimal during these hours, Hub 5's HPs rely on electricity sourced from the main grid. However, during higher production intervals spanning 17:00–24:00, power contributions from HSs, CAESs, and WFs in both hubs significantly increase, allowing HPs in these hubs to operate efficiently using energy provided directly by EHs. Across all operation hours presented in these findings, the total active power output from EH systems remains consistently positive. This signifies that EHs not only support internal energy demands but also effectively function as producers supplying active electrical energy to the external grid throughout their operation.

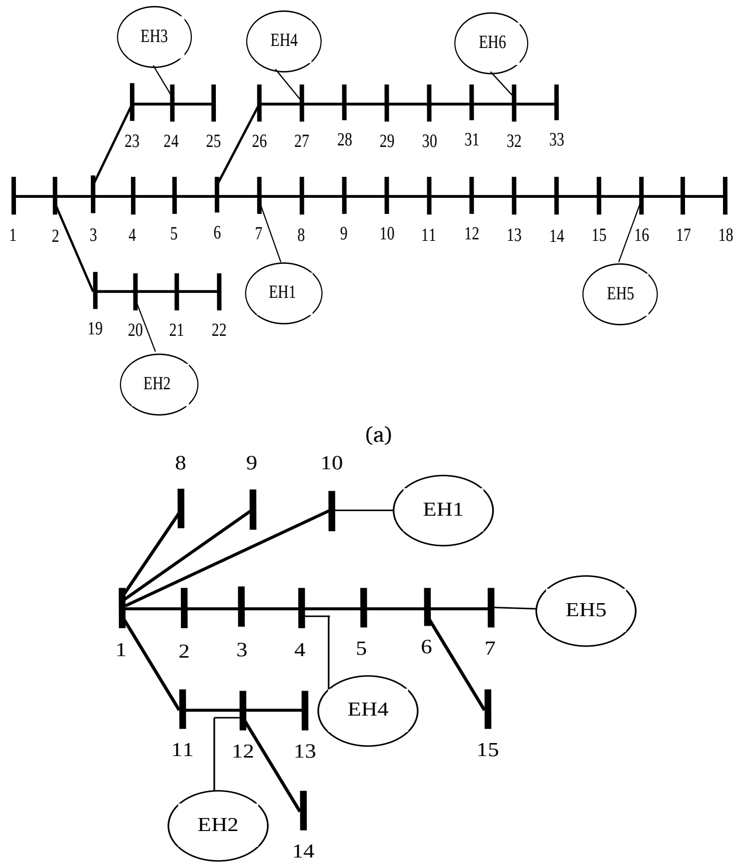

Figure 1. Test network, a) IEEE 33-bus electrical system [19], b) 14-node Madumvej district heating grid [20].

Tabe 1. Number of energy sources and storage units for energy hubs at different locations.

EH	Sources	Storages
1	120 BUs	40 CAESs, 40 TESs
2	120 BUs	80 HSs, 40 TESs
3	80 WTs	50 HSs
4	100 WTs, 50 HPs	30 CAESs, 25 TESs
5	1500 PVs, 40 HPs	25 CAESs, 25 TESs
6	1500 PVs	50 Ss

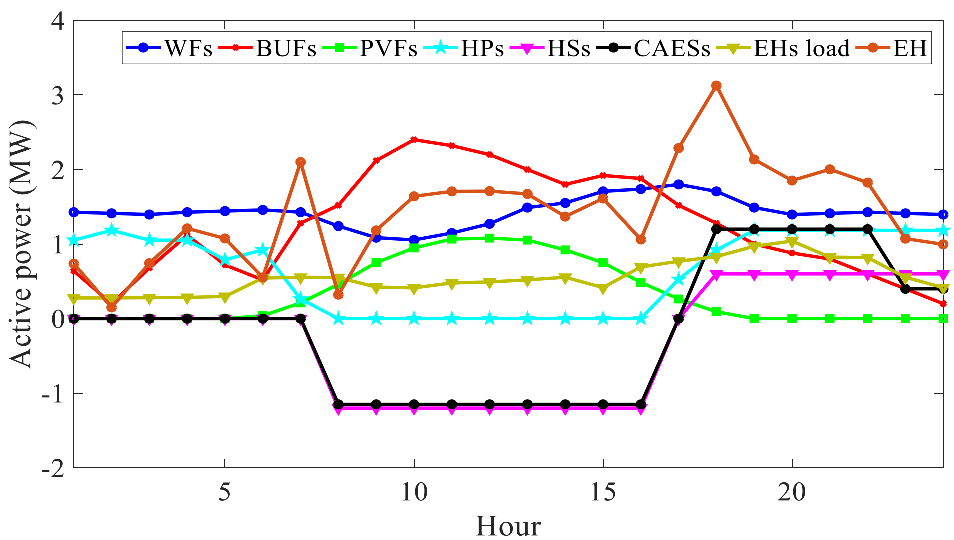

Figure 2. Expected daily active power trajectories of energy sources, storage systems, and aggregated EHs.

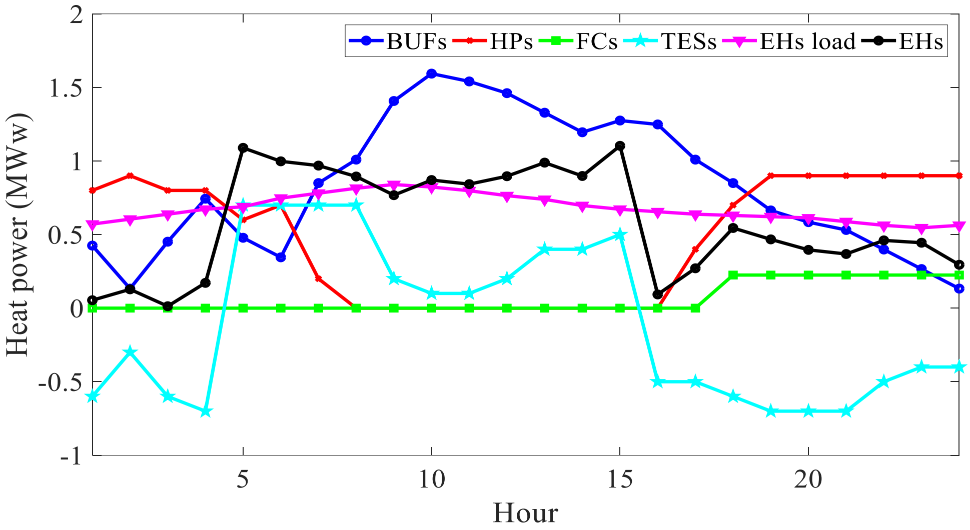

Figure 3. Expected daily heat power profiles of energy sources, storage systems, and EHs.

The heat power trends for BUFs, HPs, TESs, and EHs are illustrated in Figure 3. The daily heat power curve of BUFs closely resembles their active power curve, with only minor numerical differences. This similarity arises from Equation (16), which indicates that the heat power of a BU is directly correlated with its active power. During discharge mode, TESs experience peak thermal activity between 5:00 and 15:00, coinciding with high thermal energy prices. Discharging during these hours helps minimize costs. Outside of this period, TESs are in charge mode. Notably, during off-peak hours from 1:00 to 6:00 and 20:00 to midnight, BUFs produce less power than the demand from EHs. To avoid supplying heat power from the network to TESs during these times, HPs activate and generate heat power for EHs. Consequently, as shown in Figure 3, EHs continuously serve as energy producers, consistently injecting heat into the grid, thereby assisting in cost reduction within the heat grid.

B) *Operational Analysis of Electricity and Heat Grids Performance*: This section evaluates the key performance indicators for two distinct operational scenarios, namely Case I (Load flow analysis) and Case II (Proposed scheme). Table 2 provides a comprehensive comparison of the two cases by summarizing critical metrics, including Maximum Voltage Deviation (MVD), Maximum Temperature Deviation (MTD), Expected Energy Loss (EEL) for both the electrical network (E-EEL) and the thermal network (T-EEL), Peak Load Carrying Capacity (PLCC), and the overall operational cost (Cost) of the integrated energy networks.

In this study, energy loss within the network is defined as the difference between the total energy generated and the total energy consumed over the entire operating horizon. Voltage deviation is quantified as one minus the permissible voltage range, while temperature deviation is similarly calculated as one minus the allowable temperature range. Accordingly, MVD and MTD correspond to the maximum observed deviations in voltage and temperature, respectively, across all network nodes and time intervals. PLCC serves as an indicator of network robustness by representing the maximum peak load that the system can reliably accommodate without violating operational constraints.

As reported in Table 2, Case I reveals considerable energy losses, elevated operational costs, pronounced voltage drops, and notable temperature reductions during the energy network load distribution analysis. In addition, this case exhibits the lowest PLCC values, reflecting limited load-support capability, together with evident overvoltage occurrences and temperature fluctuations within the system.

In contrast, Case II, which strictly follows the proposed mathematical framework described by Equations (1)-(31) and incorporates energy hubs integrated with storage systems, heat pumps (HP), and renewable energy sources (RES), demonstrates a markedly improved operational performance. Relative to Case I, substantial enhancements are observed across all evaluated indicators. Specifically, the operational cost is reduced by approximately 44.1%, E-EEL decreases by 41%, T-EEL by 42.9%, and the overall EEL by 41.9%. Moreover, MVD and MTD are significantly mitigated, declining by 48.9% and 47.7%, respectively. Notably, PLCC experiences a pronounced improvement, increasing by nearly 82.5% in the electrical network and 89.5% in the thermal grid when compared to Case I, thereby confirming the superior reliability, efficiency, and load-handling capability of the proposed scheme.

Table 2. Values of operational indices under different operating scenarios.

Variable	Case I	Case II
Cost	4521.7	2527.6
E-EEL (MWh)	3.12	1.84
T-EEL (MWh)	2.54	1.45
EEL (MWh)	5.66	3.29
MVD (p.u.)	0.092	0.047
MTD (p.u.)	0.086	0.045
E-PLCC (MW)	3.72	6.79
T-PLCC (MW)	3.05	5.78

Table 3 presents the sensitivity analysis of the objective function, namely the operational Cost, with respect to variations in energy price, peak load, and renewable power penetration. In this table, the parameter α denotes the rate of increase applied to each examined factor. The results indicate that a 10% rise in energy price and peak load leads to corresponding increases in Cost of approximately 9.48% and 10.82%, respectively. In contrast, a 10% increase in renewable power generation results in a reduction of Cost by about 5.28%, highlighting the economic benefits associated with higher renewable energy integration.

An increase in peak load is typically associated with greater overall energy consumption, as higher maximum demand often reflects more intensive or extended operation of electrical and thermal equipment. Consequently, the energy required by the network from the upstream supply increases, which directly contributes to higher operational costs. Conversely, enhanced renewable energy generation reduces dependency on upstream network energy procurement, thereby lowering purchasing costs and improving overall economic performance. On the other hand, rising energy prices increase the monetary value of energy transactions within the system. While higher prices raise procurement expenses, they also amplify revenues from energy sales, ultimately causing an upward shift in the overall cost function, as reflected in the sensitivity analysis results.

Figure 4 illustrates the obtained Cost values corresponding to different solution algorithms. In this figure, IPOPT, BONMIN, and BARON are optimization solvers based on deterministic mathematical programming techniques, all of which are available within the GAMS software environment. In contrast, Particle Swarm Optimization (PSO) and the Genetic Algorithm (GA) are population-based evolutionary algorithms, and the proposed model was implemented for these solvers using the MATLAB software platform, which provides dedicated toolboxes for such metaheuristic methods.

As depicted in Figure 4, the application of different solvers to the proposed design results in distinct solutions and associated Cost values. This variation can be attributed to the inherently non-convex nature of the optimal power distribution problem in the electrical network, which may lead to multiple local optima depending on the employed solution strategy. Under such circumstances, the solver that yields the most favorable operating condition, characterized by the minimum achievable Cost, is considered the most appropriate. Based on the comparative results shown in Figure 4, the IPOPT solver demonstrates superior performance by converging to the lowest Cost value among the examined algorithms, thereby confirming its suitability and effectiveness for solving the proposed optimization problem.

Table 3. Sensitivity analysis for the objective function (Cost) based on the different parameters in Case II.

Parameter	Cost ($) for			Deviation (%)
	α = 0	α = 10%	α = 20%	
Energy price ($/MWh)	2527.6	2767.3	3007	+9.48×α
Peak load (MW)	2527.6	2801.2	3074.8	+10.82×α
Renewable power (MW)	2527.6	2394.1	2260.6	-5.28×α

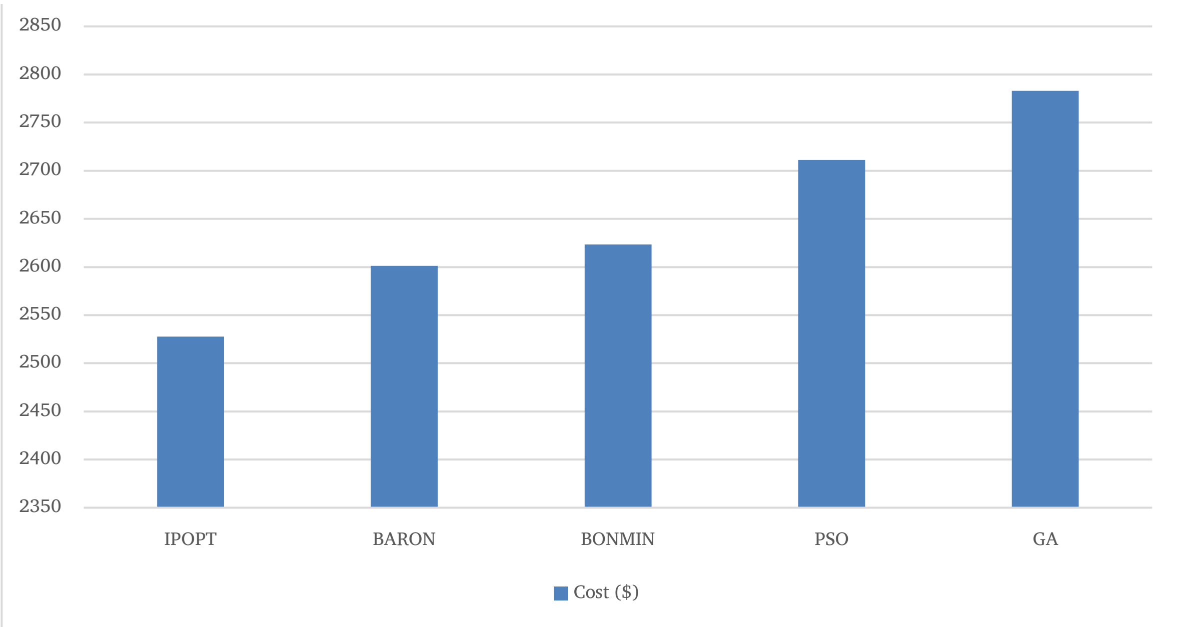

Figure 4. Value of Cost obtained by different solvers.

5. Conclusions

This study investigates the cost-effective operation of integrated thermal and electrical networks incorporating renewable EHs. These hubs encompass various components, including HS, thermal storage, compressed air storage, WTs, solar units, BUs, and HPs. The proposed solution aims to reduce operating costs by optimizing the energy management of these hubs within their operational constraints and aligning with an optimal power distribution model for the networks in question. The numerical results indicate that the approach successfully enhances the economic performance of these networks. Specifically, the study shows an approximate 44% improvement in economic efficiency compared to traditional load distribution scenarios. This method also positively impacts various operational parameters, such as power management for HPs and storage systems (compressed air, hydrogen, and thermal). Improvements are observed across key metrics like energy losses, voltage stability, temperature profiles, and load capacity, with enhancements ranging from 28% to 90% compared to previous load distribution models.

This study evaluated the performance capabilities of resources and storage systems configured as an EH within the proposed framework. However, load response is a method for managing energy and it can be useful in improving energy efficiency. This study identifies the incorporation of uncertainties in renewable resources, load demand, and energy prices as a direction for future research within the proposed framework. Therefore, stochastic, probabilistic, or robust modeling needs to be considered for them. In this paper, deterministic models were used for them, but this aspect is identified as a direction for future research within the proposed framework. To solve the proposed problem in this paper, mathematical algorithms were used. However, if the problem size increases, it is possible that mathematical solvers may encounter difficulties in converging to a feasible solution for the formulated problem, or a more powerful computing system will be required. In this case, the computational cost will increase. To compensate for this, it is necessary to use decomposition algorithms, hybrid evolutionary algorithms, and linear approximation models. These are considered future studies.

NOMENCLATURE

Variables			
Cost	Expected cost of operation ($)	PL, QL, HL	Active (MW) and reactive (MVAr) power passing through the electric distribution line, and heat power (MW) passing through the heat pipe
HB, HHP, HF	Heat power of bio-waste unit (BU), heat pump (HP), and fuel cell (FC) in MW	PM, PG	Active power of motor and generator in compressed air energy storage (CAES) in MW
HCH, HDIS	Heat power of thermal energy storage (TES) in charge and discharge mode (MW)	PS, QS, HS	Active (MW) and reactive (MVAr) power passing through the electric distribution post, and heat power (MW) passing through the heat post
PB, PV, PW	Active power of BU, photovoltaic (PV), and wind turbine (WT) in MW	T	Temperature (p.u.)
PE, PF	Active power of electrolyzer (EL) and FC in hydrogen storage (HS) in MW	V, φ	Voltage range (p.u.) and voltage angle (radian)
PEH, HEH	Active and heat power of the energy hub (EH) in MW	Parameters	
PHP	Active power of HP in MW	AE	Intersection matrix of bus and distribution line
		AH	Intersection matrix of node and heat pipe
BL, GL	Susceptance and conductance of distribution line (p.u.)	T_{miss} T_{max}	Minimum and maximum permissible temperature (p.u.)
CE	Intersection matrix of EH and the electric bus	$\bar{S}_L, \bar{S}_S$	Maximum apparent power passing through the electric distribution line and substation (MVA)
CH	Intersection matrix of EH and the heat node	V_{wisy} V_{max}	Minimum and maximum permissible voltage range (p.u.)
CL	Thermal constant of the heat pipe (p.u.)	η_{CH}, η_{DIS}	Charge and discharge efficiency in TES
$\underline{E}_{CAT}, \bar{E}_{CAT}, \hat{E}_{CAT}$	Minimum and maximum energy stored in the compressed air tank (CAT) and its initial energy (MWh)	η_H	Thermal efficiency in combined heat and power (CHP)
$\underline{E}_{HT}, \bar{E}_{HT}, \hat{E}_{HT}$	Minimum and maximum energy stored in the hydrogen tank (HT) and its initial energy (MWh)	η_{HP}	HP efficiency
$\underline{E}_{TES}, \bar{E}_{TES}, \hat{E}_{TES}$	Minimum and maximum energy stored in TES and its initial energy (MWh)	η_M	Motor and generator efficiency in CAES
$\bar{H}_{CH}, \bar{H}_{DIS}$	Charge/discharge rate in TES (MW)	η_G	Electric and thermal energy price ($/MWh)
$\bar{H}_L, \bar{H}_S$	Maximum heat power passing through the heat pipe and heat post (MW)	λ_E, λ_H	Thermal efficiency in combined heat and power (CHP)
$\bar{H}_{HP}$	Maximum heat power produced by HP (MW)	Indices	
P_D, Q_D, H_D	Active (MW), reactive (MVAr), and thermal (MW) load	b, n	Bus in the electric network, a node in the heat network
$\bar{P}_E, \bar{P}_F$	EL and FC capacity in HS (MW)	i	EH
$\bar{P}_M, \bar{P}_G$	Motor and generator capacity in CAES (MW)	j	Auxiliary index corresponding to bus or node
		t	Operating hour

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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

Ehsan Akbari received the B.Sc. degree in Electrical Power Engineering from Mazandaran University, Babolsar, Iran, in 2009 and M.S. degree in Electrical Power Engineering from Mazandaran University of Science and Technology, Babol, Iran, in 2014. He received Ph.D. in Electrical Power Engineering from Isfahan University of Technology, Isfahan, Iran in 2022. He is now a Assistant Professor at Department of Electrical Engineering, Mazandaran University of Science and Technology, Babol, Iran. He is the author of 25 books and more than 355 papers in reputed journals and conferences and won six patents in his research fields. He has obtained five provincial scientific and technological progress awards. His main areas of research are power quality, flexible AC transmission systems (FACTS), application of power electronics in power systems, power electronics multilevel converters, smart grids, control of grid-connected converters, fault location, distributed generation, energy storage systems, micro-grids, voltage stability, electrical machines, special electrical machinery, HVDC systems, harmonics, reactive power control using hybrid filters and renewable energy systems.
Email: e.akbari@ustmb.ac.ir
ORCID: 0000-0002-53185673
Contribution Statement: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Roles/Writing - original draft, Writing-review & editing.

Sasan Pirouzi received the B.Sc. degree in electrical engineering from Technical and Vocational University, Mashhad, Iran, in 2012, the M.Sc. degree from the Isfahan University of Technology, Isfahan, Iran, in 2014, and the Ph.D. degree from the Shiraz University of Technology (SUTECH), Shiraz, Iran, in 2017. His research interests include power system operation and planning, electric vehicles, DERs, and the application of optimization methods in power systems.
Email: s.pirouzi@sutech.ac.ir
ORCID: 0000-0001-5966-4432
Contribution Statement: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Roles/Writing - original draft, Writing-review & editing.

Abdolreza Behvandi was born in 1987 in Iran. He received his B.Sc., M.Sc., and Ph.D. degrees all in Electrical Engineering (Power Systems) in 2010, 2012, and 2019 from Isfahan University of Technology, Isfahan University, and Shahid Chamran University of Ahvaz, respectively. Currently, he is an Assistant Professor at Department of Electrical Engineering, Ramhormoz Branch, Islamic Azad University, Ramhormoz, Iran. His special interests are power system studies, power system protection, renewable energy, and microgrids.
Email: rezabehvandi@gmail.com
ORCID: 0000-0001-5966-4432
Contribution Statement: Data curation, Formal analysis, Investigation, Resources, Validation.