



Optimal Scheduling of Multi-Energy Systems with Wind-Solar Power and Hydrogen Storage Integration

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ARTICLE INFO

Article history:

Received: 30 November 2024

Revised: 30 January 2025

Accepted: 1 March 2025

Online: 20 July 2026

Keywords:

Optimal scheduling

Multi-energy systems

Hydrogen storage

Energy hubs

Wind-solar power

ABSTRACT

This paper presents an optimization framework for scheduling a grid-connected multi-energy system that converts electricity from the power grid and natural gas to electricity and heat consumption, integrating wind-solar power and hydrogen storage. The study aims to develop a model that efficiently schedules energy usage while accounting for excess wind-solar power utilization, storage capabilities, and hydrogen scheduling. By incorporating dynamic pricing mechanisms, such as real-time pricing, and a stochastic model to address load fluctuations during peak periods, the proposed method provides a more realistic and adaptive approach to energy management. A combination of linear programming (LP) and particle swarm optimization (PSO) is employed to balance supply demand and minimize total operating costs. The results demonstrate significant improvements in coordinated operation efficiency and cost savings under various scenarios. Additionally, although the proposed technique demonstrates faster convergence, it requires longer runtime computation while delivering a more near-optimal global solution compared to conventional PSO. This framework offers a solution for enhancing efficiency, cost reduction, and operational flexibility of multi-energy systems, paving the way for a more sustainable and economically viable energy future.

1. INTRODUCTION

In the modern era, the incorporation of several different energy systems that are composed of many energy carriers is paving the way for a more sustainable future [1]. One of the most significant characteristics of this system is that it has multiple energy carriers, not only electricity. Synergies among different types of energy are seen to provide a substantial capability for system development [2, 3]. In addition to the possibilities of modern technology, state-of-the-art, emerging, and upcoming energy technologies, such as fuel cell (FC), are considered [4]. The multi-energy system (MES) is the solution to decrease the operating cost and promote carbon neutrality. The energy hub (EH) concept is used to consider efficiently supplying energy in each section using many kinds of energy. The EH infrastructure was first discovered in [2], and the basic concept of an EH is shown in Fig. 1. However, this concept will achieve the main goal of industrial, commercial, and residential consumers emphasizing how to minimize total operating costs (TOC) [5].

The trending technology in the MES with the EH model is combined heat and power (CHP) such as micro-turbine (MT) can dispatch two energies consisting of heat and electricity energy, power-to-gas (PtG) such as electricity

energy to hydrogen gas, and gas-to-power (GtP) such as hydrogen gas to electricity energy [6, 7]. In this framework, PtG technology converts renewable energy (RE) to hydrogen gas by electrolyzer (EL). When RE generates excess energy, it can be utilized, stored, or distributed when it is synergized with a system called “Hydrogen Storage (HS)”. GtP technology converts hydrogen gas to electricity energy via FC in HS. CHP technology dispatches electricity and heat demand by fueling natural gas (NG) [8, 9].

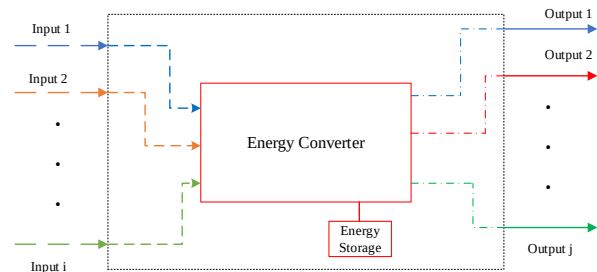


Fig. 1. The basic concept of an EH.

Hydrogen production is defined in various color codes depending on the manufacturing process and cleanliness. It can be categorized into five colors: grey, brown, blue,

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turquoise, and green hydrogen [10]. Grey hydrogen is produced from fossil fuels such as NG through steam reforming, emitting around 10 tons of CO₂ during the process [10, 11]. It's commonly used in petroleum-based chemicals and ammonia production. Brown hydrogen, derived from coal gasification, also releases significant CO₂. Blue hydrogen mitigates these emissions by employing carbon capture and storage. Turquoise hydrogen, generated via methane pyrolysis, produces solid carbon soot instead of CO₂. Green hydrogen, the cleanest, is produced using RE sources, such as wind or solar but faces challenges related to system efficiency and energy intermittent. Integrating HS can address these challenges [10]–[13].

Consequently, a significant amount of research has been proposed on MES with the EH model. Thanh-tung et al. [9] proposed a model of residential area load including electricity and heat from dispatching a multi-energy source (electricity and NG). Using mixed integer programming (MIP) based-general algebraic modeling system (GAMS) software to minimize the energy usage cost. The optimal results show that off-peak energy demand is primarily supplied by the grid, while normal and peak-hour demand is partially met by converting energy from NG to electricity, reducing system peaks, and lowering customer costs. The integration of multiple energy types improves electricity supply reliability. Then, Ha et al. [14] presented an integrating battery energy storage systems (BESS), photovoltaic panels (PVP), and solar energy model for residential areas. The case study is divided into four scenarios, each comprising variations such as with or without BESS and PV systems. The energy usage cost minimization using MIP-GAMS illustrates that the result in each case is decreasing. When PVP and BESS are integrated, the TOC is lowest. Moreover, Liu et al. [15] studied an EH model in different energy integrated. The study separated three kinds of EH cases to assess how different combinations of energy equipment. The components of EH include a boiler, cogeneration unit, chiller boiler, electric heat pump, and energy storage to dispatch electricity, heat, and cooling demand from electricity and NG as a source. The optimization process aims to minimize the TOC of the energy system, ensuring efficient energy utilization and balancing between different energy sources. The result shows that the optimal EH configuration is the most collaborative of energy. It can significantly reduce energy costs by coupling electricity, gas, and heat networks while optimizing the use of equipment like CHP and heat pumps.

Additionally, Javadi et al. [16] focused on BESS integration to enhance the operational efficiency of a multi-carrier EH through optimal scheduling. The EH consists of various components, including micro-combined heat, electric heat pumps, boilers, absorption chillers, and battery storage with the energy management problem modeled using mixed-integer nonlinear programming (MINLP). The

optimization aims to reduce costs and improve battery life by considering energy prices and battery state of charge. Simulation results highlight the importance of optimizing energy storage, leading to lower operational costs, better load management, and improved system reliability. Also, Geng and Jia [17] proposed a hybrid genetic algorithm and particle swarm optimization (GA-PSO) strategy, which combines PSO with GA to solve the optimal operation of EH. The EH model is comprised of electricity storage and heat storage coordinated with a gas turbine, gas boiler, electric chiller, and absorption chiller to dispatch electricity, heat, and cooling demand. When comparing a proposed algorithm GA-PSO with the conventional PSO, the results emphasize that GA-PSO significantly enhances convergence capability while also demonstrating a better economy in optimizing EH operations.

In addition, Wang [18] proposed the strategy of optimal scheduling for multi-energy microgrids that integrates electricity and thermal energy sources, considering demand response and BESS integration. Using MILP solved by CPLEX, the study simulates the operation of a grid-connected microgrid consisting of FC, wind turbines (WTs), PVP, and thermal storage. Three different energy dispatch schemes are tested, with the third scheme incorporating demand responses showing the best results. This scheme not only reduces operational costs but also turns grid interactions into profit opportunities by smoothing energy demand and optimizing the use of RE and storage. The research demonstrates how integrating demand responses can enhance system flexibility, lower costs, and promote sustainable energy use. Furthermore, Timothée et al. [19] investigated the optimal dispatch of a multi-storage and multi-energy hub, integrating PVP, WTs, boilers, internal combustion generators, and cogeneration plants, alongside both heat and electricity storage systems. The study employed an evolutionary algorithm (EA) for optimization and compared the results with PSO. Results highlighted the volatility in dispatch strategies, which could be mitigated by increasing battery storage capacity. The results indicate that both the battery and internal combustion generators are utilized to meet peak power demand and export electricity to the grid when prices are elevated. In terms of heat demand, the boiler operates at full capacity, with the cogeneration plants unit contributing a smaller portion of the heat supply compared to the boiler. The research emphasizes the importance of optimizing EH to manage demand, renewable variability, and grid interactions, ensuring cost-effective and efficient energy distribution.

As a result, infrastructure MES with EH necessitates a significant amount of research and development [20]–[24]. This paper proposes a multi-energy system with wind-solar power and hydrogen storage (MES-WSPHS), incorporating energy management strategies for dispatching electricity and heat demands. The framework accounts for electricity tariffs based on time-of-use (TOU) and a constant NG price,

speed condition, it is shut down to prevent damage. A wind turbine power output can be expressed (3) [27]:

$$P_{WT}(h) = \begin{cases} 0 & \text{for } 0 < v_{WT}(h) < v_{cut-in}, \\ P_{WT,rated} \times \left(\frac{v_{WT}(h)}{v_{WT,rated}} \right)^3 & \text{for } v_{cut-in} < v_{WT}(h) < v_{WT,rated}, \\ P_{WT,rated} & \text{for } v_{WT,rated} < v_{WT}(h) < v_{cut-off}, \\ 0 & \text{for } v_{WT}(h) < v_{cut-off}. \end{cases} \quad (3)$$

The total wind power per hour from (3), can be determined as the sum of each wind turbine, which can be modeled in (4).

$$P_{WTS}(h) = \sum_{k=1}^{NT} P_{WT,k}(h). \quad (4)$$

The PVP can be modeled as (5) which considers solar energy convert into electrical energy. The output is DC power and needs to be converted into AC power through an inverter [28].

$$P_{PVP}(h) = A \times \beta \times SI(h). \quad (5)$$

When the wind and solar power are excessed, it can be stored in the form of hydrogen. Therefore, the grid-injected wind and solar power at time h can be shown in (6)-(11).

$$P_{WTS}(h) = P_{WTS}^i(h) + P_{WTS}^{ex}(h), \quad (6)$$

$$P_{PVP}(h) = (P_{PVP}^i(h) \times \eta_{DC/AC}) + P_{PVP}^{ex}(h), \quad (7)$$

$$P_{WSP}(h) = P_{WTS}(h) + P_{PVP}(h), \quad (8)$$

$$P_{WSP}^{ex}(h) = \begin{cases} 0 & \text{if } P_{WSP}(h) \leq L_E(h) \\ P_{WSP}(h) - L_E(h) & \text{if } P_{WSP}(h) > L_E(h) \end{cases}, \quad (9)$$

$$P_{WSP}^i(h) = \begin{cases} P_{WSP} & \text{if } P_{WSP}(h) \leq L_E(h) \\ L_E(h) & \text{if } P_{WSP}(h) > L_E(h) \end{cases}, \quad (10)$$

$$P_{EL}(h) = (P_{WTS}^{ex}(h) \times \eta_{AC/DC}) + P_{PVP}^{ex}(h). \quad (11)$$

2.3. Conversion technologies

The conversion devices are TR, GB, and MT. In the electrical energy sector, TR is used to convert the grid voltage to the load. The TR efficiency model can be expressed as (12) when electricity flows through the TR to supply loads.

$$P_{TR} = P_E \eta_{TR}. \quad (12)$$

In the NG energy sector, GB and MT are employed to convert NG to power [9, 14]. The efficiencies of the GB and MT are utilized to determine the load supply from NG

formed as in (13) and (14). When considering NG cost, the power from NG can be defined as (15).

$$P_{GB} = P_{NG}^2 \eta_{GB}, \quad (13)$$

$$P_{MT}^{E,H} = \begin{cases} P_{NG}^1 \eta_{MT}^E; & \text{for electricity output} \\ P_{NG}^1 \eta_{MT}^H; & \text{for heat output} \end{cases}, \quad (14)$$

$$P_{NG} = P_{NG}^1 + P_{NG}^2. \quad (15)$$

2.4. HS mechanism

HS has gained considerable attention in recent studies and research efforts. In these systems, hydrogen is produced by EL when the power generated by WTs and PVP exceeds the power demand and is stored as a chemical substance. This stored hydrogen can later be used in the FC, where it reacts with oxygen from the air to generate electricity in its gaseous state. HS enables long-term energy retention, as highlighted in [29]. By applying Faraday's law, the molar flow rate of hydrogen is produced by the EL. The FC turns hydrogen into electricity, and hydrogen consumption is directly proportional to its power output [1, 30]. The molar flow of EL and FC can be described as a function in (16) and (17), respectively.

$$n_{H_2,EL} = \frac{\eta_{EL} P_{EL}}{LHV_{H_2}}, \quad (16)$$

$$n_{H_2,FC} = \frac{P_{FC}}{\eta_{FC} LHV_{H_2}}. \quad (17)$$

In the operation of HS, FC and EL cannot be operated simultaneously. Therefore, Y_{EL} and Y_{FC} representing binary numbers (0,1) are introduced for FC and EL operating conditions as shown in (18) [1, 30].

$$Y_{EL} = \begin{cases} 1 & \text{when } Y_{FC} = 0 \\ 0 & \text{when } Y_{FC} = 1 \end{cases}. \quad (18)$$

A key control variable in the HS system is the hydrogen tank pressure at each hour. The tank pressure reflects the amount of hydrogen contained in the storage vessels and molar flow from (16) and (17) are used to calculate the pressure at each hour. The pressure calculation for the hour h is dependent on the previous time step, as shown in (19) [1, 30].

$$p_{\text{tank}}(h) = p_{\text{tank}}(h-1) + \left(\frac{RT_{H_2}}{V_{H_2}} n_{H_2,EL}(h) - n_{H_2,FC}(h) \right). \quad (19)$$

3. PROBLEM FORMULATION

3.1. Objective function

The proposed method uses the PSO-LP technique to find the optimal scheduling of MES-WSPHS. The multiple energy deliveries are formed as variables on an hourly basis, to find the optimal solution for the system that makes it the minimum operating cost. The analysis considers the TOU tariff and RTP as separate factors throughout the day. Therefore, the objective function is to minimize total operating costs while accounting for the TOU tariff and RTP independently, with a penalty function incorporated to address any constraints violations, as shown in (20).

$$\text{Minimize TOC} = \sum_{h=1}^{24} (C_E(h)P_E(h) + C_{NG}(h)P_{NG}(h)) + PNF. \quad (20)$$

Subjected to the power balance constraints in (21)-(22),

$$L_E(h) - P_{FC}(h) - P_{WSP}^i(h) = P_{TR}(h), \quad (21)$$

$$L_H(h) = P_{GB}(h) + P_{MT}^H(h), \quad (22)$$

and the limit constraints of each conversion device as demonstrated by (23)-(28),

$$0 \leq P_{TR}(h) \leq P_{TR, rated}, \quad (23)$$

$$0 \leq P_{MT}^{E,H}(h) \leq P_{MT, rated}^{E,H}, \quad (24)$$

$$0 \leq P_{GB}(h) \leq P_{GB, rated}, \quad (25)$$

$$0 \leq Y_{EL} P_{EL}(h) \leq P_{EL, rated}, \quad (26)$$

$$0 \leq Y_{FC} P_{FC}(h) \leq P_{FC, rated}, \quad \text{and} \quad (27)$$

$$p_{\text{tank}, \min} \leq p_{\text{tank}}(h) \leq p_{\text{tank}, \text{rated}}. \quad (28)$$

In this paper, the initial pressure which is indicated in the content of the HS tank is set to the final pressure when the day is over, as shown in (29),

$$p_{\text{tank}}(h = \text{initial}) = p_{\text{tank}}(h = 24). \quad (29)$$

In addition, penalty function terms can handle some constraints, which can't define a lower and upper boundary such as (25) and (26). The penalty function can be defined as a Karush–Kuhn–Tucker condition (KKT) in (30)

$$PNF = \lambda_1 [(p_{\text{tank}}(h) - p_{\text{tank}, \min})^2 + (p_{\text{tank}}(h) - p_{\text{tank}, \text{rated}})^2] + \lambda_2 [(p_{\text{tank}}(h = 24) - p_{\text{tank}}(h = \text{initial}))^2]. \quad (30)$$

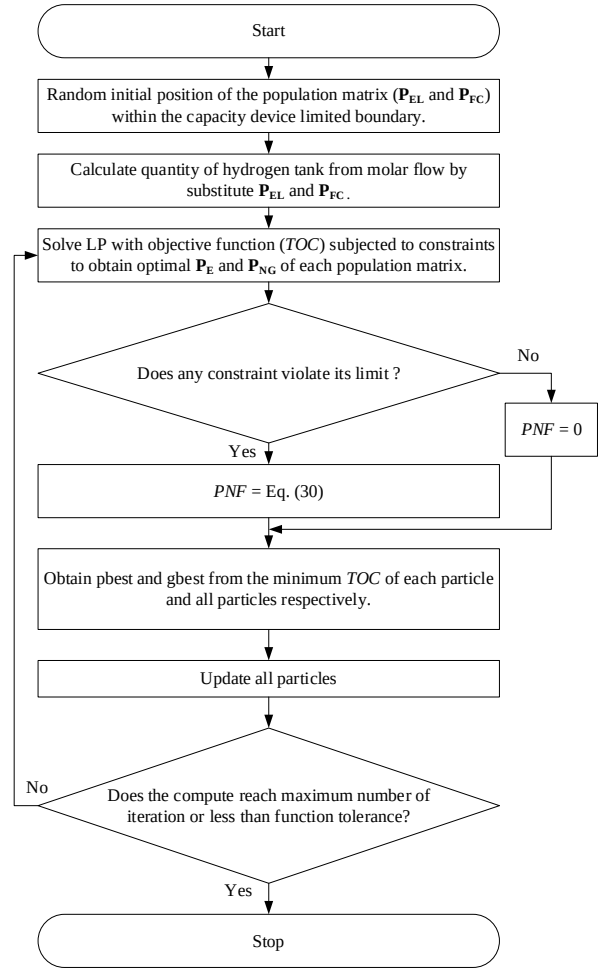


Fig. 3. The workflow of the PSO-LP technique under TOC.

The operation of this work procedure, which involves calculating the objective function while handling constraints, follows the workflow depicted in Fig. 3

3.2. PSO-LP technique

The HS scheduling is a continuous variable (P_{EL} and P_{FC}), while the relation of power from the grid and NG (P_E and P_{NG}) can be formed as a linear problem. Therefore, we modify the mathematical formulation of the problem to account for utilizing a heuristic algorithm in the main loop and utilizing a deterministic algorithm in the subroutines. LP will optimize the problem in subroutines. Then, the main loop will be optimized by PSO. The overview concept of hybrid PSO-LP is shown in Fig. 4. The hybrid PSO-LP technique is an enhanced version of the traditional PSO algorithm, designed to be more efficient. The PSO is used for searching for optimal HS scheduling incorporating the optimal condition of electricity from the power grid and NG, under wind and solar power, electricity load, and heating load conditions.

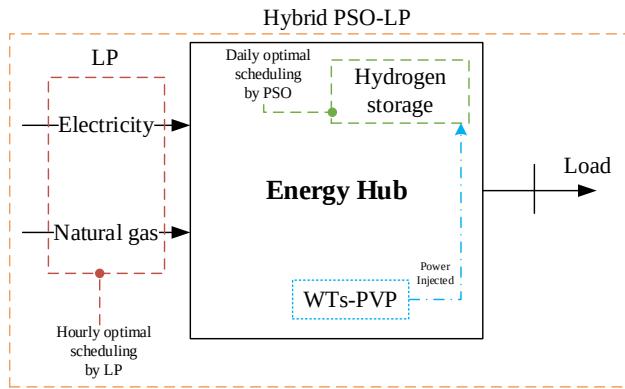


Fig. 4. The overview of hybrid PSO-LP.

The PSO algorithm is a stochastic optimization technique inspired by the collective behavior of bird flocks and their emergent dynamics. In PSO, a population of potential solutions, referred to as particles, is used to search for the optimal result. This population is called a swarm, and each particle represents a possible solution. The algorithm begins by randomly assigning positions to the particles within the search space. These particles then update their positions in successive iterations, adjusting based on their velocities. Each particle keeps track of its best position, referred to as $pbest(i,h)$, and updates its velocity based on that. Particles also communicate with one another to adjust their movement. If a particle finds a solution better than its previous $pbest$, the value is replaced. Among the entire population, the best solution found is called the global best ($gbest$). In this paper, the population is formulated as follows (31) [31]:

$$\mathbf{P}_{EL,FC} = [P_{EL,FC}(1), P_{EL,FC}(2), \dots, P_{EL,FC}(h), \dots, P_{EL,FC}(24)]. \quad (31)$$

The matrix in (31) will solve the individual objective function simultaneously. Then this matrix is used to update each particle's velocity as displayed in (32), and the next step of the matrix is updated by velocity as shown in (33) [31].

$$v(i, h+1) = wv(i, h) + c_1 rand_1(pbest(i, h) - \mathbf{P}_{EL,FC}(i, h)) + c_2 rand_2(gbest(i, h) - \mathbf{P}_{EL,FC}(i, h)), \quad (32)$$

$$\mathbf{P}_{EL,FC}(i, h+1) = \mathbf{P}_{EL,FC}(i, h) + v(i, h+1). \quad (33)$$

3.3. Stochastic load model

In practical terms, electricity and heat loads fluctuate based on user activity. Consequently, at the peak electricity and heat loads can be probabilistically modeled using a normal distribution. The normal distribution is a widely utilized probability density function (PDF) that represents continuous random variables with a characteristic bell-shaped curve. The PDF of the normal distribution is given by [32]:

$$f_{L_E}(L_E) = \frac{1}{\sqrt{(2\pi)\sigma_{L_E}}} \exp\left(-\frac{(L_E - \mu_{L_E})^2}{2\sigma_{L_E}^2}\right), \quad (34)$$

$$f_{L_H}(L_H) = \frac{1}{\sqrt{(2\pi)\sigma_{L_H}}} \exp\left(-\frac{(L_H - \mu_{L_H})^2}{2\sigma_{L_H}^2}\right). \quad (35)$$

4. RESULTS AND DISCUSSION

This section presents the data and simulation results for four case studies. MATLAB programming is used to develop an optimal daily scheduling algorithm for the proposed MES-WSPHS. Each case represents a distinct scenario, such as the inclusion of HS and coordination between electricity and NG systems. Different scheduling scenarios are analyzed.

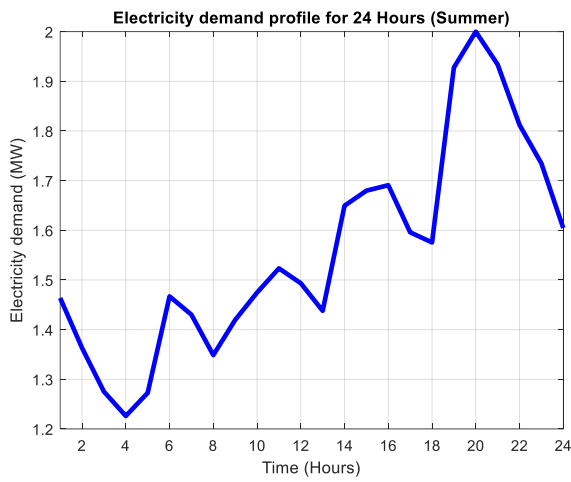
4.1. Data acquired and assumptions

To evaluate the performance and feasibility of the MES-WSPHS configuration, it is essential to analyze the efficiency and capabilities of its individual components as shown in Table 2 [8, 20]. The electricity load profile utilized in this study was obtained from a typical summer day in the northeastern region of Thailand, with a peak load defined at 2 MW [27] as shown in Fig. 5(a). The heat load profile was acquired from [33] as illustrated in Fig. 5(b). The wind and solar profile were derived from data collected on a summer day in Pakchong, Thailand [27].

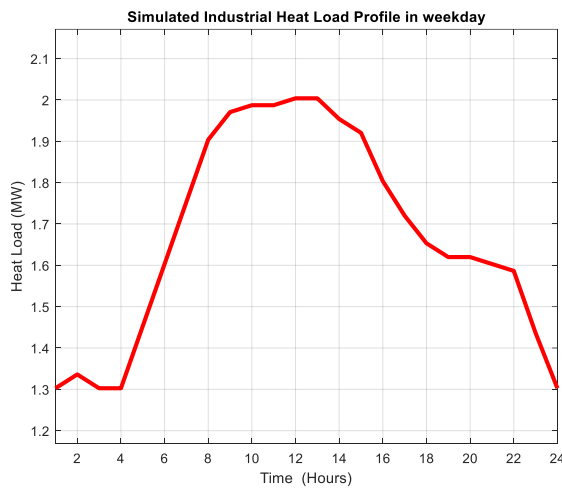
This study examines a wind power system with four turbines rated at 500 kW each ($NT = 4$), as shown in Fig. 6. Subplots 1 and 2 in Fig. 6 illustrate wind speed conversion to power. Hourly solar irradiance and PVP output are shown in Fig. 7, subplots 1 and 2, respectively. Fig. 8 highlights excess wind and solar power over demand. Electricity costs follow TOU tariffs [34], while NG prices remain constant. Furthermore, RTP, which reflects dynamic price adjustments, both are described in Fig. 9.

Table 2. The efficiency and rated device of each component

List	Component	Efficiency	Rated
No.1	Transformer	98%	2500 kVA
No.2	Electrolyzer	70%	500 kW
No.3	Fuel cell	60%	500 kW
No.4	Micro-turbine	40%, 50%	500 kW
No.5	Gas boiler	88%	1600 kW
No.6	Converter	95%	-
No.7	Pressure tank	-	100 bar



(a)



(b)

Fig. 5. The load profile (a) electricity (b) heat

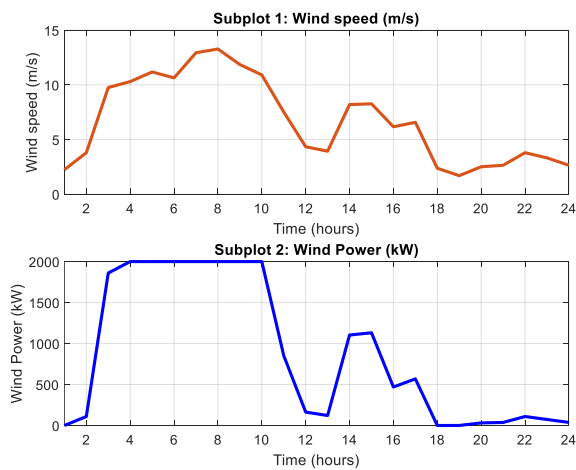


Fig. 6. The wind profile.

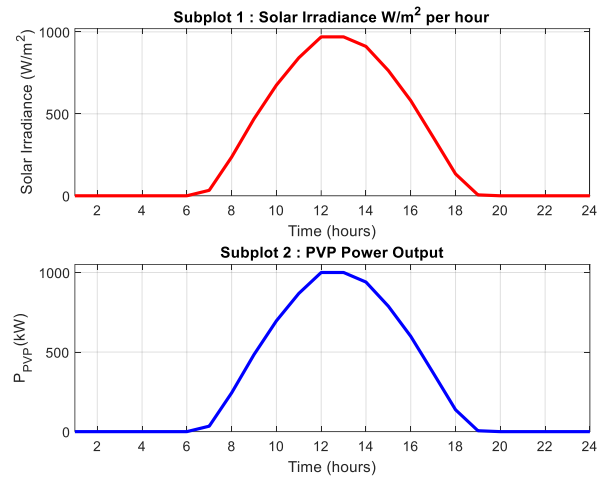


Fig. 7. The solar profile

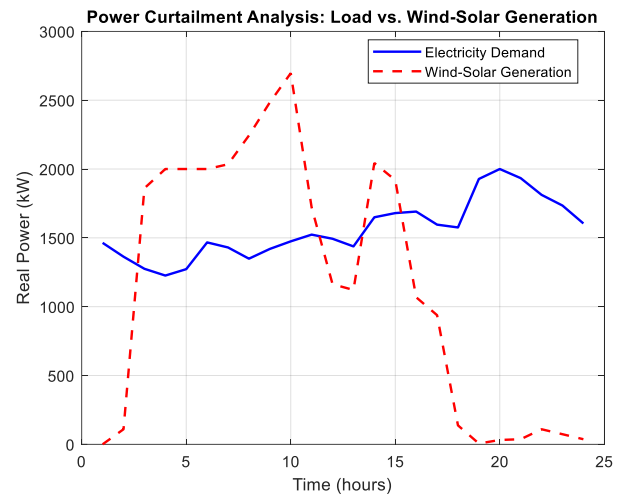


Fig. 8. The excess wind-solar generation.

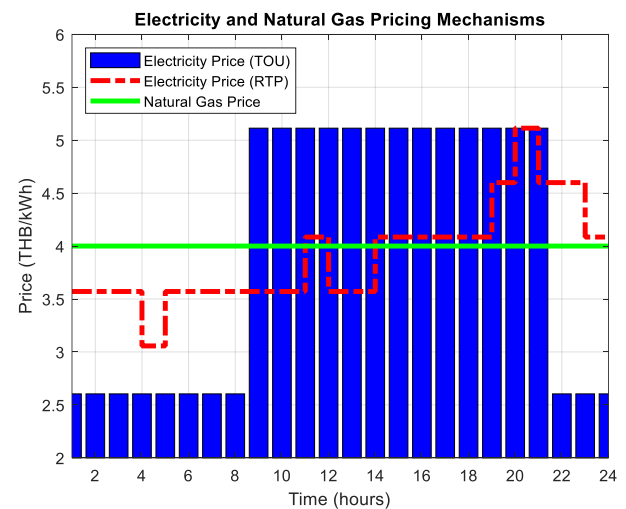


Fig. 9. The electricity and natural gas pricing mechanism.

4.2. The simulation results

The case studies, illustrated in Fig. 10, are divided into four scenarios for analysis, as follows:

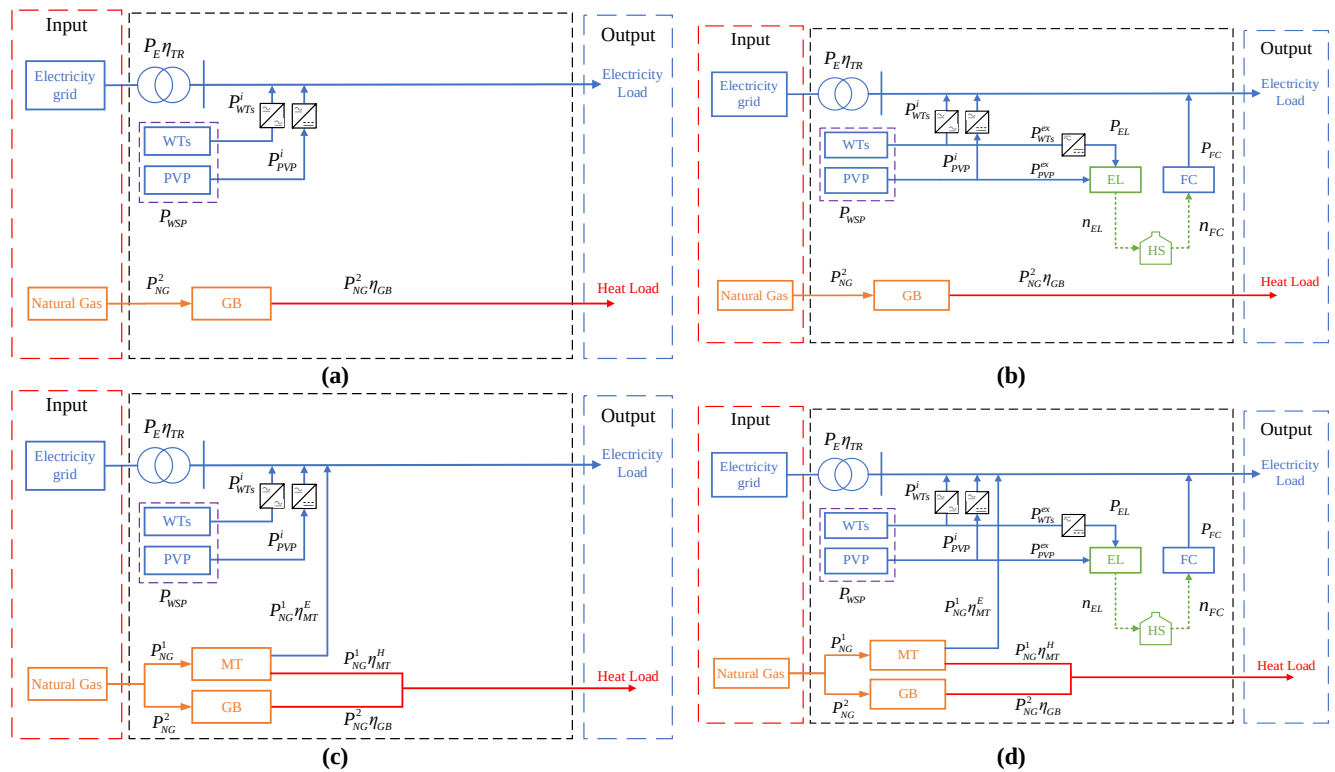


Fig. 10. Illustration of each case study (a) Case I, (b) Case II, (c) Case III, and (d) Case IV.

Table 3 Summary of power scheduling and energy costs for each sector

Case	Energy scheduling (kWh)									Operation costs (THB)		
	Energy through components					Demand-side				Electricity	NG	Total
	TR	MT	WSP	FC	GB	Gen	Used	Loss	Curtailed			
1	16,956	-	27,835	-	40,130	90,382	77,530	5,818	7,034	68,887	182,410	251,297
2	15,024	-		1,933		84,996		5,779	1,687	61,711	182,410	244,121
3	15,356	3,600		-	38,130	90,679		5,913	7,236	60,538	189,319	249,857
4	13,424	3,600		1,933		85,090		5,873	1,687	50,453	189,319	239,772

Case I: MES-WSP without HS, operating with uncoordinated electricity and NG under TOU tariffs.

Case II: MES-WSP with HS, but without coordinated operations between electricity and NG, under TOU tariffs.

Case III: MES-WSP with coordinated operations between electricity and NG, but without HS, under TOU tariffs.

Case IV: MES-WSP with HS and coordinated electricity and NG operations, under TOU tariffs.

In each case, the scheduling of energy proportions varies depending on the scenario. For cases without HS, only LP is employed to find the solution since there are no variables for the FC and EL. However, in scenarios incorporating HS, a hybrid PSO-LP method is utilized. This approach first optimizes the operation of the fuel cell and EL using PSO, and the results are subsequently processed using LP. The scheduled energy output for each component, as well as the costs associated with each energy sector, are summarized in

Table 3. Furthermore, since HS is considered in Cases II and IV, with PSO-LP employed to derive the solutions, Figs. 11 to 16 provide detailed insights into the power balance, optimization algorithm, and the impact of HS on the proposed system. The figures are organized by case: (a) Case II and (b) Case IV, and they highlight the effectiveness of the proposed optimization in achieving optimal solutions. While demonstrating the role of HS integration with and without coordinated operation of NG-electricity to balance multiple types of energy with energy demand. However, in case of MT integration, more power loss occurs from operation efficiency than without MT integration but helps to significantly reduce TOC.

Various energy sources are utilized to meet output demands through multiple energy scheduling in the EH. In Table 3, Case I represents no cooperation between electricity and NG systems, where each sector operates independently, focusing solely on its efficiency. Conversely,

Case III involves coordinated operation between electricity and NG, with NG being used to dispatch the electricity load via MT to reduce electricity consumption. Excess wind and solar power, as shown in Fig. 8, is not utilized, resulting in no additional energy savings.

Case II integrates HS without coordination with the electricity and NG systems, whereas Cases IV incorporates both HS and coordinated operation, referred to as MES-WSPHS. This significantly enhances energy management strategy since HS stores excess wind and solar energy, which is then discharged at other times. The power balance in each energy sector is depicted in Fig. 11(a) and 11(b) for electricity and in Figs. 12(a) and 12(b) for heat. Both Figs 11 and 12 focus exclusively on cases involving HS integration.

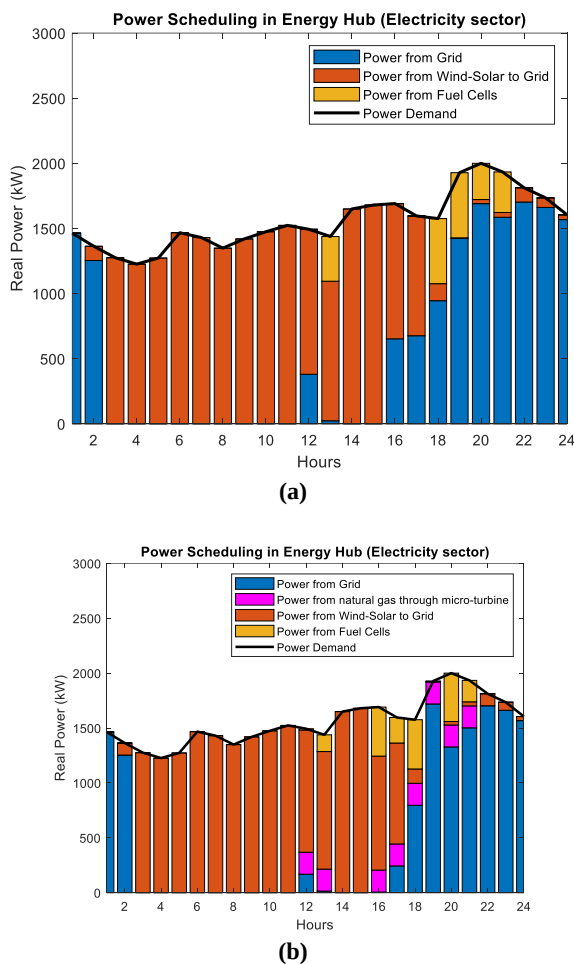


Fig. 11. Power scheduling in EH (electricity sector) (a) Case II and (b) Case IV.

The energy flow through the MT, which operates in Cases III and IV produces both electricity and heat. In Case III and Case IV, the MT is scheduled to operate from 12 a.m. to 9 p.m. During these periods, NG costs are lower than the peak electricity costs in TOU tariffs. However, when energy generation is sufficient to meet demand, the MT does not

operate in that hour. Figs 11(b) and 12(b) show the NG through MT do not operate at 2 p.m. and 3 p.m.

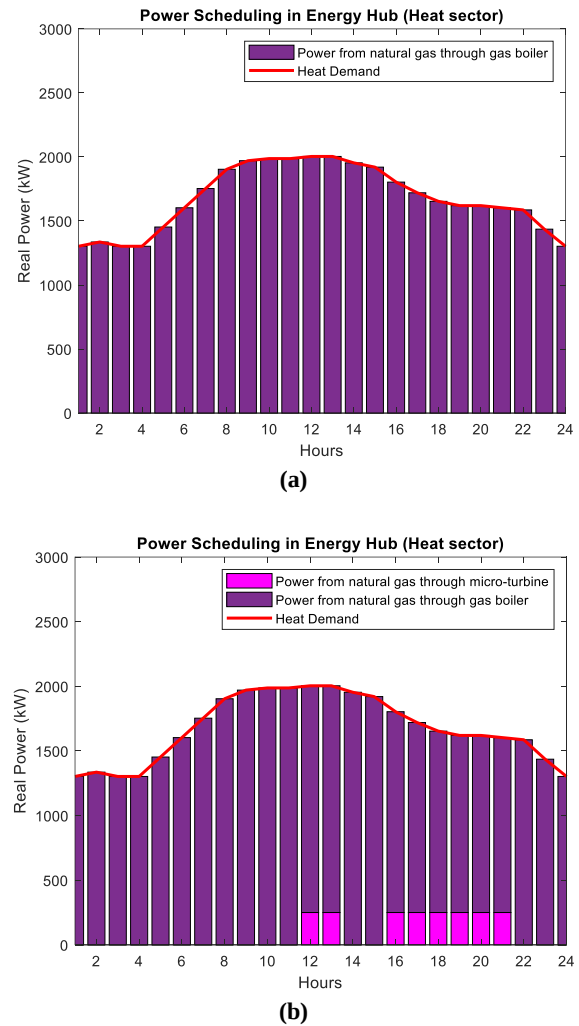
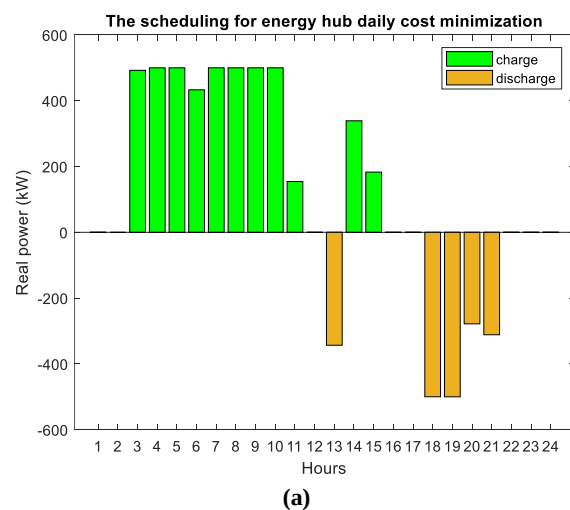


Fig. 12. Power scheduling in EH (heat sector) (a) Case II and (b) Case IV.



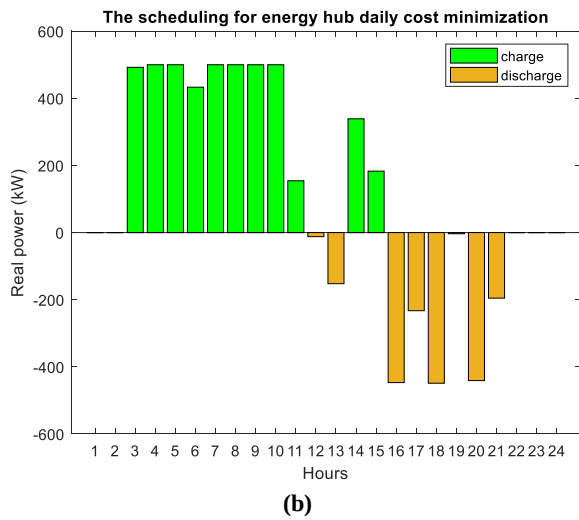


Fig. 13. HS scheduling for 24 hours ((a) Case II and (b) Case IV.

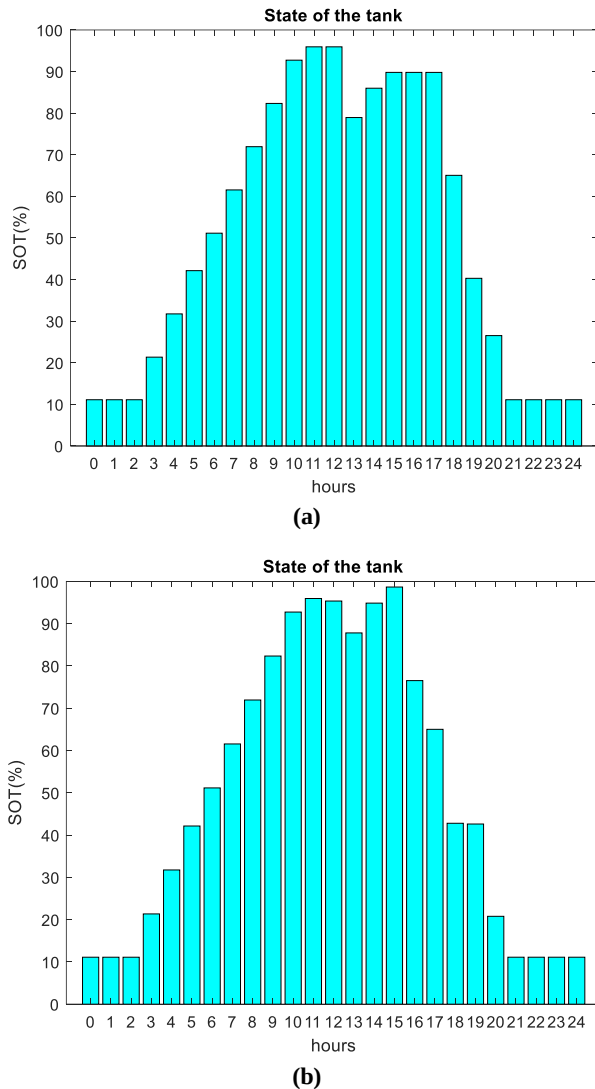


Fig. 14. State of the tank (%SOT) in HS (a) Case II and (b) Case IV.

Case II and Case IV with HS integration, EL turns an excess wind and solar power from 3 a.m. to 11 a.m. and 2 p.m. to 3 p.m. to HS. Then FC turns hydrogen into electricity to reduce electricity from the grid, the schedule of HS operation varies from case to case. Case II and Case IV have different patterns of FC scheduling. However, the power from FC operated is performing in the peak electricity costs period to reduce energy from the grid, resulting in a lower TOC and energy curtailment. The TOU tariff is utilized to define the objective, resulting in the FC operating as illustrated in Fig. 13 (a) Case II and (b) Case IV. In the study, the initial hydrogen tank pressure is set at 20 bar. During HS scheduling, the tank pressure is maintained within a range of no more than 100 bar and no less than 10 bar, which is defined in the state of the tank (SOT) is 100% and 0%, respectively. With the pressure at the final hour of the day equal to that of the initial hour. As shown in Fig. 14 (a) Case II and (b) Case IV, SOT is displayed as a percentage, representing the hydrogen energy storage model.

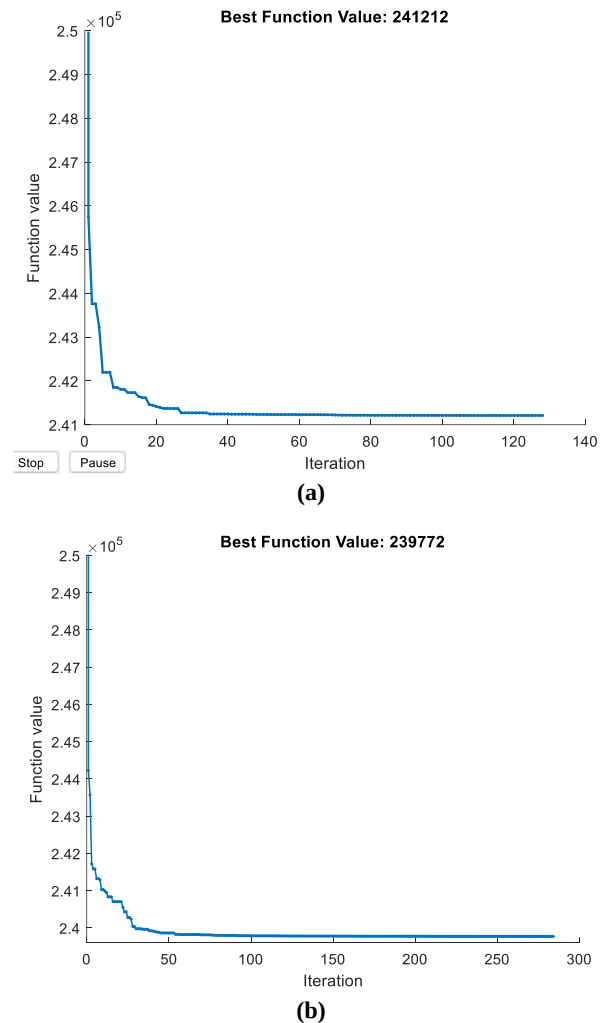


Fig. 15. The PSO-LP convergence plot (a) Case II and (b) Case IV.

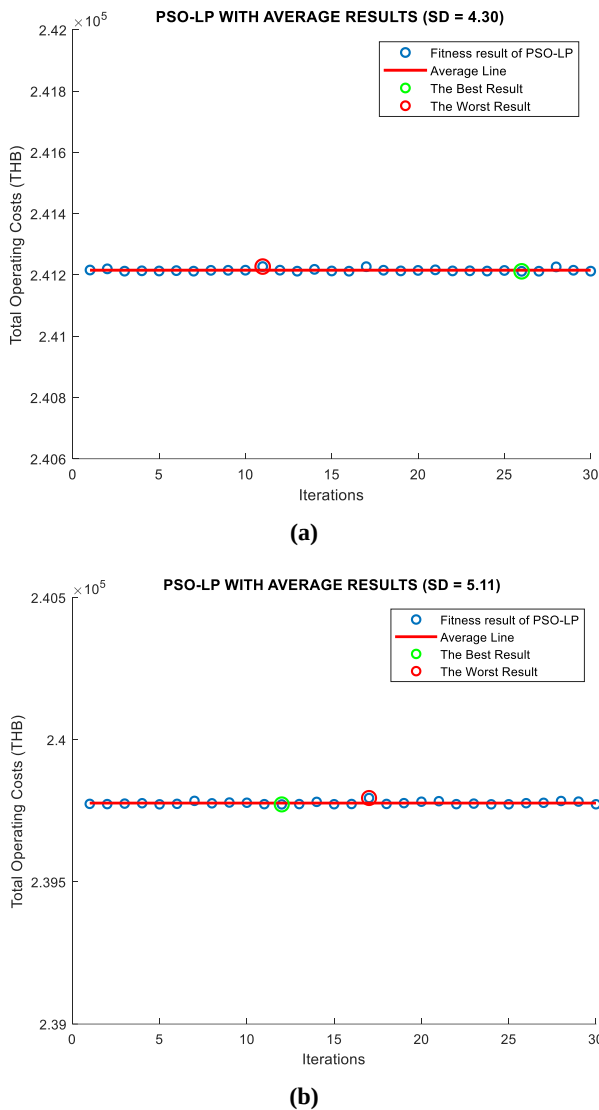


Fig. 16. The PSO-LP fitness results with 30 iterations (a) Case II and (b) Case IV.

Figure 15 (a), and (b) show the convergent PSO-LP solutions of Case II and Case IV, respectively. The best function value is TOC in both cases. Case II starts converging around 20 iterations and stops finding the optimal solution in 128 iterations. Case IV starts converging around 30 iterations and stops finding the optimal solution in 285 iterations. However, both cases can converge before the maximum iteration setting because the final solution is less than the function tolerance.

Figure 16 (a) and (b) demonstrate the results from 30 trials of Case II and Case IV which show the best, worst, and average lines of solutions, indicate that the fitness results of PSO-LP are clustered, with the standard derivations (SD) of 4.30 and 5.11, respectively. Therefore, the proposed method is demonstrated to be reliable and has the potential to find the optimal solutions.

4.3. MES-WSPHS with RTP mechanism

In this section, the impact of RTP on the operation of the MES-WSPHS is analyzed. The study investigates how dynamic electricity pricing influences the scheduling of various energy resources, ensuring cost-effective and efficient energy management. Fig. 17(a) and 17(b) illustrates the power scheduling for each energy sector. In the electricity sector, MT and HS are scheduled to operate between 7 p.m. and 10 p.m., that reflects the RTP mechanism indicates higher electricity prices during this period.

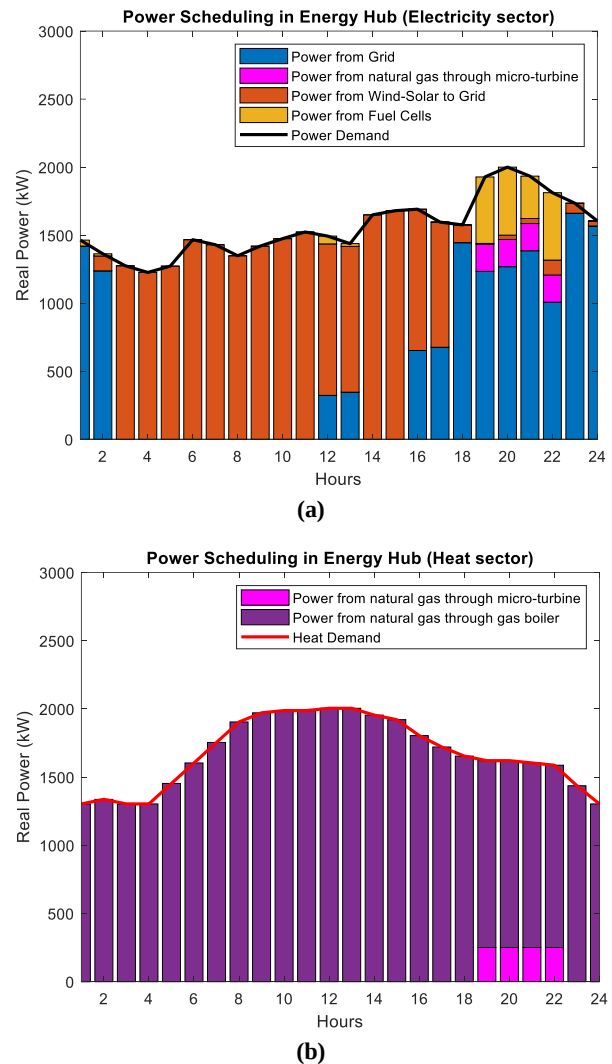
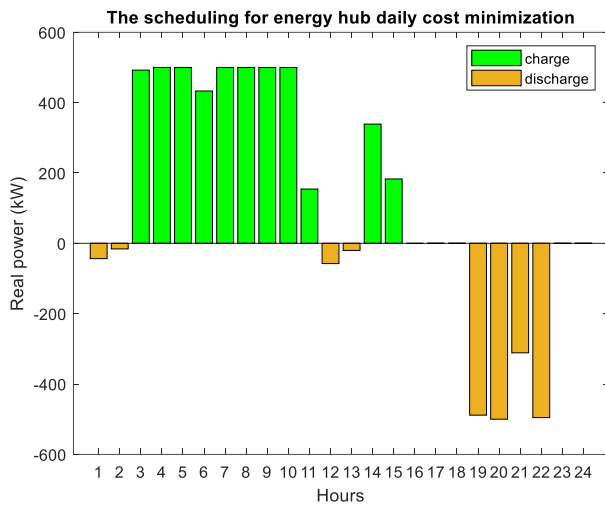


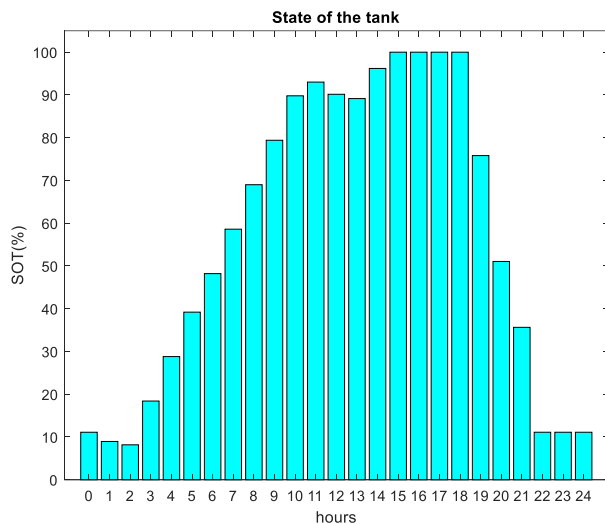
Fig. 17. Power scheduling in EH (a) electricity and (b) heat

The integration of HS further enhances system flexibility, as depicted in Fig. 18(a), which illustrates the charge and discharge patterns of the HS system. It can be observed that hydrogen is primarily stored during low electricity price periods and discharged during peak price hours, aligning with the cost-minimization strategy. SOT is displayed in Fig. 18(b). The quantity of hydrogen in tank shows

hydrogen reserves gradually increasing during the daytime and depleting as energy is discharged in the evening.



(a)



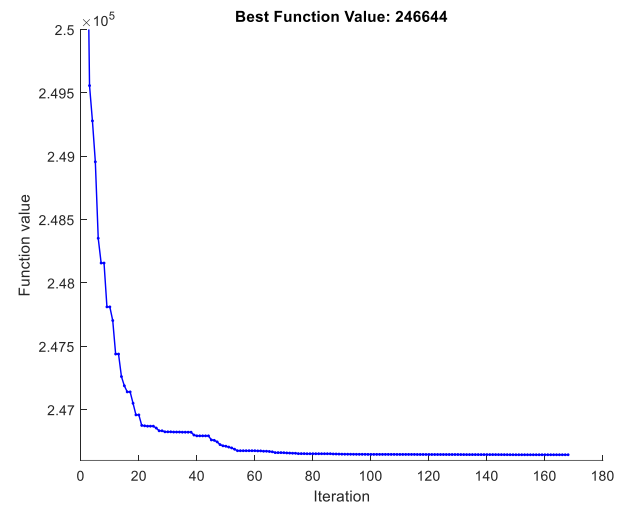
(b)

Fig. 18. (a) HS scheduling and (b) %SOT

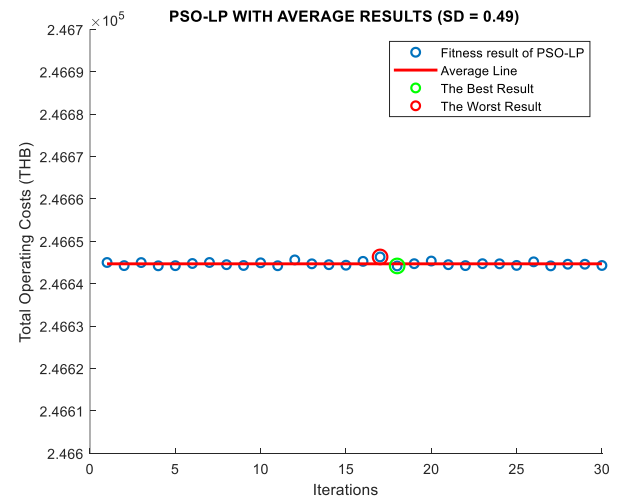
Figure 19 (a) and (b) demonstrate the results from 30 trials of MES-WSPHS under RTP which show the best, worst, and average lines of solutions, indicate that the fitness results of PSO-LP are clustered, with the standard derivations (SD) of 0.49. This study is reliable and has the potential to find optimal solutions more than TOU tariff.

4.4. The comparison between PSO and PSO-LP

This section illustrates a different solution between the PSO and PSO-LP technique under the TOC as an objective function and demonstrated in Case IV. The aim is to highlight the performance of each approach that can minimize TOC effectively. To ensure a fair comparison between algorithms, the study established consistent parameters, as outlined in Table 4.



(a)



(b)

Fig.19. The PSO-LP (a) convergence plot and (b) fitness results with 30 iterations

Table 4. The parameters of the PSO and PSO-LP settings

Variable	Settings
Swarm sizes	100
Iterations	500
Function Tolerance	$<10^{-6}$
w	[0.1,1.1]
c_1	1.49
c_2	1.49
$rand_1, rand_2$	[0,1]

Table 5. The runtime of the PSO and PSO-LP

Algorithm	Runtime (s)
PSO	611
PSO-LP	3,000

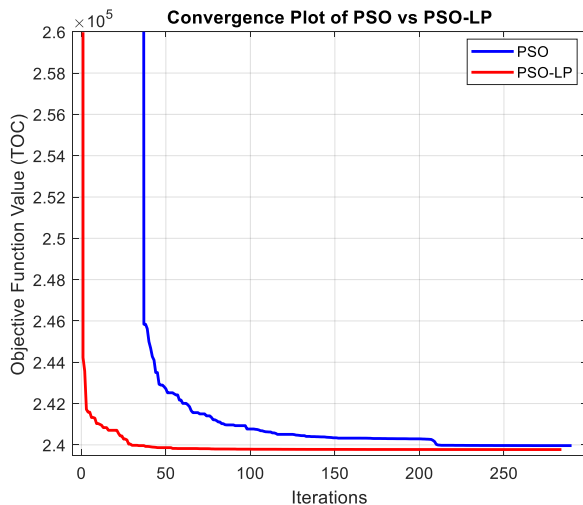
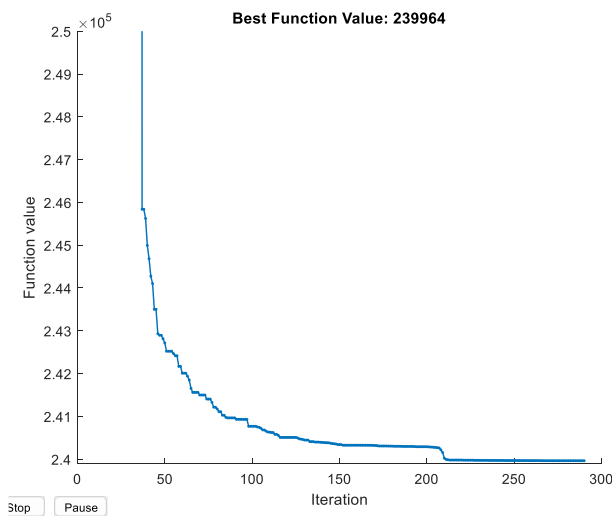
**Fig. 20. Convergence comparison between PSO and PSO-LP.**

Figure 20 presents a comparison between PSO and PSO-LP, illustrating that both algorithms demonstrate similar convergence behavior. However, the proposed PSO-LP terminates the optimization process at 285 iterations, due to the predefined convergence criteria based on the tolerance between the current particle swarm and the previous swarm, with a function tolerance of less than 10^{-6} . This enables PSO-LP to achieve a near-optimal global solution. In contrast, PSO requires 291 iterations to terminate, taking slightly longer and failing to reach a near-optimal solution.

**Fig. 21. The PSO convergence plot.**

On the other hand, PSO-LP requires significant computational resources due to its two-step process: running

PSO in the main loop and executing LP as a subroutine. This results in a longer runtime for PSO-LP compared to conventional PSO. Nevertheless, both algorithms are suitable for this problem, as the scheduling process must be completed within a day. The runtime details for this study are provided in Table 5.

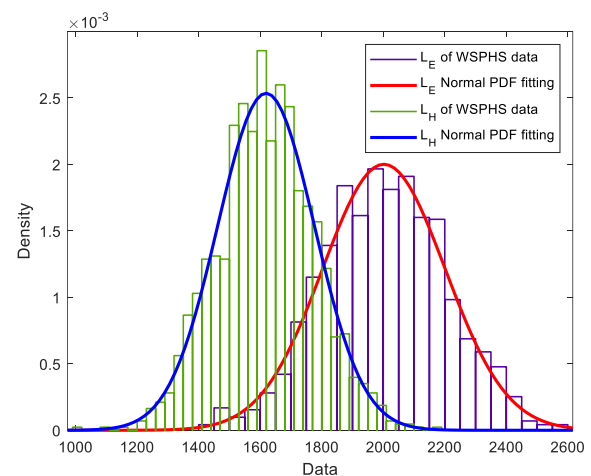
The PSO convergence plot in Fig. 21 indicates a final TOC value of 239,964 THB, whereas the PSO-LP convergence plot in Fig. 15 (b) shows a final TOC value of 239,772 THB. This comparison highlights that PSO-LP achieves a more optimal solution than the conventional PSO algorithm.

4.5. MES-WSPHS with stochastic load model

The results of the Monte Carlo analysis demonstrate the effectiveness of the MES-WSPHS under varying stochastic load conditions at the peak time. Random load samples were generated until the tolerance criteria were satisfied, resulting in a probabilistic set of the load data. This dataset includes the mean value, standard deviation, and a fitting curve based on a normal distribution, allowing for an evaluation of the system's ability to adapt to uncertainty. Figure 22 shows the variability of the stochastic load at peak hour (one spotted), representing realistic fluctuations in demand. The peak electricity demand scenario represented by the stochastic load PDF for normal distribution is illustrated in Fig. 22. The parameter setting of MCS can be shown in Table 6.

Table 6. MCS parameters

Parameters	The mean value		The standard deviation	
	μ_E	μ_H	σ_E	σ_H
Values	$L_{E,at E \max}$	$L_{H,at E \max}$	$0.1 \times \mu_E$	$0.1 \times \mu_H$

**Fig. 22. Stochastic load PDF for MES-WSPHS at the peak electricity demand scenario.**

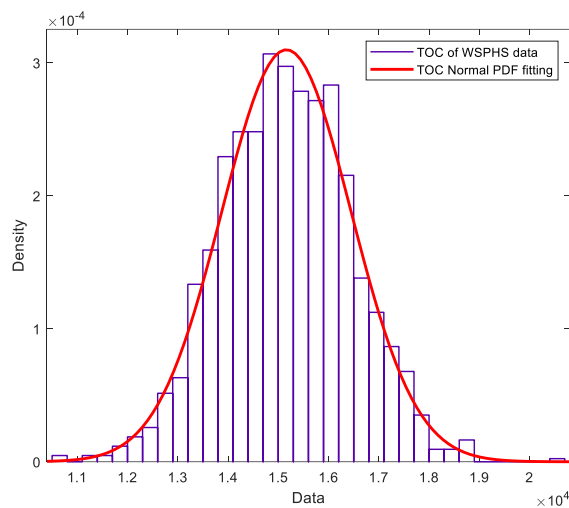


Fig. 23. Solution PDF for MES-WSPHS illustrates TOC at the peak electricity demand scenario.

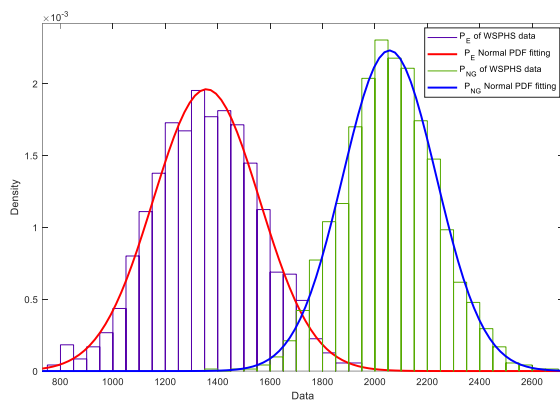


Fig. 24. Solution PDF for MES-WSPHS illustrates electricity and NG scheduling at the peak electricity demand scenario.

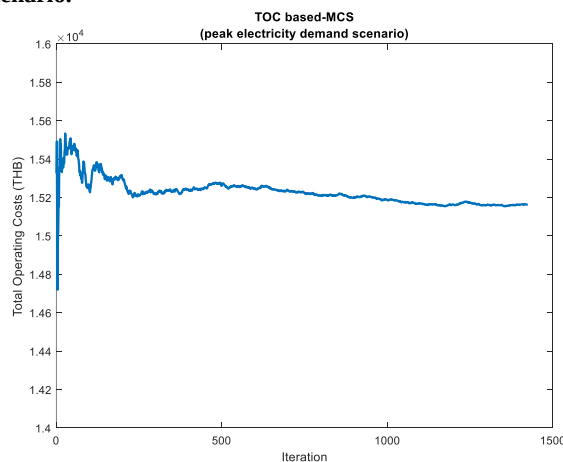


Fig. 25. The convergence plot TOC based-MCS at the peak electricity demand scenario.

When applying MCS to simulate the stochastic load model for determining the optimal scheduling of MES-

WSPHS, the results, including TOC, electricity scheduling, and NG scheduling, are represented as PDF, as shown in Figs. 23 and 24. The convergence plot as shown in Fig 25 highlights the changes in the objective function with repeatability. The trend of the MCS procedure shows an increase as the number of iterations grows. Convergence analysis is essential for assessing the reliability of the proposed method and ensuring its ability to produce accuracy and uniform results.

As a result, the proposed MES-WSPHS utilizes PSO-LP to determine the TOC minimization under TOU tariff and considers that, under probabilistic peak load conditions, the results can fit in a normal distribution perfectly. The mean value and the standard deviation of the normal distribution in each probabilistic variable follow in Table 7.

Table 7. The mean value and the standard deviation of the normal distribution

Parameters	The mean value (μ)	The standard deviation (σ)
L_E	2,001.95	199.356
L_H	1,619.01	157.347
P_E	1,357.02	203.425
P_{NG}	2,055.69	178.803
TOC	15,161.9	1,287.77

5. CONCLUSIONS

In this paper, the optimal scheduling of MES-WSPHS, using PSO-LP, to minimize TOC is proposed. The proposed approach was assessed using the MES with the EH model utilizing the electricity load profile of the northeastern region of Thailand, the wind speed and solar irradiance profile from one day in summer, and the heat load profile from the normalized profile of industry on weekdays. The study can be divided into four cases to thoroughly analyze the individual and combined impacts of HS and the coordination strategies between electricity and NG. The influence of RTP and the stochastic model is proposed to demonstrate a practical condition. Additionally, a comparison between conventional PSO and PSO-LP is discussed, highlighting that PSO-LP performs fast convergence and is more accurate than PSO under the same conditions. The results showed that the proposed method can effectively minimize TOC, enhance the economic operation of MES-WSPHS, and efficiently adapt to uncertainties and real-time price variations. The integration of RTP and stochastic modeling further emphasizes the robustness and practicality of the proposed approach in real-world scenarios.

ABBREVIATIONS

Variable

P	The matrix contains a scheduling variable.
η	Efficiency (%).
<i>P</i>	The power inputs or the power flow through the device (kW).
<i>L</i>	The power outputs or power demands (kW).
<i>NT</i>	The total number of wind turbines.
ν	The velocity (m/s).
<i>Y</i>	The parameter indicates the operation state.
<i>C</i>	The cost of the energy input (THB/kWh).
<i>PNF</i>	The penalty functions.
λ	The Lagrange multiplier.
<i>LHV</i>	The low heat value (MJ/kmol).
$\mathcal{R}$	The gas constant (J/mol·K).
<i>T</i>	The mean temperature (K).
<i>V</i>	The volume (m ³).
<i>p</i>	The pressure (bar).
<i>n</i>	The molar flow (mol/s).
<i>h</i>	The times (hour).
<i>z</i>	The height (m).
α	The power law exponent.
<i>A</i>	Area of PVP installed (m ³).
β	PVP efficiency (%)
<i>SI</i>	Solar irradiance (W/m ²)
<i>w</i>	Inertia weight.
<i>c</i>	Learning factor.
<i>rand</i>	A random number between 0 and 1.
<i>pbest</i>	personal best.
<i>gbest</i>	global best.
<i>f</i>	The probability density function.
σ	The standard deviation of the normal distribution.
μ	The mean value of the normal distribution.
<i>SOT</i>	The state of the tank (%).
<i>TOC</i>	The total operating costs (THB).

Subscript and Superscript

<i>1</i>	The number which indicates the order.
<i>2</i>	The number which indicates the order.
<i>E</i>	Electricity.
<i>H</i>	Heat.
<i>NG</i>	Natural gas.
<i>H₂</i>	Hydrogen.
<i>EL</i>	Electrolyzer.
<i>FC</i>	Fuel cell.
<i>MT</i>	Micro-turbine.
<i>TR</i>	Transformer.
<i>GB</i>	Gas boiler.
<i>WSP</i>	Wind-solar power.
<i>AC/DC</i>	AC-to-DC converter.
<i>DC/AC</i>	DC-to-AC converter.
<i>r</i>	Reference.
<i>WTs</i>	Wind turbines.

<i>i</i>	Power injected into the grid.
<i>ex</i>	The excess power.
<i>PVP</i>	Photovoltaic panels.
<i>tank</i>	The storage of hydrogen.
<i>rated</i>	The maximum limit.
<i>min</i>	The minimum limit.

ACKNOWLEDGEMENTS

We express our sincere gratitude to Suranaree University of Technology (SUT) for providing the essential resources and supportive environment that made this research possible.

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