INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

IJIE

Vol. 16 No. 5 (2024) 341-358
https://publisher.uthm.edu.my/ojs/index.php/ijie

Energy Scheduling in the Multiple Energy System with Optimal Operation of the Responsive Loads

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DOI: https://doi.org/10.30880/ijie.2024.16.05.026

Article Info

Received: 17 January 2024
Accepted: 21 June 2024
Available online: 12 August 2024

Keywords

Optimal scheduling, energy hub shiftable loads, non-dominated pareto solutions, decision-making method

Abstract

In this research, an approach is presented for the optimal scheduling of a smart energy Hub system with multiple objectives in the day ahead. The objectives include minimizing emission pollution and operation costs on the generation side, reducing the loss of energy supply probability on the demand side, and minimizing the deviation of electrical and thermal loads from their optimal profiles in the day ahead. To achieve the third objective of flattening the electrical and thermal demand profiles, a Demand response strategy is proposed, which involves the optimal shifting of electrical and thermal shiftable loads. Additionally, stochastic modelling of renewable energy sources and energy loads using the Monte Carlo technique is conducted. The proposed approach utilizes the ε-constraint method to obtain non-dominated Pareto solutions for the objectives. Finally, several case studies are performed to validate the proposed approach.

1. Introduction

1.1 Aims and Motivations

Over the past few years, the incorporation of multi-carrier energy systems in residential structures has been a response to the growing energy requirements and the necessity to lower greenhouse gas emissions [1]. These systems involve the utilization of various energy carriers like electricity, heat, and gas in a synchronized and effective way [2]. A significant factor contributing to the increase in sustainable energy production is the spike in energy usage.As the global population continues to grow, so does the demand for energy to power homes, businesses, and industries [3]. This increased energy consumption has strained traditional fossil fuel-based energy sources, leading to a search for alternative and sustainable energy solutions [4]. The incorporation of multi-carrier energies has become crucial to meet this growing demand for energy while minimizing the environmental impact. Residential buildings, in particular, have been targeted for the implementation of these systems because of their significant energy consumption and potential for energy efficiency improvements [4]. The benefits of incorporating multi-carrier energies into residential buildings are numerous. Firstly, it allows for a more diversified and resilient energy supply, reducing the risk of energy shortages or disruptions. Secondly, it promotes energy efficiency by utilizing energy carriers as efficiently and cost-effectively as possible [5]. This can lead to significant energy savings and reduced energy bills for homeowners. By adopting these methodologies, it is possible to attain an improvement in the reliability and effectiveness of energy systems [6]. Moreover, multi-carries energy systems

Nomenclature Indices and sets	
b, B	Index/set of Boiler
d, D	Index/set of DG
ess, ESS	Index/set of ESS
EG	Index/set of Electrical grid
m, M	Index/set of CHP units
NGG	Index/set of Natural gas grid
pv, PV	Index/set of Photovoltaic (PV)
t, T	Index/set of time period
TG	Index/set of Thermal grid
tss, TSS	Index/set of TSS
s, S	Scenario indices
w, W	Index/set of Wind turbine (WT)
Parameters	
a, b, c	Cost factors of DGUs, which by other fuels are supplied
d, e, f	Emission factors of DGUs, which by other fuels are supplied
c_w	Scale index of WT
CO_2,SO_2,NO_x	The greenhouse gases consisting of carbon dioxide (CO2), sulfur dioxide (SO2) and nitrogen oxides (NOx)
$D_E(s, t)$	Electrical demand in scenario s and at time t (MW)
$D_T(s, t)$	Thermal demand in scenario s and at time t (MW)
$D_G(s, t)$	Natural gas demand in scenario s and at time t (m3)
$D_E^{NRC}(s,t), D_E^{RC}(s,t)$	Electrical demand of non-responsive customers and responsive customers in scenario s and at time t (MW)
$D_T^{NRC}(s,t), D_T^{RC}(s,t)$	Electrical demand of non-responsive customers and responsive customers in scenario s and at time t (MW)
D_E^{OP}, D_T^{OP}	Optimal level of electrical and thermal demands (MW)
$C_{ESS}^{OP}, C_{TSS}^{OP}$	Operating cost of ESS and TSS systems
$P_{N,WT}$	Total rated power of WT (MW)
S_{PV}	Total area of PV (m^2)
V_R, V_{Ci}, V_{Co}	Rated speed, cut-in speed, cut-off speed of WT, m/s)
α, β	Beta distribution function of PV
ξ_E, ξ_T	Participation level of RCs in electrical and thermal SLs shifting, %
η_{PV}	Efficiency of PV, %
π_p^{EG}	Electrical price in EG, $/MW
π_p^{TG}	Thermal price in TG ($/MW)
π_p^{gas}	Natural gas price in NGG ($/m3)
$\eta_{dis}^{ESS}, \eta_{ch}^{ESS}$	Efficiency of ESS in discharge and charge state (%)
$\eta_{dis}^{TSS}, \eta_{ch}^{TSS}$	Efficiency of TSS in discharge and charge state (%)

σ_d , μ_d	Standard deviation and mean for the demand values
Decision variables	
C_B	Operation cost of boiler, $
C_m	Operation cost of CHP, $
C_{DG}	Operation cost of DG, $
C_{ESS}	Operation cost of ESS, $
C_{TSS}	Operation cost of TSS, $
C_{EG}	Operation cost of EG, $
C_{TG}	Operation cost of TG, $
C_{NGG}	The cost of purchased natural gas, $
$D_E^{RC}(s,t,t')$	Demand shifted of electrical SLs by RC at time t to t' in scenario s, MW
$D_T^{RC}(s,t,t')$	Demand shifted of thermal SLs by RC at time t to t' in scenario s, MW
E_B	Emission pollution of boiler, kg
E_m	Emission pollution of CHP, kg
E_{DG}	Emission pollution of DG, kg
E_{EG}	Emission pollution of EG, kg
E_{TG}	Emission pollution of TG, kg
E_{ESS}, E_{TSS}	Energy of ESS and TSS, MW/h
T_b	Thermal generated by boiler, MW
T_m	Thermal generated by CHP, MW
T_{TG}	Thermal generated by TG, MW
$P_{ESS}^{dis}, P_{ESS}^{ch}$	Electrical generated by ESS, MW
$T_{TSS}^{dis}, T_{TSS}^{ch}$	Electrical generated by ESS, MW
P_{PV}	Electrical generated by PV, MW
P_{WT}	Electrical generated by WT, MW
P_d	Electrical generated by DG, MW
P_m	Electrical generated by CHP, kW
P_{EG}	Electrical generated by EG, kW
G_{NGG}	Purchased natural gas by SEHS, m3
ρ_s^{PV} , ρ_s^{WT} , ρ_s^{L}	Probability of PV, WT and demand in Scenario s
p_s	Probability of Scenario s
$\mu_{EES-dis}$, μ_{EES-ch}	Binary variable of ESS in discharge and charge state
$\mu_{TSS-dis}$, μ_{TSS-ch}	Binary variable of TSS systems in discharge and charge state
μ_{PST} , μ_{TST}	Binary variable of electrical and thermal shortage

the capability to integrate with smart grid technology to presenting opportunities like demand side energy optimization and energy storage via the implementation of energy management approaches in smart homes [6]. Smart multi-carries energy systems can be named the integration of multi-carrier energies in smart grids. However, the operation and performance of energy hub system are anticipated to face numerous challenges, specifically uncertainties related to various energies and interactions among the demand and generation sides [7]. These uncertainties may be effective, underscoring the importance of taking proactive measures to tackle them. However, it is imperative to examine the impacts of uncertainties to attain a dependable degree in the decision-making procedure for attaining optimal energy operation. Among the most widespread uncertainties is uncertainty in energy prices which emerges in real-time prices fluctuations of fossil fuels in global markets [8][9]. Hence, the implementation of strategies like demand-side engagement for efficient energy usage and energy storage systems can serve as effective remedies for covering uncertainties in energy prices. Through demand-side engagement, consumers can effectively regulate their energy consumption during peak periods by making optimal adjustments to their energy usage [9][10]. Also, energy storage systems play a crucial role in meeting the energy demand at peak times. Various types of energy storage systems are available each designed to cater to specific applications and performance requirements [11]. These include chemical energy storage, mechanical energy storage, thermal energy storage, and more [12].

The loads in energy systems are usually random variables, but they can be regulated by offering economic incentives, it considerably affects the stability of energy systems [13] [14]. Therefore, in order to maximize the benefits of load on energy systems, demand response mechanisms must be developed, which some strategies are shown in Figure 1 [15]. The main challenge faced by these resources is the uncertainty in their power output because natural parameters are naturally random [16]. Predicting the output values of these resources can become inaccurate if the ambiguity around energy management is ignored. Consequently, scholars have put forth a range of techniques, encompassing both deterministic and non-deterministic methodologies [17]. Power system management now faces additional difficulties as a result of the grid's integration of energy storage systems. Having efficient ways to enhance grid management is crucial, particularly when there are a lot of renewable energy sources available [18]. The inclination of earlier techniques to converge towards local spots and the lack of a strong global search engine in these algorithms are two of their drawbacks [19].

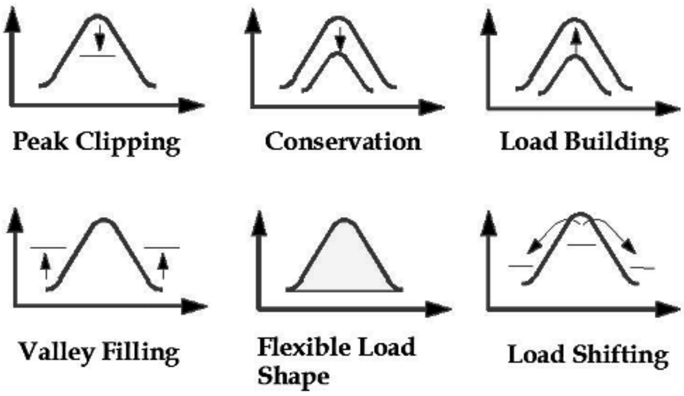

Fig. 1 *Demand response strategies*

1.2 Related Research and Contributions

This section encompasses previous research conducted on energy systems in different contexts. In [20], the authors delve into the modeling energy hub within an integrated energy system for infrastructures. The study focuses on solving efficiency using an engineering equation solver. The aim is to achieve cost-efficient and decarbonized performance on the generation side. The lexicographic technique is employed in [21] to address the energy optimizing strategy of multi-energy systems, focusing on economic and environmental indicators. This approach aims to enhance the overall satisfaction of consumers by incorporating demand management implementation. In [22], the objective of minimizing operational costs is achieved by utilizing peer-to-peer power flow and ensuring with electric vehicles (EVs) in the face of uncertain electricity prices and varying driving patterns of EVs. On the other hand, the authors in [23] concentrated on an approach that employs fuzzy logic to effectively address the optimal energy operation. In [24], the objective is to reduce operation cost and emission by implementing solar-powered compressed air energy storage by Quasi-optimization. This optimization is carried out while considering the uncertainty associated with solar irradiance, and energy demand. On the other hand, authors in [25] introduce the utilization of the non-dominant genetic algorithm II (NSGA-II) for energy operation without load management. This approach aims to enhance the performance of appliances in terms of energy consumption via reducing bills and improving efficiency. In [26], the energy hub is operated via compressed air storage and EVs to address the uncertainty of electricity prices in robust optimization. Meanwhile, authors in [27] introduce a meta-heuristic and robust optimization approaches to modeling uncertainties in energy prices and demand for minimizing energy costs. In [28] a bi-level energy operation is expressed for optimal performance of the cascaded demand of thermal, power and cold in energy planning. Moreover, there are several research gaps which can be addressed by following items:

(1) The objective of many research endeavors is to address the energy system requirements at the lowest operation cost often overlooking demand-side management strategies. The models put forth in these studies are typically designed to adhere to the technical limitations of the system. Consequently, these investigations lack suitable models aimed at enhancing the system's adaptability to uncertainty of gas and electrical prices.

(2) The demand-side management strategies are modeled in the literature based on energy prices in the energy markets. However, in our study, demand-side management strategies are modeled based on the optimal consumption and bidding prices in the day-ahead.

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In this paper, an approach is presented for the optimal scheduling of a smart energy Hub system with multiple objectives in the day ahead. The objectives include minimizing emission pollution and operation costs on the generation side, reducing the loss of energy supply probability on the demand side, and minimizing the deviation of electrical and thermal loads from their optimal profiles in the day ahead. To achieve the third objective of flattening the electrical and thermal demand profiles, a Demand response strategy is proposed, which involves the optimal shifting of electrical and thermal shiftable loads. Additionally, stochastic modelling of renewable energy sources and energy loads using the Monte Carlo technique is conducted. The proposed approach utilizes the ε-constraint method to obtain non-dominated Pareto solutions for the objectives.

2. Energy Hub System Modeling

In this section, the energy hub is outlined to describe the proposed scheduling problem. The SEHS comprises various key components such as natural gas grid (NGG), thermal grid (TG), electrical grid (EG), distributed generation units (DGUs), and the customers [29]. All these elements are interconnected through a bilateral communication link with the system operator to ensure coordination between sides during operation. For instance, the operator can notify the customers about pricing in the energy markets to prompt appropriate responses from the customers based on the current status [30]. The prices of energy purchased from markets may vary during operation, and operators have the ability to coordinate the demand side for optimal energy consumption [31]. In this study, the focus is on two distinct categories of customers on the demand side: 1) non-responsive customers, who do not alter their behavior in response to the system 2) responsive customers (RCs), who adjust their consumption based on the system's status [32]. The paper utilizes load shifting strategies from demand response to schedule demand. DGUs are photovoltaics (PV) systems, thermal storage systems (TSSs), boilers, diesel generator (DG), combined heat and power (CHP), wind turbines (WT) and electrical storage systems (ESSs). Figure 2 illustrates an energy hub system [33].

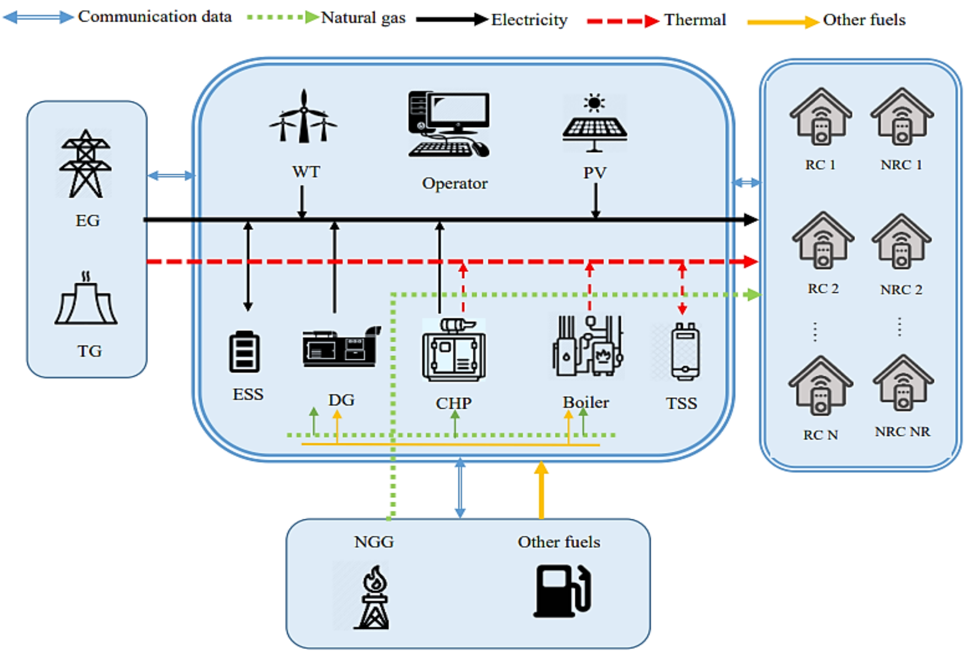


Fig. 2 *Energy hub system*

3. Uncertainty Model

This study utilizes a Monte Carlo technique to conduct scenario-based probabilistic modeling for forecasting WT and PV output and demands. The Probability Density Function (PDF) is employed to determine the probability in each state [34].

3.1 PV and WT Model

The PV and WT energy output is determined by measuring the solar irradiance and wind speed, and a model of solar irradiance and wind speed using Beta PDF and Weibull PDF is utilized, as shown in equations (1) and (2), respectively [35] [36].

$$f^{PV}(si) = \begin{cases} \dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} si^{\alpha-1}(1-si)^{\beta-1} & 0 \le si \le 1, \alpha \ge 0, \beta \ge 0 \\ 0 & otherwise \end{cases} \tag{1}$$

$$f^{WT}(v) = \begin{cases} \dfrac{k}{c_w} \times \left(\dfrac{v}{c_w}\right)^{k-1} \times e^{-\left(\frac{v}{c_w}\right)^k} & v \ge 0 \\ 0 & otherwise \end{cases} \tag{2}$$

$$P_{PV}(si) = \eta_{PV} \times S_{PV} \times si \tag{3}$$

$$P_{WT}(v) = \begin{cases} 0 & if \quad v \le V_{Ci} \\ P_{N,WT} \times \left(\dfrac{v - V_{Ci}}{V_R - V_{Ci}}\right) & if \quad V_{Ci} \le v \le V_R \\ P_{N,WT} & if \quad V_R \le v \le V_{Co} \\ 0 & if \quad V_{Co} \le v \end{cases} \tag{4}$$

The equations (3) and (4) are power of PV and WT, respectively.

3.2 Load Model

The uncertainty of loads can be articulated through the Gaussian PDF by (5) and multiplying Probability of system is modeled by (6) [37]:

$$L(d) = \frac{1}{\sqrt{2\pi\sigma_d^2}} e^{-\frac{(d-\mu_d)^2}{2\sigma_d^2}} \tag{5}$$

$$\rho_s = \rho_s^{PV} \times \rho_s^{WT} \times \rho_s^{L} \tag{6}$$

4. Objective Functions

The primary goals within the field of energy hub are categorized as objectives and articulated as follows:

4.1 Operation Cost

The reduction of cost and environmental pollution from power generation is the primary focus of the model, outlined as follows:

$$\min f_1 = \sum_{s=1}^{S} \rho_s \sum_{t=1}^{T} \left(\sum_{d=1}^{D} C_{DG}(s,t,d) + \sum_{b=1}^{B} C_B(s,t,b) + \sum_{m=1}^{M} C_M(s,t,m) + C_{EG}(s,t) + C_{TG}(s,t) + C_{NGG}(s,t) + \sum_{ess=1}^{ESS} C_{ESS}(s,t,ess) + \sum_{tss=1}^{TSS} C_{TSS}(s,t,tss) \right) + \sum_{t=1}^{T} \left(\sum_{d=1}^{D} E_{DG}(t,d) + \sum_{b=1}^{B} E_B(t,b) + \sum_{m=1}^{M} E_M(t,m) + E_{EG}(t) + E_{TG}(t) \right) \tag{7}$$

Where:

$$C_{DG}(s,t,d) = \left\{ aP_d^2(s,t,d) + bP_d(s,t,d) + c \right\} + \left\{ \pi_p^{gas} \times P_d(s,t,d) \right\} \tag{8}$$

$$C_B(s,t,b) = \left\{ aT_b^2(s,t,b) + bT_b(s,t,b) + c \right\} + \left\{ \pi_p^{gas} \times T_B(s,t,b) \right\} \tag{9}$$

$$C_m(s,t,m) = \left\{ \pi_p^{gas} \times (T_m(s,t,m) + P_m(s,t,m)) \right\} \tag{10}$$

$$C_{EG}(s,t) = \pi_p^{EG} \times P_{EG}(s,t) \tag{11}$$

$$C_{TG}(s,t) = \pi_p^{TG} \times T_{TG}(s,t) \tag{12}$$

$$C_{NGG}(s,t) = \pi_p^{gas} \times G_{NGG}(s,t) \tag{13}$$

$$C_{ESS}(s,t,ess) = \left\{ C_{ESS}^{OP} \times P_{ESS}^{dis}(s,t,ess) \right\} + \left\{ C_{ESS}^{OP} \times P_{ESS}^{ch}(s,t,ess) \right\} \tag{14}$$

$$C_{TSS}(s,t,tss) = \left\{ C_{TSS}^{OP} \times T_{TSS}^{dis}(s,t,tss) \right\} + \left\{ C_{TSS}^{OP} \times T_{TSS}^{ch}(s,t,tss) \right\} \tag{15}$$

$$E_{DG}(t,d) = \left\{ dP_d^2(t,d) + eP_d(t,d) + f \right\} + \left\{ \left(CO_2^d + SO_2^d + NO_X^d \right) \times P_d(t,d) \right\} \tag{16}$$

$$E_B(t,b) = \left\{ dT_B^2(t,b) + eT_B(t,b) + f \right\} + \left\{ \left(CO_2^b + SO_2^b + NO_X^b \right) \times T_b(t,b) \right\} \tag{17}$$

$$E_m(t,m) = \left\{ \left(CO_2^m + SO_2^m + NO_X^m \right) \times P_m(t,m) \right\} \tag{18}$$

$$E_{EG}(t) = \left\{ \left(CO_2^{EG} + SO_2^{EG} + NO_X^{EG} \right) \times P_{EG}(t) \right\} \tag{19}$$

$$E_{TG}(t) = \left\{ \left(CO_2^{TG} + SO_2^{TG} + NO_X^{TG} \right) \times T_{TG}(t) \right\} \tag{20}$$

4.2 Loss of Energy Supply Probability

In the second objective, the minimization of loss of energy supply probability is the focus. and it is represented through a model:

$$\min f_2 = \sum_{s=1}^{S} \rho_s \left\{ \left(\frac{\sum_{t=1}^{T} P_{ST}(s,t)}{\sum_{t=1}^{T} D_E(s,t)} \right) + \left(\frac{\sum_{t=1}^{T} T_{ST}(s,t)}{\sum_{t=1}^{T} D_T(s,t)} \right) \right\} \tag{21}$$

4.3 Demand Shifting Model

The optimization of the demand profile through minimizing deviations from the optimal level is demonstrated by the third objective. This objective allows for the adjustment of electrical and thermal demand by RCs.

$$\min f_3 = \sum_{s=1}^{S} \rho_s \left\{ \left(\sum_{t=1}^{T} \left| D_E(s,t) - D_E^{OP} \right| \right) + \left(\sum_{t=1}^{T} \left| D_T(s,t) - D_T^{OP} \right| \right) \right\} \tag{22}$$

Where:

$$D_E(s,t) = D_E^{NRC}(s,t) + D_E^{RC}(s,t) \tag{23}$$

$$D_T(s,t) = D_T^{NRC}(s,t) + D_T^{RC}(s,t) \tag{24}$$

$$D_E^{RC}(s,t) = \sum_{t'} D_E^{RC}(s,t',t) - \sum_{t'} D_E^{RC}(s,t,t') \tag{25}$$

$$D_T^{RC}(s,t) = \sum_{t'} D_T^{RC}(s,t',t) - \sum_{t'} D_T^{RC}(s,t,t') \tag{26}$$

$$0 \le \sum_{t'} D_E^{RC}(s,t,t') \le \xi_E \times \sum_{t=1}^{T} D_E^{RC}(s,t) \tag{27}$$

$$0 \le \sum_{t'} D_T^{RC}(s,t,t') \le \xi_T \times \sum_{t=1}^{T} D_T^{RC}(s,t) \tag{28}$$

$$D_E^{OP} = \frac{\sum_{t=1}^{T} D_E}{T} \tag{29}$$

$$D_T^{OP} = \frac{\sum_{t=1}^{T} D_T}{T} \tag{30}$$

5. Constraints

Several considerations are taken into account when it comes to the constraints in an energy hub system. The energy balance constraint is expressed through equations (31) to (33) to ensure that the generation-side matches the demand-side for all energies in each scenario and time.

$$\sum_{d=1}^{D} P_d(s,t,d) + \sum_{m=1}^{M} P_m(s,t,m) + \sum_{ess=1}^{ESS} P_{ESS}^{dis}(s,t,ess) + P_{EG}(s,t) + \sum_{pv=1}^{PV} P_{PV}(s,t,pv) + \sum_{w=1}^{W} P_w(s,t,w) + P_{ST}(s,t) = D_E(s,t) + \sum_{ess=1}^{ESS} P_{ESS}^{ch}(s,t,ess) \tag{31}$$

$$\sum_{b=1}^{B} T_b(s,t,b) + \sum_{m=1}^{M} T_m(s,t,m) + \sum_{tss=1}^{TSS} T_{TSS}^{dis}(s,t,tss) + T_{TG}(s,t) + T_{ST}(s,t) = T_D(s,t) + \sum_{tss=1}^{TSS} T_{TSS}^{ch}(s,t,tss) \tag{32}$$

$$G_{NGG}(s,t) - \sum_{d=1}^{D} P_d(s,t,d) - \sum_{m=1}^{M} P_m(s,t,m) - \sum_{b=1}^{B} T_b(s,t,b) = D_G(t) \tag{33}$$

The energy limitations of various components, DGUs are indicated by the constraints (34) to (41), encompassing both lower and upper bounds.

$$P_d^{\min} \le P_d(s,t,d) \le P_d^{\max} \tag{34}$$

$$T_b^{\min} \le T_b(s,t,b) \le T_b^{\max} \tag{35}$$

$$P_m^{\min} \le P_m(s,t,m) \le P_m^{\max} \tag{36}$$

$$T_m^{\min} \le T_m(s,t,m) \le T_m^{\max} \tag{37}$$

$$P_{dis}(s,t,ess) / \eta_{dis}^{ESS} \le P_{dis}^{\max} \times \mu_{ESS-dis}(s,t,ess) \tag{38}$$

$$P_{ch}(s,t,ess) \times \eta_{ch}^{ESS} \le P_{ch}^{\max} \times \mu_{ESS-ch}(s,t,ess) \tag{39}$$

$$T_{dis}(s,t,tss) / \eta_{dis}^{TSS} \le T_{dis}^{\max} \times \mu_{TSS-dis}(s,t,tss) \tag{40}$$

$$T_{ch}(s,t,tss) \times \eta_{ch}^{TSS} \le T_{ch}^{\max} \times \mu_{TSS-ch}(s,t,tss) \tag{41}$$

The discharge and charge state of storage systems can be determined using equations (38)–(41) respectively. It is important to note that storage systems cannot discharge and charge simultaneously, as indicated by constraints (42) and (43).

$$\mu_{ESS-dis}(s,t,ess) + \mu_{ESS-ch}(s,t,ess) \le 1 \tag{42}$$

$$\mu_{TSS-dis}(s,t,tss) + \mu_{TSS-ch}(s,t,tss) \le 1 \tag{43}$$

The constraints pertaining to the shortage of energy to meet the required demand can be outlined as follows:

$$0 \le P_{ST}(s,t) \le D_E(s,t) \times \mu_{PST}(s,t) \tag{44}$$

$$0 \le T_{ST}(s,t) \le T_E(s,t) \times \mu_{TST}(s,t) \tag{45}$$

The technical limitations of storage systems, such as energy dynamic constraints, are articulated through equations (46) and (47):

$$E_{ESS}^{\min} \le E_{ESS}(s,t,ess) \le E_{ESS}^{\max} \tag{46}$$

$$E_{TSS}^{\min} \le E_{TSS}(s,t,tss) \le E_{TSS}^{\max} \tag{47}$$

Where

$$E_{ESS}(s,t,ess) = E_{ESS}(s,t-1,ess) + \left[P_{ESS}^{dis}(s,t,ess)/\eta_{dis}^{ESS} - P_{ESS}^{ch}(s,t,ess)\times\eta_{ch}^{ESS}\right] \tag{48}$$

$$E_{TSS}(s,t,tss) = E_{TSS}(s,t-1,tss) + \left[T_{TSS}^{dis}(s,t,tss)/\eta_{dis}^{TSS} - T_{TSS}^{ch}(s,t,tss)\times\eta_{ch}^{TSS}\right] \tag{49}$$

6. Solving Method

The ε-constraint method involves formulating a mathematical model that represents the multi-criteria problem. This model includes the objective functions that need to be optimized and the constraints that need to be satisfied. This method introduces a set of small positive numbers called epsilon values. These epsilon values act as thresholds or constraints on the multi-criteria problem. The goal is to find solutions that minimize or maximize the objective functions while satisfying these ε-constraint methods. During the optimization process, the method generates a set of candidate solutions that satisfy the epsilon constraints. These solutions are evaluated based on their objective function values and feasibility concerning the constraints. The Pareto frontier denotes the collection of solutions that cannot be enhanced in one objective without considering the performance in another. These solutions are considered efficient and optimal since they embody the compromises between various objectives. Consequently, the ε-constraint method adheres to a sequence of steps to obtain solutions on the Pareto frontier. The -constraint method is implemented as follow [38][39]:

$$\min_{x\in X} f_j(x) \tag{50}$$

Where:

$$f_z(x) \le \varepsilon_z \qquad z = 1,2,\ldots,Z \qquad z \ne j$$

6.1 Decision-Making Model

In the realm of optimization, the objectives are to simultaneously optimize the as multi-objective functions. During this process, the formation of Pareto frontier solutions occurs where the objectives conflict with each other. Consequently, the operator must ensure the highest compatibility among the objectives by employing a decision-making approach. In the present study, decision-making method are employed to find the desired solution. To identify the optimal solution, the next course of action involves the following steps: 1) Normalize the Pareto frontier solutions obtained through step (51). 2) Utilize the value provided in step (52) to determine the minimum value among the normalized Pareto frontier solutions. This minimum value is regarded as the ideal point (P_{Ideal}). In the last step (53), the optimal solution is identified by choosing the solution that has the least distance from the ideal point [40][41].

$$\Gamma_z^k = \frac{f_z^{\max} - f_z(k)}{f_z^{\max} - f_z^{\min}} \tag{51}$$

$$P_{Ideal} = \left\{\min\Gamma_1^1 \quad \min\Gamma_2^2 \quad \ldots \quad \min\Gamma_z^k\right\} \tag{52}$$

$$\min Dis(k) = \sqrt{\left[\Gamma_1^1 - \min\Gamma_1^1\right]^2 + \left[\Gamma_2^1 - \min\Gamma_2^2\right]^2 + \ldots + \left[\Gamma_z^k - \min\Gamma_z^k\right]^2} \tag{53}$$

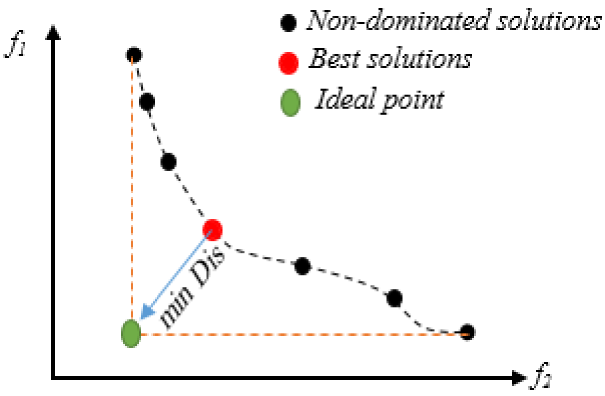


Fig. 3 Decision-making method

7. Case Studies

In this section, we conduct cases and simulations to validate the approach in the scheduling of the energy hub in 24 ahead-hours. The analysis of case studies focusing on the presence of objectives in the energy hub has been considered as follow:

Case I) Scheduling of energy hub without demand shifting.

Case II) Scheduling of energy hub with demand shifting.

Due to the uncertain mode of solar irradiance, demand and wind speed; Monte Carlo technique was utilized to generate 10 scenarios. However, an analysis has been conducted on the results associated with scenario 6, aiming to restrict the display of a significant quantity of tables and figures in overall scenarios. 1. Figure 4 illustrates the wind speed and solar irradiance, which can be found in Table 1 where the data of them is presented [42]. Figure 5 illustrates the prices of energy [43]. Table 2 presents the data for energy storage systems [44]. The demand is depicted in Figure 6. In Table 3 data of DGUs are provided [45]. Table 5 presents the energy restrictions of units [46]. The engagement of RCs in modifying electrical and thermal shifting loads is established at 70% and 60%, respectively.

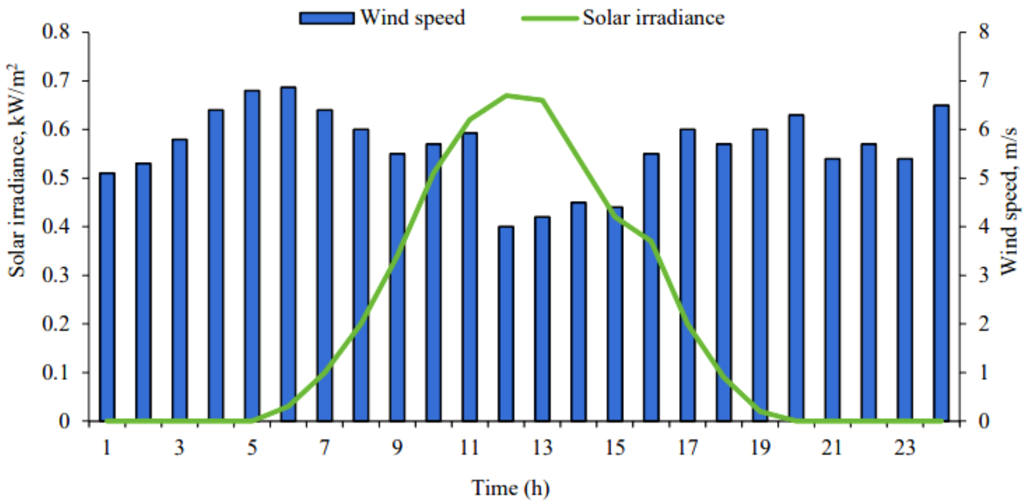


Fig. 4 *Solar irradiance and wind speed*

Table 1 *PV and WT information*

PV		WT	
Parameters	**Value**	**Parameters**	**Value**
N_{PV}	5	N_{WT}	5
S_{PV}	45 m^2	V_{Ci}, V_{Co}	3 m/s, 20 m/s
η_{PV}	25 %	V_R	15 m/s
$P_{N,PV}$	0.5 MW	$P_{N,WT}$	1.2 MW

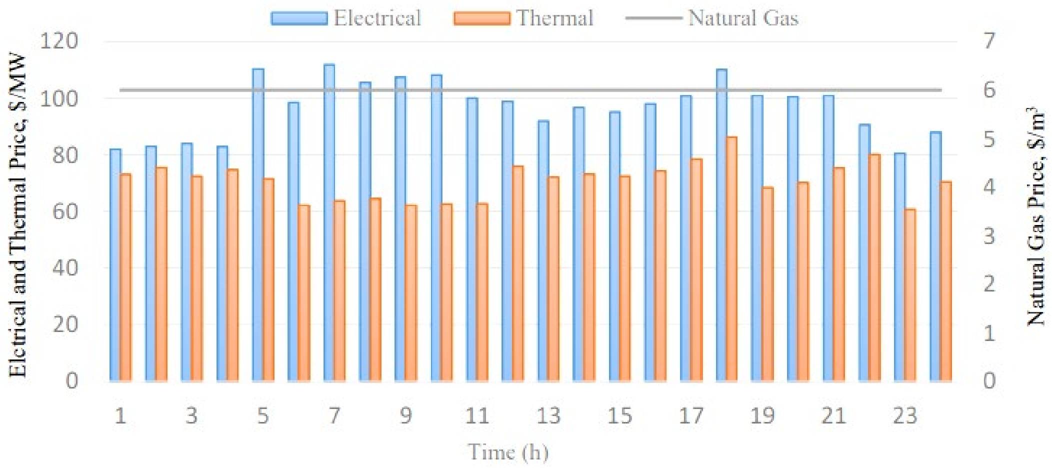


Fig. 5 *Energy prices*

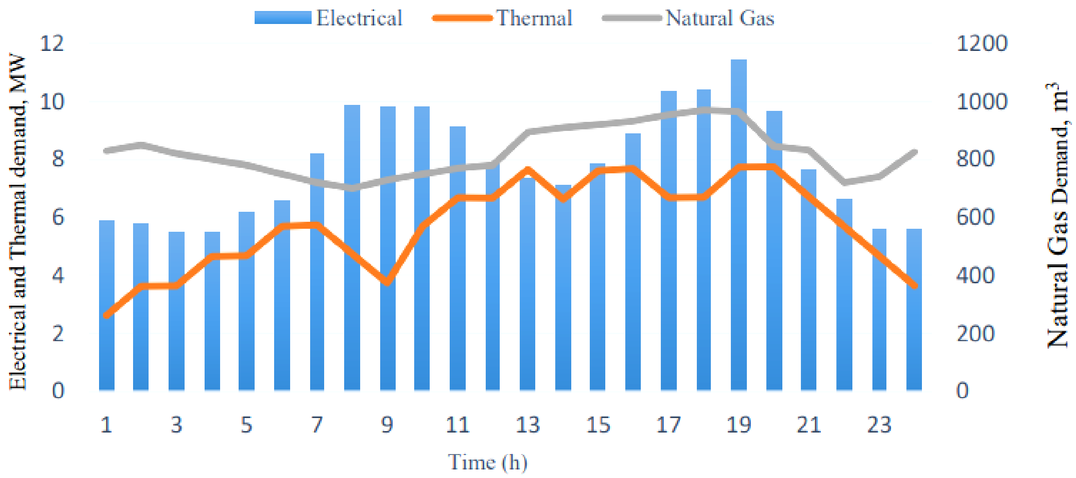


Fig. 6 *Demand of customers*

Table 2 *Storage systems' data*

ESS		TSS	
Parameters	**Value**	**Parameters**	**Value**
N_{ESS}	1	N_{TSS}	1
P^{max}_{dis}	1 MW	T^{max}_{dis}	0.5 MW
P^{max}_{ch}	1 MW	T^{max}_{ch}	0.5 MW
E^{min}_{ESS}	10 %	E^{min}_{TSS}	10 %
E^{max}_{ESS}	100 %	E^{max}_{TSS}	100 %
η^{ESS}_{ch}	90 %	η^{TSS}_{ch}	90 %
η^{ESS}_{dis}	95 %	η^{TSS}_{dis}	95 %
C^{OP}_{ESS}	140 $	C^{OP}_{TSS}	120 $

Table 3 *DGUs data*

Parameters / **Units**	**a, $/MW²**	**b, $/MW**	**c, $**	**d, kg/MW²**	**e, kg/MW**	**f, kg**
DG 1	25.5	140	102	21	154	108
DG 2	25.5	141	102	21	154	108
Boiler 1	20.5	95.7	100	21.5	90	105

Table 4 *Emission data of DGUs*

Emission type / Units	CO_2, kg/MW	SO_2, kg/MW	NO_x, kg/MW
DG 3	475.5	3.42	1.94
Boiler 2	490.3	3.54	1.26
CHP 1	468.5	3.21	0.79
CHP 2	469.2	3.15	0.15
EG	970.5	7.25	2.75
TG	951.4	7.31	1.69

Table 5 *Energy bound of DGUs*

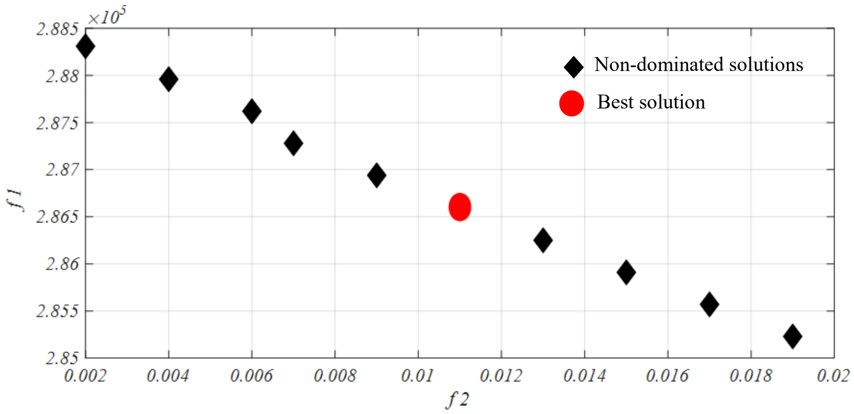
Parameters / Units	P^{min}, MW	P^{max}, MW	T^{min}, MW	T^{max}, MW
DG 1	0	0.7	-	-
DG 2	0	0.7	-	-
DG 3	0	0.53	-	-
Boiler 1	-	-	0	0.65
Boiler 2	-	-	0	0.54
CHP 1	0	0.55	0	0.51
CHP 2	0	0.53	0	0.51

7.1 Results Evaluation

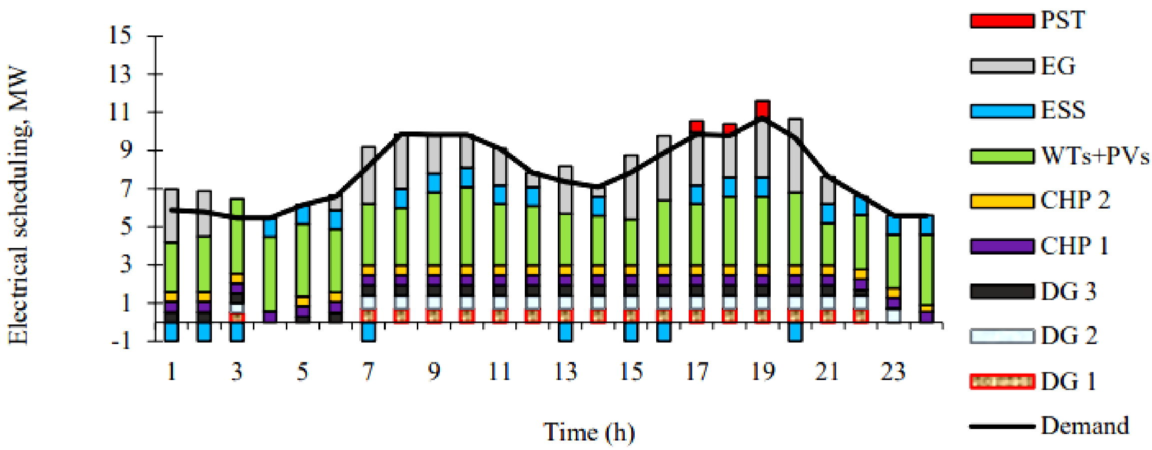
Within this section, the outcomes of numerical simulations for each individual case are deliberated, and a comparison is drawn between the various cases:

In the first case, the primary goal is to minimize costs and emission pollution in the scheduling of the generation side, while the secondary objective is to minimize loss of energy supply probability. Figure 7(a) illustrates the solutions generated using the ε-constraint method. Through a decision-making process, the best solution is chosen. The first objective in the chosen solution holds a value of 286595.27, while the second objective is valued at 0.011 MW. The correlation between maximum cost and emission can be attributed to the procurement of gas, respectively. A notable impact of high natural gas demand is observed on cost. Conversely, the unpredictable nature of DGUs and demand results in energy shortages to meet the demand, particularly in power generation. Figure 7(b) and 7(c) illustrates the energy of system. The deficit in power during the time period from 17 to 19:00 has been addressed, with a total shortage of 2.1 MW during these hours. Conversely, after incorporating DGUs to fulfill the electrical demand, energy market exhibits the highest contribution in comparison to DGUs. The power procured from electrical market amounts to 30.934 MW. The illustration in Figure 7(c) displays the thermal. It is evident from the figure that thermal grid plays a significant role in meeting the thermal demand, with a total generated thermal power of 79.101 MW.

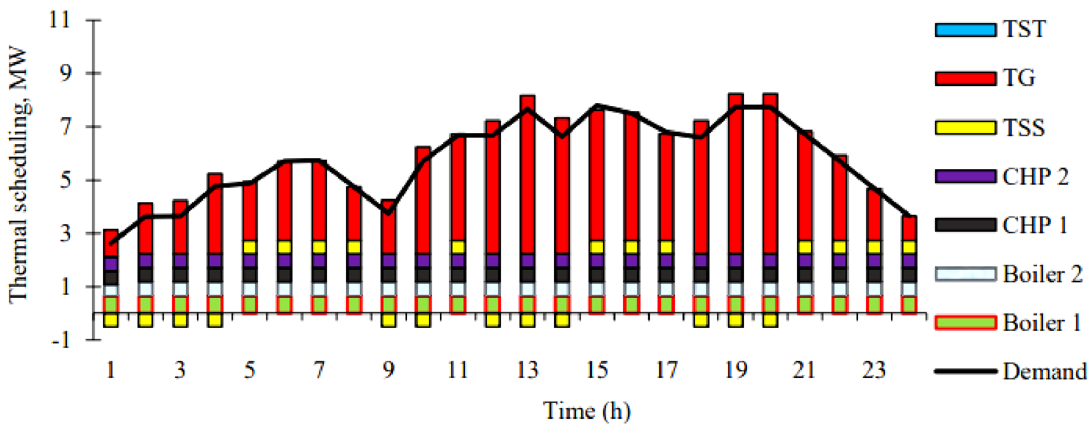
In the second case, the optimization of all objectives, including the scheduling of the generation side, and demand side simultaneously is considered. Figure 8(a) displays solutions generated using the ε-constraint method. The emission and cost and in this particular case study has amount to 67,124.98 kg and $140,510.75, respectively. The minimize loss of energy supply probability exclusively involves power production, with a total value of 0.005 MW. The deviation of the third objective, aimed at smoothing out the energy demand curve in the chosen solution, amounts to 312.11 MW. Furthermore, there has been a significant decrease in emission from the production in DGUs and energy markets. Specifically, the reduction percentages for these sources are 43.3% when compared to case I. 1. The graph in Fig. 8(b) illustrates the timetable of demand and power produced by Generation side. It is evident that the power demand exhibits a more stable curve compared to case I. Additionally, the total electrical power deficit is recorded at 0.95 MW, occurring solely at 19:00. The amount of l power purchased from market is 9.05% lower than in case I. In Figure 8(c), the allocation of demand and thermal generated is illustrated. The thermal generated by market in this case amounts to 14.1 MW, representing an 82.17% decrease compared to case I.



(a)

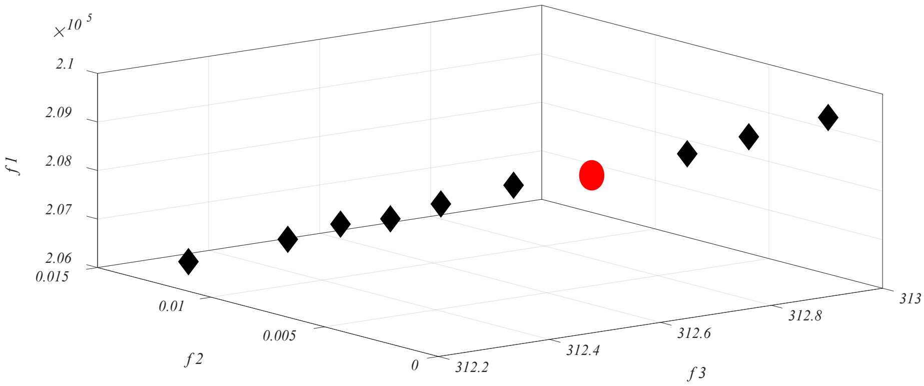


(b)

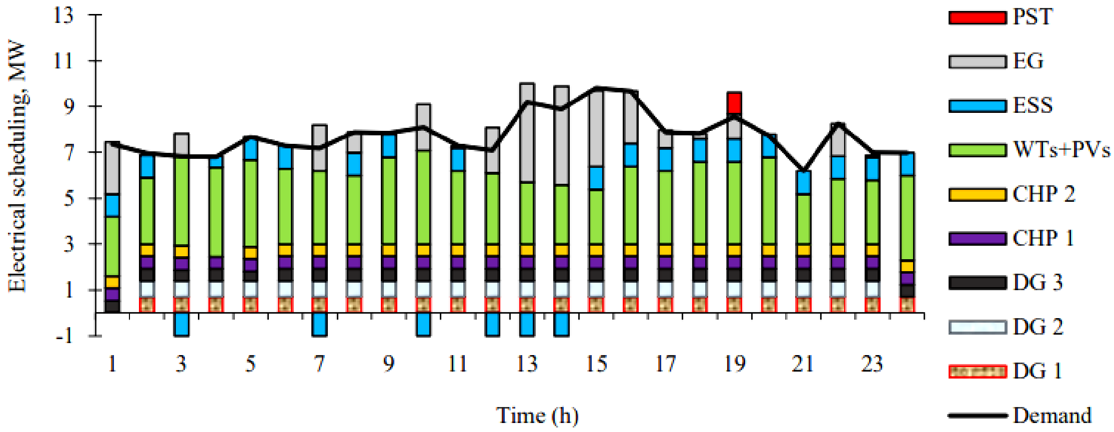


(c)

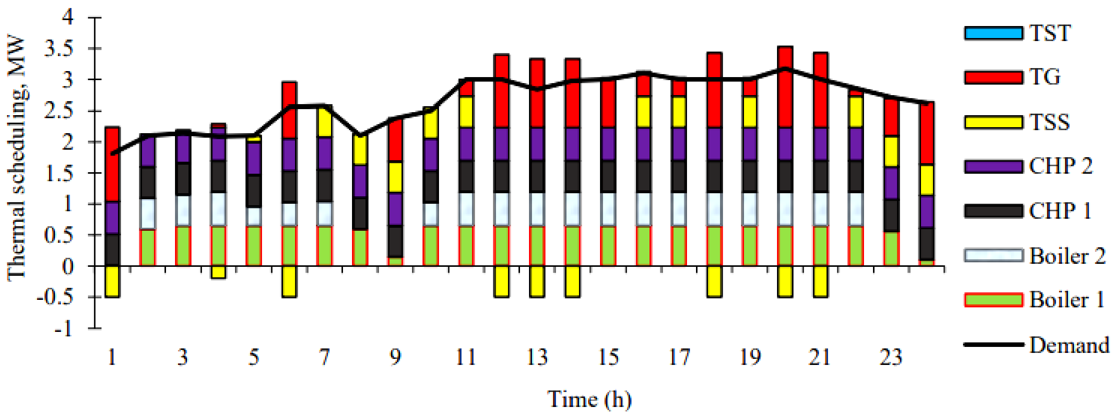
Fig. 7 *(a) Solutions in Case; (b) power scheduling in Case I; and (c) Thermal scheduling in Case I*



(a)



(b)



(c)

Fig. 7 *(a) Solutions in Case II; (b) power scheduling in Case II; and (c) Thermal scheduling in Case II*

8. Conclusion

In this study, a method is introduced for the efficient modeling of a energy Hub system with multiple goals in the day ahead. These goals consist of minimizing emission and costs on the generation side, decreasing the likelihood of loss of energy supply probability, and reducing the deviation amount of energy demand in the day ahead. To address the third goal of smoothing out the electrical and thermal demand patterns, a Demand response strategy is suggested, which entails the optimal adjustment of shiftable loads. Furthermore, stochastic modeling of renewable energy sources and energy loads using the Monte Carlo technique is carried out. The proposed method employs the ε-constraint approach to obtain non-dominated Pareto solutions for the goals. Finally, several case studies are conducted to validate the proposed method. The participation of the demand shifting leads to reduce emission, costs and loss of energy supply probability than non-participation.

Acknowledgement

The authors would like to thank their university for supporting this project.

Conflict of Interest

The authors declare that they have no known competing interests.

Author Contribution

Lucy Mariella García-Vilela, Yersi-Luis Huamán-Romaní, Ruth-Nataly Aragon-Navarrete, Soledad del Rosario Olivares Zegarra and Elio Nolasco Carbajal have equal contributions reviewing and editing the writing, formal analysis, software development and conceptualization.

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