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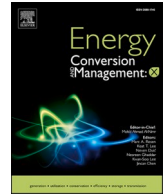
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Potential of environmentally friendly energy hubs with hydrogen and thermal storage devices on the voltage and temperature regulation in energy networks

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ABSTRACT

An energy hub is a unit that coordinates and integrates different resources, storage devices, and loads, which can manage several types of energy simultaneously. Its optimal energy management can be improved by the environmental and technical factors of various energy networks. Therefore, this study presents the energy scheduling of environmentally friendly energy hubs including renewable wind, solar, and bio-waste resources, and thermal and hydrogen storage devices in electrical and thermal distribution networks. In the proposed system, the hydrogen storage and bio-waste system include a combined heat and power system. Therefore, they also play a role in heating energy production. The proposed design minimizes the sum of the voltage profile function in the electrical network and the temperature profile function in the heating network. Of course, this objective function is subject to the optimal power flow equations and environmental constraints of the aforementioned energy networks, and the resource and storage device exploitation model in the form of an energy hub. In this design, there are uncertainties such as load and renewable phenomena. For modeling of uncertainties, stochastic programming is used. Numerical results demonstrate the effectiveness of this approach in improving both environmental and technical outcomes for thermal and electrical networks through improved energy hub management. Incorporating renewable hubs with advanced storage units has notably enhanced conditions across key indicators: voltage profile (47% – 56% improvement), temperature profile (38%–40%), energy losses (38.10%), and peak load carrying capacity (23% – 40%), compared to traditional load distribution analyses.

Nomenclature

Variables

$H_B, H_{CHb}, H_{DIS}, H_E, H_F$ Heating power (MW) for bio-waste units farm (BUF), charging and discharging operations of thermal energy storage (TES), power to hydrogen system (P2H) or electrolyzer (EL), and hydrogen to power (H2P) system of fuel cell (FC)
 H_{EH}, H_L, H_S Heating power (MW) for energy hub (EH), thermal distribution pipeline and post

P_B, P_E, P_F, P_V, P_W Power in active mode (MW) for BUF, EL, FC, photovoltaic farm (PVF), and wind farm (WF)
 P_{EH}, P_L, P_S Power in active term (MW) for EH, electrical distribution line and post
 Q_L, Q_S Power in reactive term (MVar) for electrical distribution line and post
 T, V, φ Temperature (p.u.), voltage magnitude (p.u.), and angle of voltage (radian)

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Parameters	
A_E, A_H	Intersection matrix between electrical bus and line, and between thermal node and pipeline
C_E, C_H	Intersection matrix between EH and electrical bus, and between EH and thermal node
C_L, B_L, G_L	Heating constant for pipeline in heating network (p.u.), susceptance and conductance (p.u.) for electrical distribution line
$\underline{E}_{HT}, \bar{E}_{HT}, \hat{E}_{HT}$	Lower and upper values of hydrogen tank (HT) energy, and HT initial energy (MWh)
EM^{max}	Maximum of emission (ton)
$\underline{E}_{TES}, \bar{E}_{TES}, \hat{E}_{TES}$	Min and Max values of the stored energy in TES, and TES initial energy (MWh)
$\bar{H}_{DIS}, \bar{H}_{CH}, \bar{H}_L, \bar{H}_S$	Heating capacity of TES for mode of discharging and charging, maximum thermal power of heating pipeline and post
$n_B, \varphi_B, \bar{P}_B$	Number of bio-waste units (BUs), power production rate of BU, and maximum active power of BU (MW)
$n_V, \varphi_V, \bar{P}_V$	Number of photovoltaics (PVs), power production rate of PV, and maximum active power of PV (MW)
n_{HS}, n_T	Number of hydrogen storage (HS), and TES
$n_W, \varphi_W, \bar{P}_W$	Number of wind turbines (WTs), power production rate of WT, and maximum active power of WT (MW)
Q_D, P_D, H_D	Load power in term of reactive (MVar), active (MW), and heat (MW)
$\bar{P}_E, \bar{P}_F$	Maximum active power (MW) for P2H and H2P in HS
$\bar{S}_L, \bar{S}_S$	Upper capacity (MVar) for electrical distribution line and post
$T_{min}, T_{max}, V_{min}, V_{max}$	Lower and upper values for temperature (p.u.), and magnitude of voltage (p.u.)
V_{ref}, T_{ref}	Values of voltage magnitude and temperature in reference bus (p.u.)
γ	Scenario probability
$\eta_B, \eta_H, \eta_{CH}, \eta_{DIS}, \eta_E, \eta_F$	Efficiency for BU, combined heat and power (CHP) unit, TES in charging and discharging operations, EL and FC
$\rho_{CO_2}, \rho_{SO_2}, \rho_{NO_x}$	Pollution (CO ₂ , SO ₂ , NO _x) coefficients due to supplying energy by centralized generation systems (ton/MW)

Indices	
b, i, n	Electrical bus, EH, Heating node
j	Auxiliary index for node of bus
t, w	Hour, and scenario

1. Introduction

1.1. Motivation

One effective approach under consideration for reducing emissions involves integrating renewable energy sources (RESs) in the distribution energy grids [1]. RESs include photovoltaics (PVs) and wind turbines (WTs), which generate electricity by harnessing solar irradiation and speed of wind, respectively [1]. Another noteworthy type of RES is the bio-waste unit (BU), which converts organic waste into methane gas that can subsequently be used to produce electrical energy [2]. When it includes a combined heat and power (CHP) system, such units can also generate thermal energy alongside electricity. However, renewable energy generation inherently faces challenges due to the unpredictable nature of renewable phenomena. This variability can lead to discrepancies between real-time operations and forecasts of renewable power generation, sometimes causing an imbalance between electricity supply and demand [3]. Storage devices are essential in mitigating these fluctuations, as they can adapt by providing both active and thermal power to balance renewable power variations [3]. Among the various storage technologies, batteries are widely deployed owing to their high efficiency. Nonetheless, they come with certain limitations such as constrained capacity, high installation costs and a short lifespan. An additional storage solution is hydrogen storage (HS). With an average efficiency of 75 %, HS systems are durable, not subject to size limitations, and can also incorporate CHP technology, allowing them to

produce heating energy in addition to storing electricity [4]. The effective utilization of all these resources hinges on the implementation of an appropriate energy management system (EMS) [5]. For initial stages of an EMS deployment, diverse energy units and storage devices can be integrated into a unified model resembling an energy hub (EH) to maximize operational efficiency [5]. For this framework, the operator of hub facilitates coordinated energy management by ensuring bidirectional communication between energy resources, storage systems, and network operators. This allows the operator of hub to optimize energy flow based on both its own needs and the priorities of the broader network. The establishment of an advanced EMS coupled with EHs presents a promising solution for improving the technical, economic, and environmental performance of energy grids. This integrated approach could serve as a viable strategy toward a more sustainable energy landscape.

1.2. Research background

In [6], it presents a two-layer formulation for managing energy in two interconnected hubs, collectively functioning as a virtual EH. This hub is designed to participate in the heating market. In the first layer, the framework determines the maximum power the VEH can draw from the upstream grid under hosting capacity constraints, considering the uncertainty of wind power. The second layer employs a hybrid stochastic-robust model to optimize the energy management of the VEH. In [7], a novel approach to EH management is presented by integrating electric vehicles and storage devices with demand response. The primary objective is to reduce emissions and energy costs associated with vehicles. Work of [8] primarily focuses on detecting malicious attacks on the demand side through intelligent learning algorithms. This study examines the impacts of such attacks on demand for multiple energy carriers, emphasizing the demand-supply structure within the energy hub system. Various scenarios are utilized to train and assess the effectiveness of detection algorithms. Study in [9] considers the hubs management for scheduling of their energy consumption addressing the different goals of energy grids. EHs incorporate RESs like solar power, bio-waste systems, and wind turbines, alongside storage technologies including storages of thermal, compressed air, and hydrogen. Heating energy is generated using heat pumps powered by electricity, while CHP unit is employed in both hydrogen storage systems and bio-waste units. The proposed strategy aims to minimize total energy procurement costs, improve reliability, and reduce emissions within the constraints of operational models and reliability requirements. In [10], reinforcement learning (RL), a cutting-edge artificial intelligence-based technique, is considered to achieve the suitable EMS in EH.

Work in [11] considers a versatile energy scheduling strategy tailored for EHs that integrate both electrical and thermal grids. These hubs harness electricity from wind turbines and photovoltaic systems while utilizing bio-waste units for combined electricity and heat generation. The system achieves flexibility through the use of compressed air and thermal energy storage, aiming to minimize the forecasted energy cost procured from the upstream grid. In [12], the robust energy scheduling approach is introduced for a multi-vector EH. The framework employs an adaptive robust programming to effectively manage uncertainties. Study of [13] delves into the management of energy within renewable-integrated electrical and thermal networks. These hubs leverage services such as dynamic pricing and incorporate RESs, bio-waste systems, energy storage, and demand response to enhance operational flexibility. The bio-waste units enable concurrent generation of electrical and thermal energy, while the proposed model seeks to balance operational costs against financial gains achieved through hub flexibility. In [14], it proposes a coordinated energy scheduling framework for multi-carrier networked EHs, enabling power exchanges among hubs. This collaborative approach enhances economic benefits and promotes environmental sustainability. Work of [15] examines energy hubs interfacing with heating, gas, and electrical grids, operating

as coordination platforms for distributed generation units and storage devices. Study introduces a deterministic optimization formulation designed to minimize total costs of operating across interconnected energy systems. This model accounts for power flow constraints within the networks and optimizes the configuration of energy hubs integrated with production and storage solutions.

The study referenced in [16] introduces a stochastic mixed-integer linear programming model designed for the optimized operation of a microgrid that incorporates multiple energy carriers. Given the inherent unpredictability of renewable energy generation, situations may arise where sudden surges in renewable energy output exceed immediate usage capabilities. To address this, surplus energy can be converted into alternative energy carriers. The study employs a probabilistic distribution function to implement this stochastic approach effectively. In [17], a novel application of a modified particle swarm optimization (PSO) technique is detailed, focusing on optimizing multi-energy hub systems (EHSs) to improve overall efficiency and sustainability. By utilizing PSO, the method optimizes the scheduling of diverse energy resources, including gas turbines, biomass units, and renewable sources like solar and wind power. In contrast to conventional optimization methods relying on genetic algorithms (GA) with complex encoding schemes, the PSO algorithm simplifies the process through real-valued vectors and straightforward swarm communication, thereby significantly reducing implementation complexity. Finally, the study cited in [18] proposes a comprehensive framework for an energy hub system that integrates electrical, thermal, cooling, and water infrastructures. This framework aims to modernize distribution systems while enhancing their flexibility and overall efficiency.

The summary of works in background of research is expressed in Table 1.

1.3. Research gaps

The primary research gaps in energy management for EHs integrated into the network, as highlighted through Table 1 and the study's foundational analysis, can be summarized as follows:

- One of the important indicators in electrical system is minimizing the voltage profile. Because in this situation, it is expected that the voltage drop in the distribution lines will be minimal. Therefore, the power losses in the lines will be low, and consequently the energy losses will be low. Also, if the voltage drop in the distribution lines is low, the voltage magnitude in all buses will be close to the desired value (1p.u.). Hence, a smoother voltage profile is obtained. In addition, in this situation, a suitable voltage safety margin is obtained for the network, because the voltage magnitude of the buses is maintained at a high value. In addition, the low voltage drop in the

distribution line is due to the low current in this line. So, in the aforementioned situation, it is expected that the free capacity for new loading will increase. In other words, the network will be able to supply more load, which will prevent the costs of network expansion in the near future. The aforementioned conditions can also be established for the heating network, provided that the temperature profile function is improved. Energy hubs are located at different points in the distribution network that control their active and thermal power. By controlling these powers, it can take a positive step in improving the voltage and temperature profile. However, this issue has been considered in few studies such as [6]. Of course, it only considers improving the voltage profile. EHs often depend on RESs and environmentally friendly components. Their incorporation into the network is expected to lower emissions attributed to energy supplies from centralized production units, such as power plants. Although this topic has been explored in various studies, as noted in references [6–15], the development of mathematical models to evaluate the environmental impact of hubs has been addressed in only a limited number of works [7,9,12]. This underscores a significant opportunity for further investigation and research in this area.

- Renewable energy sources manifest in diverse formats, such as WTs, PV, and bio-waste units (BUs). While extensive studies have focused on WTs and PVs, the role of BUs is still comparatively under-researched. BUs possess the capacity to convert environmental waste into electrical energy. Moreover, when integrated with CHP unit, they can efficiently produce heating and electricity energy at the same time. Nevertheless, as highlighted in studies [9,11,13], their effectiveness within EHs has been explored to a far lesser extent.
- Batteries have predominantly been the storage solution of choice in hubs across high number of works. While they offer high power density and work efficiency and, their limitations include a shorter operational lifespan, expensive upgrades to expand capacity, and substantial investment costs [19]. To overcome these drawbacks, hydrogen storage has emerged as a viable alternative. Hydrogen storage systems can be built with higher capacity, exhibit a significantly longer lifespan, and maintain a commendable work efficiency of approximately 75 %. Moreover, hydrogen storage incorporates advanced technologies such as hydrogen-to-power (H2P), which utilizes fuel cells (FC), and power-to-hydrogen (P2H), leveraging electrolyzers (ELs). These technologies can be integrated with CHP systems. Such integration allows not only the regulation of active power but also the production of thermal energy. However, it considers sparsely in the different works, with [9] being one of the few exceptions. Notably, [9] assumes that only H2P systems are equipped with CHP, highlighting an advantage of this configuration, an enhancement in the energy efficiency of hydrogen storage.

Table 1

Taxonomy of studies.

Ref.	Capability of EH on Voltage regulation	Temperature regulation	Environmental management	Model of CHP-based BU	CHP-based P2H	CHP-based H2P
[6]	✓	x	x	x	x	x
[7]	x	x	✓	x	x	x
[8]	x	x	x	x	x	x
[9]	x	x	✓	✓	x	✓
[10]	x	x	x	x	x	x
[11]	x	x	x	✓	x	x
[12]	x	x	✓	x	x	x
[13]	x	x	x	✓	x	x
[14]	x	x	x	x	x	x
[15]	x	x	x	x	x	x
[16]	x	x	x	x	x	x
[17]	x	x	✓	x	x	x
[18]	x	x	x	x	x	x
Current study	✓	✓	✓	✓	✓	✓

P2H: Power to hydrogen system, H2P: Hydrogen to power system.

1.4. Contributions

To bridge the identified research gaps, this study introduces a tailored energy scheduling approach designed for EHs into heating and electricity grids. As depicted in Fig. 1, the approach targets the voltage and temperature regulation established by network operators. The hubs under consideration integrate renewable energy sources, including photovoltaic, bio-waste and wind, alongside hydrogen storage and thermal energy storage systems. For improved energy efficiency, combined heat and power systems are utilized within bio-waste units, power-to-hydrogen units (electrolyzer), and hydrogen-to-power systems (fuel cells). These hubs generate electricity via wind turbines, photovoltaic panels, and bio-waste units, while thermal energy production is facilitated through electrolyzer, fuel cells, and bio-waste facilities. Hydrogen storage systems support the electrical operations of the hubs, while thermal energy storage units cater to thermal demands. The hydrogen storage setup encompasses components like power-to-hydrogen units, hydrogen-to-power systems, and a dedicated hydrogen tank. The framework aims to minimize the combined voltage and temperature profile functions across respective energy networks via its objective function. It incorporates constraints that include optimal power flow equations for both electrical and thermal networks, environmental conditions linked to the networks, and operational models of renewable energy sources and storage systems. Together, these elements are structured into a unified energy hub model. Additionally, the strategy addresses uncertainties associated with various parameters such as load demand, wind velocities, solar radiation intensities, and biogas generation from bio-waste units. Scenario-Based Stochastic Optimization (SBSO) is employed to model these uncertainties. This approach uses a Mont Carlo Simulation (MCS) for scenario creation and refines these scenarios through a Kantorovich method (KM). The following highlights encapsulate the key advancements and contributions offered by this innovative concept:

- Investigating the ability of energy hubs to improve the operating and security conditions of energy networks by considering voltage and temperature regulation as the objective function,
- Considering the mathematical model of environmental indicators in electrical and thermal networks to investigate the ability of storage-based renewable energy hubs to reduce environmental emissions,
- Using combined heat and power (CHP) technology for bio-waste units to produce thermal energy from renewable sources in the energy hub and improve energy efficiency, and
- Using CHP technology in P2H and H2P deployed in hydrogen storage to improve energy efficiency and multi-purpose use this storage (electricity energy storage and thermal energy production).

1.5. Paper Organization

The second section provides a comprehensive explanation of energy scheduling strategies for networked EHs. The third part focuses on modeling uncertainties through the implementation of the stochastic programming. In Part 4, simulation results obtained from diverse works are analyzed, while Part 5 concludes the discussion with summarized findings.

2. Formulation of the proposed plan

This section considers the energy scheduling strategy designed for renewable EHs that leverage flexible resources such as heating and hydrogen storages. These EHs are seamlessly incorporated into advanced electric and thermal networks. The key aim of this approach is to reduce the expected value of deviation in voltage and temperature. The system operates within defined limits based on the operational frameworks of renewable units and adaptable storages within the EH setup, combined with optimal power flow equations and environmental constraints inherent to energy networks. As a result, this strategy can be formally represented through mathematical models.

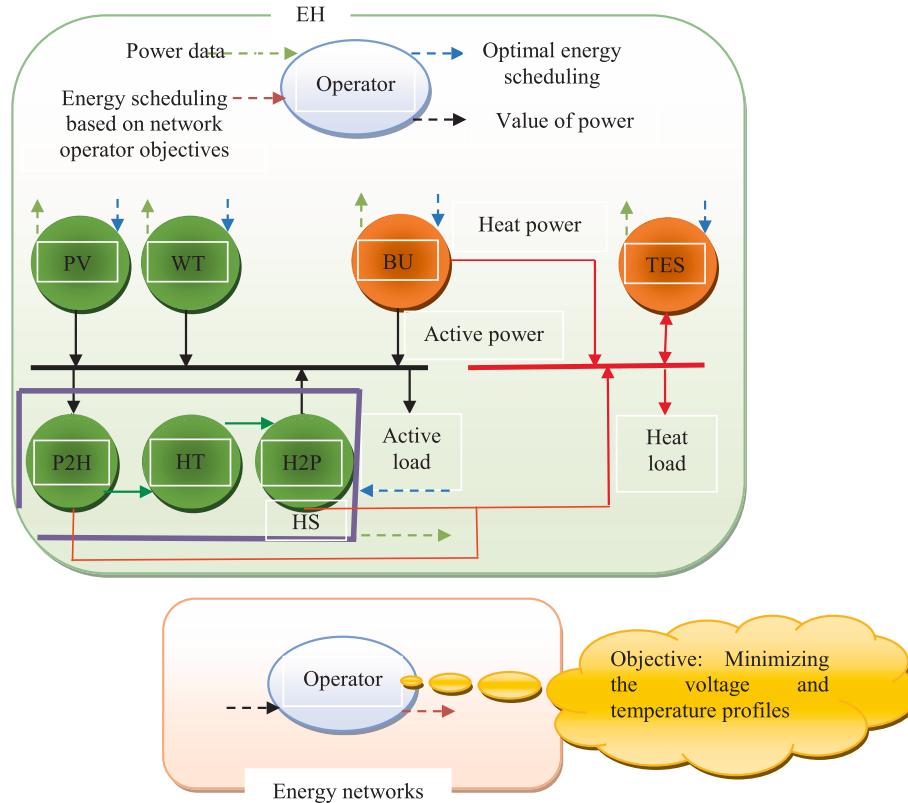


Fig. 1. Optimal energy scheduling in the energy grid with EHs.

A) Objective Function: A primary objective of the electric network operator is to enhance the network's operational performance. Central to this goal is the minimization of energy losses across the system. Key aspects include achieving a uniform or flat voltage profile, ensuring a safe voltage margin, and maintaining sufficient spare capacity in distribution lines to accommodate increased network load. To achieve these outcomes, the process focuses on minimizing the voltage profile function, which closely mirrors the structure of the first part of equation (1) [20]. This relationship introduces the voltage deviation function (VDF), and this involves reducing the expected value of deviation of bus voltages from the desired reference value (V_{ref}) [20]. By minimizing these deviations, voltage drops across distribution lines are significantly reduced, leading to lower power losses and, consequently, decreased energy losses within the electric network. Minimizing voltage drops directly aligns with keeping bus voltages near the target value, contributing to a flatter voltage profile. This adjustment not only guarantees a smoother operational condition but also ensures that the buses maintain high voltage amplitudes, creating a substantial safe voltage margin for the network. Furthermore, reducing line voltage drops means limiting the power flowing through distribution lines, thereby freeing up additional capacity to accommodate future demands. This principle also extends to thermal networks, where the concept of temperature takes the place of voltage. In such cases, the minimization target shifts to optimizing the temperature profile function within the heating network, as described in the second part of equation (1). This relationship introduces the temperature deviation function (TDF). In the proposed scheme, the effective amount (RMS) of voltage and temperature is used. Note that the unit of voltage and temperature deviation is in per-unit (p. u.). In other words, their units are the same. In addition, according to Section 4.1, the range of voltage and temperature should change between 0.9 and 1.1p.u. Therefore, the changes range of voltage and temperature deviation is the same. Also, voltage deviation changes have no effect on temperature deviation changes. Therefore, in this situation, equation (1) can be used, so that there is no need for multi-objective optimization.

$$\min \sum_{b,t,w} \gamma_w (V_{b,t,w} - V_{ref})^2 + \sum_{n,t,w} \gamma_w (T_{n,t,w} - T_{ref})^2 \quad (1)$$

B) Operation Model of Energy Networks Based on Environmental Conditions: The operation of energy networks is governed by a set of constraints and equations that ensure optimal power flow within thermal and electrical systems under environmental considerations. Constraints (2) through (15) encapsulate these governing principles. Constraints (2) to (9) focus specifically on the optimal power flow within electrical distribution networks [21,22], incorporating an environmental index. Eqs. (2) and (3) are responsible for maintaining balance in power, i.e. active and reactive mode, at electricity nodes, respectively. Meanwhile, equations (4) and (5) describe the flows of active and reactive power along electrical distribution lines [23]. The technical limits of the electrical network are outlined in constraints (6) to (8) [21,22]. Here, Eq. (6) ensures voltage magnitude remains within acceptable limits at the buses, equation (7) restricts apparent power flow through distribution lines, and equation (8) sets operational constraints on distribution posts. Environmental impacts affecting the electrical network are addressed in Eq. (9), which quantifies emissions, namely CO_2 , NO_x , and SO_2 , linked to centralized industrial connections [24]. The total emissions are defined through a combined parameter, denoted as coefficient ρ , representing environmental factors like carbon dioxide, nitrogen oxide, and sulfur dioxide emission coefficients [24]. Eqs. (10) to (15) provide a corresponding framework for optimal power flow in heating networks while incorporating environmental considerations [25,26]. Eq. (10) governs the balance of thermal power across nodes in the heating network, while equation (11) accounts for thermal power transfer through pipelines. Technical constraints for heating networks are organized from equations (12) to (14). Specifically, Eq. (12) places limits on node temperatures, equations (13) and (14) regulate the transmission of thermal power

through pipelines and substations, respectively. Finally, Eq. (15) captures environmental pollution limits tied to heating network operations, with emissions resulting from upstream energy infrastructure supply. These include restrictions on CO_2 , NO_x , and SO_2 emissions.

$$P_{S\ b,t,w} + \sum_i C_{E\ i,b} P_{EH\ i,t,w} + \sum_j A_{E\ j,b} P_{L\ b,j,t,w} = P_{D\ b,t,w} \quad \forall b, t, w \quad (2)$$

$$Q_{S\ b,t,w} + \sum_j A_{E\ j,b} Q_{L\ b,j,t,w} = Q_{D\ b,t,w} \quad \forall b, t, w \quad (3)$$

$$P_{L\ b,j,t,w} = G_{L\ b,j} (V_{b,t,w})^2 - V_{b,t,w} V_{j,t,w} \left\{ \frac{G_{L\ b,j} \cos(\varphi_{b,t,w} - \varphi_{j,t,w})}{B_{L\ b,j} \sin(\varphi_{b,t,w} - \varphi_{j,t,w})} \right\} \quad \forall b, j, t, w \quad (4)$$

$$Q_{L\ b,j,t,w} = -B_{L\ b,j} (V_{b,t,w})^2 + V_{b,t,w} V_{j,t,w} \left\{ \frac{B_{L\ b,j} \cos(\varphi_{b,t,w} - \varphi_{j,t,w})}{G_{L\ b,j} \sin(\varphi_{b,t,w} - \varphi_{j,t,w})} \right\} \quad \forall b, j, t, w \quad (5)$$

$$V_{min} \leq V_{b,t,w} \leq V_{max} \quad \forall b, t, w \quad (6)$$

$$(P_{L\ b,j,t,w})^2 + (Q_{L\ b,j,t,w})^2 \leq \bar{S}_{L\ b,j} \quad \forall b, j, t, w \quad (7)$$

$$(P_{S\ b,t,w})^2 + (Q_{S\ b,t,w})^2 \leq \bar{S}_{S\ b} \quad \forall b, t, w \quad (8)$$

$$\sum_{b,t,w} \gamma_w (\rho_{CO2} + \rho_{SO2} + \rho_{NOx}) P_{S\ b,t,w} \leq EM^{max} \quad (9)$$

$$H_{S\ n,t,w} + \sum_i C_{H\ i,n} H_{EH\ i,t,w} + \sum_j A_{H\ j,n} H_{L\ n,j,t,w} = H_{D\ n,t,w} \quad \forall n, t, w \quad (10)$$

$$H_{L\ n,j,t,w} = C_{L\ n,j} (T_{n,t,w} - T_{j,t,w}) \quad \forall n, j, t, w \quad (11)$$

$$T_{min} \leq T_{n,t,w} \leq T_{max} \quad \forall n, t, w \quad (12)$$

$$|H_{L\ n,j,t,w}| \leq \bar{H}_{L\ n,j} \quad \forall n, j, t, w \quad (13)$$

$$|H_{S\ n,t,w}| \leq \bar{H}_{S\ n} \quad \forall n, t, w \quad (14)$$

$$\sum_{n,t,w} \gamma_w (\rho_{CO2} + \rho_{SO2} + \rho_{NOx}) H_{S\ n,t,w} \leq EM^{max} \quad (15)$$

C) Operational Model of Renewable Energy Hubs with Storage Systems: The operational mechanisms and constraints governing EHs incorporating RESs and storage devices are detailed in equations (16)–(31). Constraints (16) and (17) emphasize the balance between thermal and electrical energy within EHs. These constraints stipulate that thermal energy is exclusively generated by BUs, while electrical energy is contributed by RESs such as Wind Turbines (WT), Photovoltaic (PV), and BU. Furthermore, the Fuel Cell (FC) and electrolyzer (EL) augment thermal energy generation, whereas the electrolyzer functions as an active power consumer. Regulation of power in active term within EHs are managed by the Hydrogen Storage (HS) system, while Thermal Energy Storage (TES) is responsible for control of heating power. The operational framework for RESs includes Farms of PV, wind and BU (PVF, WF and BUF), delineated within formulation (18) through (21). In these systems, the active power output is calculated as the product of the system's capacity, number of units, and power production rate [27,28]. The production rate for WT depends on wind speed, which operates across four distinct zones [27]. In zones one and four, where wind speeds are either below the cut-in threshold or above the cut-out limit, no power is generated. Within zone two, wind speed between nominal and cut-in speeds, the generation rate includes a linear formulation based on wind speed. For zone three, when wind speeds exceed the nominal speed but remain below the automatic shutdown level, power generation stabilizes at its peak rate [27]. For PV systems, the power generation rate is derived from the ratio of current solar radiation to maximum possible

photovoltaic irradiation levels [28]. In contrast, constraint (20) outlines methods for determining active power output for BUF. Research indicates that BU systems employ CHP unit, enabling simultaneous production of both electrical and thermal energy. The amount of heating energy generated by BU aligns proportionally with its active power capacity, as specified by equation (21). For BUF, the production rate hinges on the bio-waste gas availability relative to maximum bio-waste gas limits [27]. Constraints (22)–(27) focus on HS operational models [27], comprising three main components: FC, EL, and Hydrogen Tank (HT). With this configuration, hydrogen obtains with EL during charging cycles and stored in HT before being utilized by FC during discharge cycles to deliver both thermal and electrical energy to EHs [27]. Both FC and EL integrate CHP technology for concurrent outputs; FC generates active power alongside thermal energy during discharge, while EL enables thermal production alongside energy consumption during charging operations. Constraints (22) and (23) define respective capacity limits for FC and EL. Constraint (24) ensures operational exclusivity, preventing simultaneous charging and discharging modes for HS components. Constraint (25) specifies limitations on the hydrogen energy storage within HT, accounting for initial stored energy, retention during charging, and release during discharging phases [27]. CHP-specific models for FC and EL are further outlined in constraints (26) and (27), stating that thermal output correlates to active power generation. Finally, TES operation is discussed within relations (28)–(31) [15]. Constraints (28) and (29) designate permissible charge/discharge rates for TES systems. Relation (30) prohibits simultaneous charging and discharging processes within TES to maintain system integrity. Constraint (31) regulates thermal energy storage, accounting for retention levels over time [15]. In this article, it is assumed that the value of the self-discharging rate of each storage device is zero during the hours when they are off.

$$P_{EH,i,t,w} = P_{W,i,t,w} + P_{V,i,t,w} + P_{B,i,t,w} + (P_{F,i,t,w} - P_{E,i,t,w}) - P_{D,i,t,w} \quad \forall i, t, w \quad (16)$$

$$H_{EH,i,t,w} = H_{B,i,t,w} + H_{E,i,t,w} + H_{F,i,t,w} + (H_{DIS,i,t,w} - H_{CH,i,t,w}) - H_{D,i,t,w} \quad \forall i, t, w \quad (17)$$

$$P_{W,i,t,w} = n_W \bar{P}_W \varphi_{W,i,t,w} \quad \forall i, t, w \quad (18)$$

$$P_{V,i,t,w} = n_V \bar{P}_V \varphi_{V,i,t,w} \quad \forall i, t, w \quad (19)$$

$$P_{B,i,t,w} = n_B \bar{P}_B \varphi_{B,i,t,w} \quad \forall i, t, w \quad (20)$$

$$H_{B,i,t,w} = \frac{(1 - \eta_B) \eta_H}{\eta_B} P_{B,i,t,w} \quad \forall i, t, w \quad (21)$$

$$0 \leq P_{F,i,t,w} \leq n_{HS} \bar{P}_{Fi} \quad \forall i, t, w \quad (22)$$

$$0 \leq P_{E,i,t,w} \leq n_{HS} \bar{P}_{Ei} \quad \forall i, t, w \quad (23)$$

$$P_{F,i,t,w} P_{E,i,t,w} = 0 \quad \forall i, t, w \quad (24)$$

$$n_{HS} \bar{E}_{HTi} \leq n_{HS} \hat{E}_{HTi} + \sum_{h=1}^t \left(\eta_E P_{E,i,t,w} - \frac{1}{\eta_F} P_{F,i,t,w} \right) \leq n_{HS} \bar{E}_{HTi} \quad \forall i, t, w \quad (25)$$

$$H_{E,i,t,w} = \frac{(1 - \eta_E) \eta_H}{\eta_E} P_{E,i,t,w} \quad \forall i, t, w \quad (26)$$

$$H_{F,i,t,w} = \frac{(1 - \eta_F) \eta_H}{\eta_F} P_{F,i,t,w} \quad \forall i, t, w \quad (27)$$

$$0 \leq H_{DIS,i,t,w} \leq n_T \bar{H}_{DISi} \quad \forall i, t, w \quad (28)$$

$$0 \leq H_{CH,i,t,w} \leq n_T \bar{H}_{CHi} \quad \forall i, t, w \quad (29)$$

$$H_{DIS,i,t,w} H_{CH,i,t,w} = 0 \quad \forall i, t, w \quad (30)$$

$$n_T \bar{E}_{TESi} \leq n_T \hat{E}_{TESi} + \sum_{h=1}^t \left(\eta_{CH} H_{CH,i,t,w} - \frac{1}{\eta_{DIS}} H_{DIS,i,t,w} \right) \leq n_T \bar{E}_{TESi} \quad \forall i, t, w \quad (31)$$

3. Uncertainty modeling

The proposed plan considers parameters such as load (P_D , Q_D , and H_D), renewable power rates for the wind system (φ_W), solar unit (φ_V), and bio-waste system (φ_B) as uncertain parameters. To address these uncertainties, a stochastic programming methodology is employed, which integrates Monte Carlo Simulation (MCS) and the Kantorovich Method (KM) [29]. The MCS generates a large number of potential scenarios by assigning random values to the unknown parameters for each case. The allocation of load and renewable power rates is based on their mean and standard deviation values. The Normal Probability Density Function (PDF) is utilized to estimate the likelihood of selected values for load and bio-waste power rates. Meanwhile, Weibull and Beta PDFs are applied to evaluate the probabilities of wind power and solar power rates, respectively. Each generated scenario is assigned a probability (γ^0), calculated as the product of the probabilities of all uncertainty parameters within that specific scenario. Since MCS typically produces a vast number of scenarios, reducing the scenario set becomes essential to minimize computational complexity. Various scenario reduction methods are discussed in the literature [29], but this study opts for the Kantorovich Method due to its high accuracy and minimal computational overhead. This method determines the distance between scenarios to identify the least probable or dissimilar ones, as detailed in [29]. Ultimately, the probability of each reduced scenario is recalculated by dividing the original MCS probability (γ^0) by the sum of probabilities of the selected scenarios. This approach ensures a manageable and efficient evaluation of stochastic uncertainties in the system.

4. Numerical simulation

4.1. Data

Fig. 3 demonstrates the application of the energy management system discussed in this part to both the 94-bus Portuguese electricity distribution grid [30] and the 42-node heating network in Naestved [31]. The electrical network is characterized by a base power of 1 MVA and an operating voltage of 15 kV. Bus 1 serves as the reference bus, maintaining a voltage angle of zero and an amplitude of voltage (V_{ref}) set at 1 p.u., with permitted fluctuations in voltage amplitude ranging from 0.9 to 1.1 p.u. [32–36]. Distribution line and post specifications are elaborated in [30], where the upper reactive and active loads for various buses are also detailed. Load at different time intervals is calculated by multiplying the maximum load by the load factor curve [37–41], which is represented in Fig. 4(a), showcasing the anticipated daily load factor curve for the electricity grid [27]. When sourcing electricity energy from upstream grid, the sum of CO₂, SO₂, and NO_x factors reach 918.2 tons/MW [24]. Regarding the heating network, it operates with a base power of 1 MW and maintains a standard temperature of 100 °C. Node 0 acts as the slack node, holding a temperature (T_{ref}) of 1 p.u., with acceptable node temperature ranges defined between 0.9 p.u. and 1.1 p.u. Additional information on pipeline and heat post characteristics is provided in [31]. Data on peak loads for specific nodes is also available in Ref. [30], while the daily projected curve for the heat load factor is included in Fig. 4(a) [15]. Emissions associated with heating energy generation, encompassing CO₂, SO₂, and NO_x are measured at 714.6 tons/MW for the heat post. As illustrated in Fig. 3, the system integrates six hubs for its operation. EM^{max} is 20 tons [42]. Placement of hubs are shown in Fig. 3. In hubs 1 to 6, there are 120 BUs, 120 BUs, 80 WTs, 100 WTs, 1500 PVs, and 1500 PVs, respectively. In these hubs, there are 40, 80, 50, 30, 25, and 50 hydrogen storage (HS) devices, respectively. Also, hubs 1, 2, 4, and 5 have 40, 40, 25, and 25 thermal storage devices,

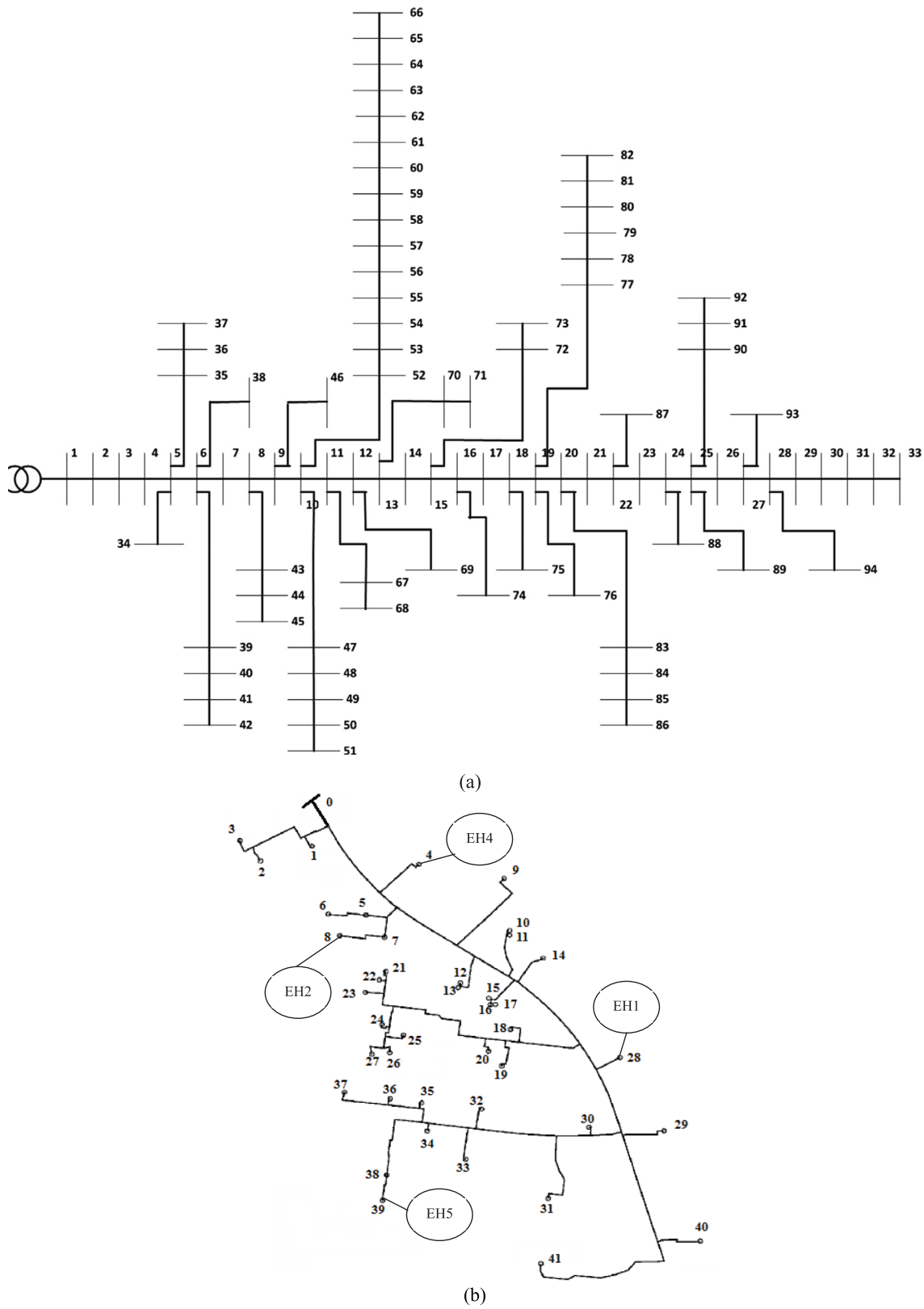


Fig. 3. Test network, a) 94-bus Portuguese electrical distribution grid [30], b) Naestved 42-node heating network [31].



Fig. 4. Expected daily curve for, a) load factor in the different networks [15,27], b) power generation rate of renewable units [27,28].

respectively. Each WT has a capacity of 10 kW, the BU capacity is 10 kW, and the PV capacity is 0.36 kW. The expected daily power generation rate curve for different renewable sources is shown in Fig. 4(b) [27,28,43,44]. In the hydrogen storage device, the capacity of the fuel cell with an efficiency of 51 % [27], the electrolyzer with an efficiency of 75 % [27] is 10 kW. The capacity of the hydrogen tank is 50 kWh, and the minimum energy and initial energy in this tank are 5 kWh. In the thermal storage device, the charge and discharge rates are 10 kW, so that the charge and discharge efficiencies are 81 % and 79 %, respectively. The capacity of this storage device is 50 kWh, and the initial and minimum energy are 5 kWh. BU efficiency is 37 %, heat efficiency in BU, P2H and H2P systems is 39 %. The load assigned to each hub corresponds directly to its position within the network. A standard deviation of 10 % is applied to account for uncertainties in both the load and the power generation rates of renewable energy sources. MCS generates 2000 scenario samples, and KM applies 80 scenario samples to the proposed problem.

4.2. Results and discussion

This section involves conducting the simulation within the GAMS software. The proposed plan is resolved utilizing the IPOPT solver as outlined in reference [45]. The resulting quantitative data is then

detailed in the following segment.

A) *Analysis of the voltage and temperature regulation*: The sensitivity analysis of the objective function including voltage and temperature deviation functions (VDF and TDF) for changes in peak load, maximum emission (EM^{max}), and renewable resource capacity ($\bar{P}_W$, $\bar{P}_V$ and $\bar{P}_B$) is examined in this section. The numerical results for the increase rate (κ) between 0 % and 30 % are shown in Table 2. According to this table, it is observed that with the increase in peak load in the electrical and thermal networks, VDF and TDF increase by approximately 0.5κ and 0.48κ , respectively. In other words, a 5 % increase in peak load leads to an increase of approximately 2.5 % in VDF and TDF functions. According to Table 2, the least changes in the objective function are for changes in maximum emission. Thus, with an increase in this parameter, VDF and TDF increase by approximately 0.06κ and 0.05κ , respectively. This means that a 5 % increase in EM^{max} can increase VDF and TDF by 0.25 %. Increasing the capacity of renewable resources has led to a decrease in VDF and TDF. Because these resources are located at the consumption points according to Fig. 3. Therefore, by feeding some of the consumers in the consumption area, they can increase the voltage and temperature to near the desired value (V_{ref} and T_{ref}). According to Table 2, increasing the capacity of renewable resources leads to a decrease in VDF and TDF by about 0.33κ and 0.29κ , respectively. In other words, a 5 % increase in the capacity of renewable resources leads to a decrease in VDF and TDF

Table 2

Value of VDF and TDF for different value of peak load, renewable system capacity, and maximum emission.

Objective function		VDF (p.u.)			TDF (p.u.)		
Parameter		Peak load	Renewable system capacity	Maximum emission	Peak load	Renewable system capacity	Maximum emission
Rate of increase (κ)	$\kappa = 0$	5.58	5.58	5.58	2.46	2.46	2.46
	$\kappa = 5\%$	5.73	5.48	5.57	2.52	2.42	2.47
	$\kappa = 10\%$	5.88	5.38	5.59	2.58	2.39	2.47
	$\kappa = 15\%$	6.01	5.29	5.61	2.63	2.36	2.48
	$\kappa = 20\%$	6.14	5.20	5.62	2.68	2.33	2.48
	$\kappa = 25\%$	6.25	5.11	5.63	2.73	2.30	2.49
	$\kappa = 30\%$	6.36	5.02	5.64	2.78	2.27	2.49
	Deviation (%)	$\approx 0.5\kappa$	$\approx -0.33\kappa$	$\approx 0.06\kappa$	$\approx 0.48\kappa$	$\approx -0.29\kappa$	$\approx 0.055\kappa$

by 1.6 %.

B) *Performance Assessment of Renewable Energy Hubs Utilizing Storage Systems:* Figs. 5 and 6 illustrate the expected daily trends for active and thermal power across various sources, storage units, and EHs. In Fig. 5 (a), the daily energy generation curves for wind farm (WFs), solar, bio-

waste sources, and all renewable energy sources collectively are presented. The graph numerically represents the power generation rates from the wind system, photovoltaic farm (PVF), and bio-waste unit farm (BUF), aligning with the trends displayed in Fig. 4(b). This correlation arises because, as defined by equations (18)-(20), the production of

**Fig. 5.** Time changes of power in term of active for, a) RES, b) HSs and EHs.

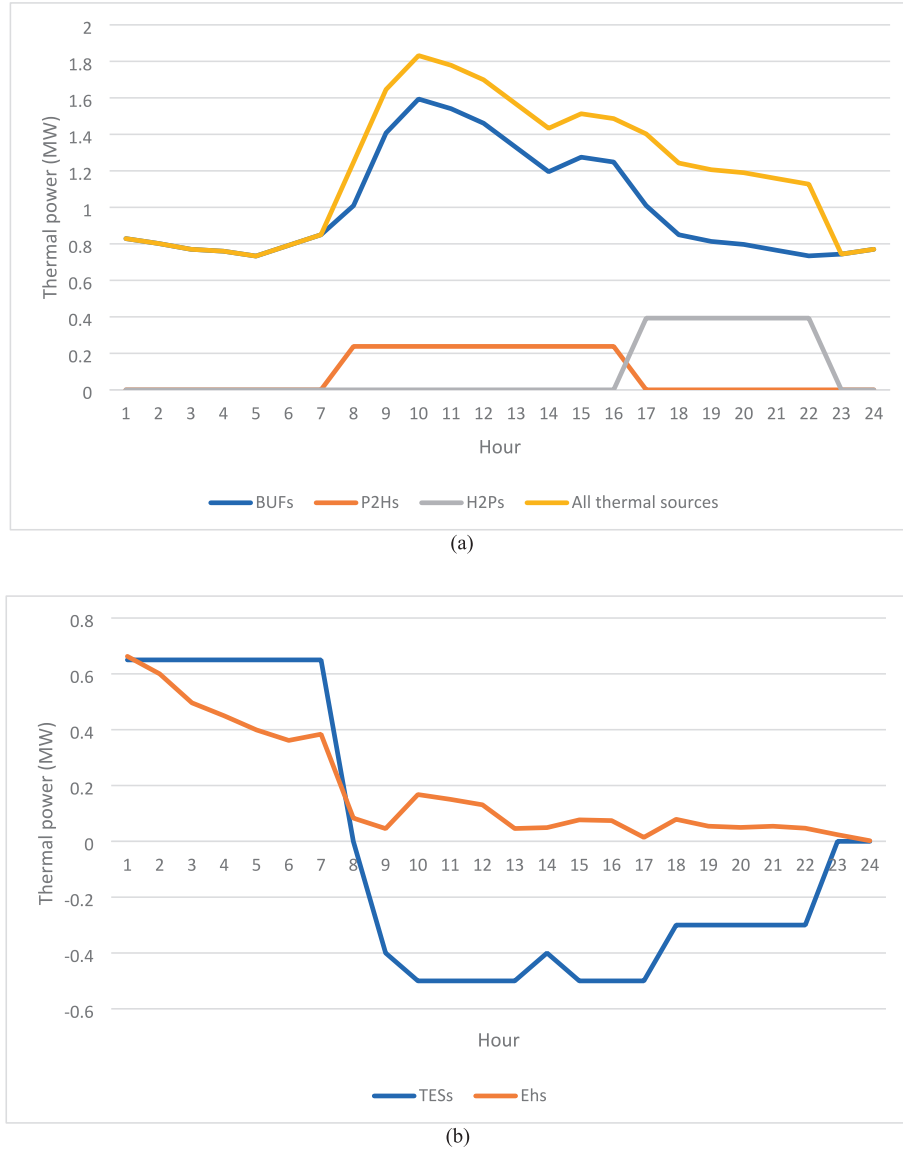


Fig. 6. Expected daily thermal power curve of, a) BUFs and HSs, b) TESs and EHs.

active power from RESs is contingent on their generation rates. Analyzing Fig. 5(a), it is evident that WF, BUF, and PVF yield maximum active power outputs of 1.8 MW, 2.4 MW, and 1.08 MW, respectively. Regarding the behavior of hydrogen storage (HS) systems, Fig. 5(b) shows that these systems remain inactive during off-peak hours (1:00–7:00). However, during mid-load hours (8:00–16:00), they switch to charge mode with active power supplied to electrolyzers (ELs) or power-to-hydrogen (P2H) systems from the hubs. This operational behavior is attributed to the high active power generation from RESs during these periods, where direct injection into the electrical grid could cause excessive voltage levels. To mitigate overvoltage risk, the storage systems absorb excess energy. Consequently, during this interval, HSs can meet their energy demands entirely through RES generated power. Between 17:00 and 22:00, HSs transition to discharge mode, wherein fuel cells (FCs) or hydrogen-to-power (H2P) systems deliver active power back to the grid, supporting its demand. In contrast, during the earlier off-peak hours, HSs remain inactive since RES power production, as depicted in Fig. 5(a), is relatively low. Utilizing storage units during these hours would likely require a portion of their energy consumption to be drawn from the electrical network, failing to optimize the objective function defined in equation (1). Moreover, the operational strategy of

these storage systems ensures that EHs consistently act as producers of electrical energy. As indicated in Fig. 5(b), EHs are capable of supplying active power to the electrical grid throughout their entire operating schedule. This operational behavior aligns with the objective of minimizing voltage deviations across the network.

Fig. 6 illustrates the thermal power time curve for BUFs, TESs, P2Hs, H2Ps, and EHs. The daily thermal power pattern of BUFs mirrors their active power profile closely, with only slight numerical deviations, as highlighted in Figs. 5(a) and 6(a). This alignment results from the application of Eq. (21), which demonstrates that a BU's thermal power is directly proportional to its active power. Similar correlations are evident for H2Ps and P2Hs, as deduced from Fig. 6(a) and Eqs. (26) and (27). TESs, when operating in discharge mode, encounter a thermal peak between 1:00 and 8:00, during which their discharge activity plays a crucial role in minimizing the objective function. Outside these hours, TESs switch to charge mode. From 9:00 to 22:00, the combined output from BUFs, P2Hs, and H2Ps exceeds the thermal demand of EHs. During this interval, TESs absorb thermal power supplied by both BUFs and HSs. In addition, Fig. 6(b) conveys the steady role of EHs as energy contributors. They consistently inject thermal power into the network, helping to reduce temperature fluctuations and maintain the stability of the

thermal system.

C) *Analysis of the Operational Status of Electrical and Thermal Networks:* In order to investigate the capabilities of the proposed scheme, numerical results are reported for the following case studies.

- *Case I:* Load flow analysis in thermal and electrical networks.
- *Case II:* The proposed problem with EHs including only renewable sources
- *Case III:* Case II + HSs and TESs

This text highlights various operational indices used to analyze electrical and thermal grids, providing insights into their performance across three different case studies. The indices include the Peak Load Carrying Capacity (PLCC) for both electrical (E-PLCC) and thermal (T-PLCC) systems, Maximum Temperature Drop (MTD), Maximum Voltage Drop (MVD), Maximum Over Temperature (MOT), Maximum Over Voltage (MOV), and Expected Energy Loss (EEL) in electricity (E-EEL) and heating (T-EEL) grids. These metrics are critical in assessing network operation and efficiency. PLCC represents the maximum peak load that the network can handle while conforming to the daily load curve illustrated in Fig. 4(a). Analyzing Figs. 7-10, Case I demonstrates the most significant energy losses, voltage declines, and temperature drop during load flow simulations. Additionally, this scenario exhibits the lowest values across PLCC, over-voltage, and over-temperature metrics. In Case II, the inclusion of renewable energy sources at the hubs enhances several operational indices, except for over-voltage and over-temperature. Compared to Case I, notable improvements include reductions in E-EEL by approximately 26.33 %, T-EEL by 27.46 %, combined EEL by 26.85 %, MVD by 35.33 %, and MTD by 25.45 %, as detailed in Table 3. Furthermore, PLCC rises by about 15 % for electrical networks and 25.73 % for thermal networks. However, MOV and MOT experience slight increases, transitioning from zero in Case I to 0.017 p.u. and 0.010 p.u., respectively, as depicted in Figs. 8 and 9. Case III achieves optimal operational performance by integrating the full system model (1)-(31) alongside hubs equipped with hydrogen storage, thermal energy storage, and RESs. This scenario showcases substantial improvements compared to Case I, with reductions in E-EEL, T-EEL, combined EEL, MVD, and MTD by approximately 37.87 %, 38.38 %, 38.10 %, 56 %, and 38.18 %, respectively, according to data from Figs. 7-9 and Table 3. Simultaneously, PLCC experiences a noteworthy increase of about 40.29 % for electrical networks and 23.33 % for thermal networks, as illustrated in Fig. 10 and Table 3. Additionally, MOV and MOT show significant declines of 47.06 % and 40 %, respectively, compared to Case II, as indicated by Figs. 8-9 and Table 3.

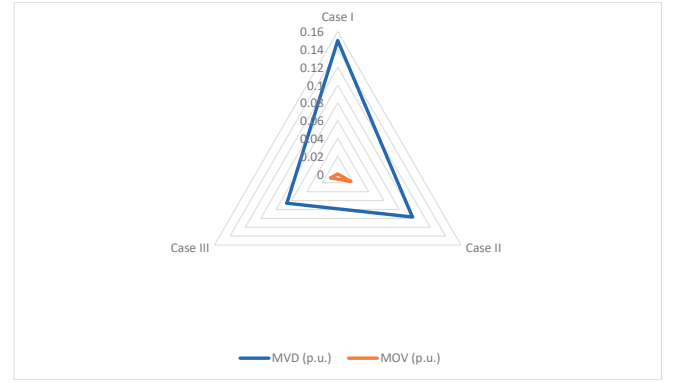


Fig. 8. Value of MVD and MOV in the different networks and cases.

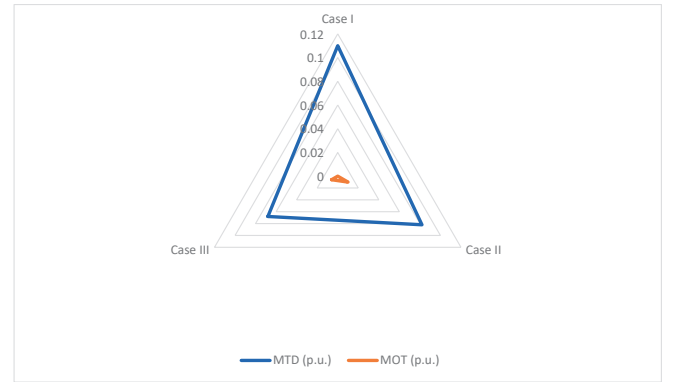


Fig. 9. Value of MTD and MOT in the different grid and cases.

respectively, compared to Case II, as indicated by Figs. 8-9 and Table 3.

In Ref. [22], economic exploitation based on voltage security in the electric distribution network using electric vehicles and demand response is carried out. In other words, it considers an objective function to improve economic and operational goals, and considers an objective function to improve the voltage security. However, the features of using voltage deviation and temperature function in the objective function are to improve the operating conditions and security in different energy networks. In [27] and [28], the sizing of hydrogen storage devices in off-grid system and distribution networks is considered, respectively, which

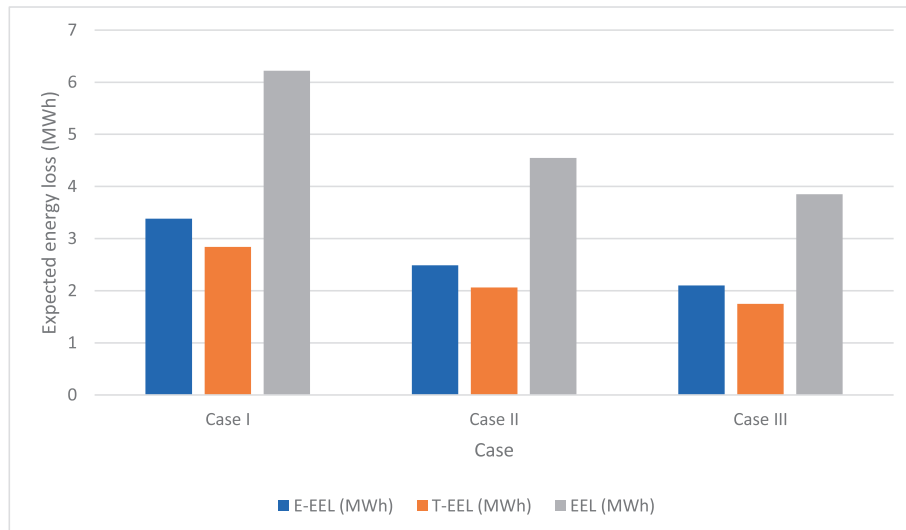


Fig. 7. Expected value of energy loss in the different systems and cases.

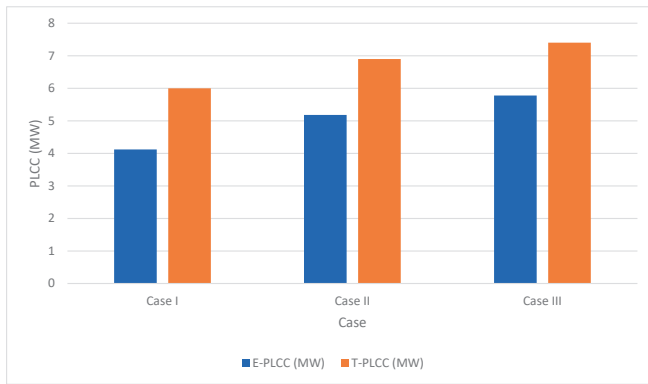


Fig. 10. PLCC value in the different systems and cases.

Table 3

Improvement percentage for operation indicators in Cases II and III compared to load flow studies (Case I).

Variable	Case II	Case III
E-EEL	26.33 %	37.87 %
T-EEL	27.46 %	38.38 %
EEL	26.85 %	38.10 %
MVD	35.33 %	56 %
MOV	Increased to 0.017p.u.	47.06 % compared to Case II
MTD	25.45 %	38.18 %
MOT	Increased to 0.010p.u.	40 % compared to Case II
E-PLCC	25.73 %	40.29 %
T-PLCC	15 %	23.33 %

is based on economic goals. In other words, in [13,22,27,28], the voltage and temperature regulation model, environmental formulation, and CHP model for hydrogen storage device are not used. In addition, they only consider the electric network model. But, this paper considers these issues.

5. Conclusions

This article explores the functioning of thermal and electrical networks integrated with renewable energy hubs, incorporating systems like hydrogen and thermal storage, wind turbines, solar panels, and bio-waste units, all assessed through environmental indices and infrastructure reliability. In this plan, in order to improve the security and operation conditions of energy networks in the presence of energy hubs, the objective function is equal to minimizing the sum of voltage and temperature profile functions. This function is also subject to the equations of optimal power flow in electrical and thermal networks, environmental constraints in the aforementioned networks, and the energy hub operation model with various storage devices and renewable sources. The aforementioned plan is accompanied by uncertainties in load and renewable power. Scenario-based stochastic optimization was used to model these uncertainties. Based on the numerical results, it was observed that renewable resources inject power equal to their maximum capacity into the hub during all operating hours, in accordance with weather conditions. Hydrogen storage is in charging mode during hours when renewable resources have high active power production, and in discharging mode during peak load hours. Thermal storage is also in charging mode during hours when the thermal power produced by the bio-waste system and hydrogen storage is high, but in discharging mode during peak load hours. This performance of the storage has enabled hubs to appear as producers of electrical and thermal energy in energy networks during most operating hours. Furthermore, with the optimal performance of the hubs, energy losses, voltage and temperature profiles, and maximum feedable load have been improved by about 38.10 %, 47 %-56 %, 38 %-40 %, and 23 %-40 %, respectively, compared to

load flow studies.

In the proposed design, only the power and energy management of the storage devices was considered based on the charging and discharging rate limit and the stored energy limit. However, a storage device comes with a degradation cost. Also, when it is off, it is possible that the self-discharging rate occurs for storage system. This issue will be added to the proposed design as future work. Demand-side management system or demand response is one of the energy management solutions that has a favorable ability to improve the economic, technical and environmental conditions of energy networks. Therefore, the proposed design based on modeling demand response in electric and thermal networks or energy hubs is considered as a future work. In the proposed design, the efficiency of P2H and H2P technologies in the hydrogen storage device is considered constant. However, over time, their value may change. In addition, a linear relationship between power and heat is used in the hydrogen storage device, since it is assumed that this storage device operates in the linear region. However, the proposed design based on the changes in the efficiency of the hydrogen storage device and the actual power-heat model is considered as a future work. The proposed problem is nonlinear, which is solved by mathematical algorithms in this paper. If the problem size increases, many mathematical algorithms will not be able to solve the problem or will be accompanied by high computational time. One way to compensate for this issue is to use powerful computing systems. However, this leads to an increase in computational cost. To compensate for this, metaheuristic evolutionary algorithms, relation linearization, or decomposition algorithms are suitable methods to solve the problem. This issue is considered as future work in the proposed design.

CRedit authorship contribution statement

Ehsan Akbari: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Adel Mohseni:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Saeid Shahmoradi:** Writing – review & editing, Writing – original draft, Visualization, Validation. **Farshad Khalafian:** Writing – review & editing, Writing – original draft, Visualization, Validation. **Sasan Pirouzi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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.

Data availability

The data that has been used is confidential.

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