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

IJIE

Vol. 16 No. 9 (2024) 385-397
https://publisher.uthm.edu.my/ojs/index.php/ijie

# Optimal Operation of Autonomous Energy System Based on Multi-objective Approach

**Paul Rodrigues[1], Ashish Singh[2], Vikas Kaushik[3], Jasgurpreet Singh Chohan[4,5], Mustafa Adnan Abdulrahman[6], Layth Hussein[7,8,9], Y.S Romaní[10]***

[1] *Department of Computer Engineering, College of Computer Science, King Khalid University, Al-Faraa, KSA*
[2] *NIMS School of Electrical and Electronics Engineering, NIMS University Rajasthan, Jaipur, INDIA*
[3] *Department of Mechanical Engineering, Chandigarh Engineering College, Chandigarh Group of Colleges-Jhanjeri, Mohali-140307, Punjab, INDIA*
[4] *School of Mechanical Engineering, Rayat Bahra University, Kharar, Punjab 140103, INDIA*
[5] *Faculty of Engineering, Sohar University, PO Box 44, Sohar, PCI 311, OMAN*
[6] *Department of Medical Laboratories Technology, AL-Nisour University College, Baghdad, IRAQ*
[7] *Department of computers Techniques engineering, College of technical engineering, The Islamic University, Najaf, IRAQ*
[8] *Department of computers Techniques engineering, College of technical engineering, The Islamic University of Al Diwaniyah, Al Diwaniyah, IRAQ*
[9] *Department of computers Techniques engineering, College of technical engineering, The Islamic University of Babylon, Babylon, IRAQ*
[10] *Madrid Institute for Advanced Studies in Energy, Madrid, SPAIN*

*Corresponding Author: yersi.luis.ro@gmail.com
DOI: https://doi.org/10.30880/ijie.2024.16.09.031

**Article Info**

Received: 3 May 2024
Accepted: 14 September 2024
Available online: 30 December 2024

**Keywords**

Technical and economic performance, demand management, voltage indices, fuzzy method, non-dominated solutions

**Abstract**

This research aims to explore the scheduling strategies for an autonomous energy system (AES), with multi-objectives modeling. It has been proposed that implementing demand management can enhance both technical and economic performance during operations. This study aims to reduce operational expenses and improve voltage metrics by employing a load optimization strategy. The Particle Swarm Optimization (PSO) algorithm is utilized to address the problem of optimizing complex functions and finding optimal solutions in various fields, including engineering, computer science, and economics. The ideal optimal solution, found among the non-dominated solutions, is achieved through the fuzzy method. Case studies are conducted on the 33 bus test system to evaluate the effectiveness of the proposed strategy. By implementing demand management, operational costs are reduced by 6.12%, while voltage indices show an improvement of 9.65% compared to the absence of demand management practices.

## 1. Introduction

Research has been heavily concentrated on enhancing energy sources for providing energy to consumers, reducing operational expenses and technical indicators, and considering technical limitations [1]. Energy hybrid systems have been implemented to address economic, environmental, and reliability requirements, while also taking into account consumer behavior, in order to achieve this objective. Energy hybrid systems combine different sources of energy, such as solar, wind, and battery storage, to create a more efficient and reliable energy system. By integrating multiple sources of energy, these systems can better meet the varying demands of consumers while also reducing costs and environmental impact [2]. One of the key benefits of energy hybrid

This is an open access article under the CC BY-NC-SA 4.0 license.

**Nomenclature**

| | |
|---|---|
| **Indices and Sets** | |
| $t, T$ | Time |
| $d, D$ | DG |
| $n, N$ | Consumers |
| $i, j, \Lambda$ | Bus |
| **Parameters** | |
| $\mathrm{N}, \Omega, \Upsilon$ | DGs' fuel cost |
| $C_{SU}, C_{SD}$ | Cost of start up and down for DGs |
| $RU, RD$ | Ramp up and down of DGs |
| $D_{DM}$ | Bid demand to Demand management |
| $D_{eq}$ | Active demand |
| $QD_{eq}$ | Reactive demand |
| $\Theta_{DM}$ | Bid price to demand management |
| $V_{ref}$ | Voltage reference |
| **Decision variables** | |
| $C_{DM}$ | Demand management operation cost |
| $C_d$ | DGs' cost |
| $P_d$ | Active power of DG |
| $Q_d$ | Reactive power of DG |
| $V_\Lambda$ | Voltage profile |
| $\theta_{DM}$ | Binary variable of demand management |
| $a_{DM}, b_{DM}$ | The starting time and the ending time Binary variables for the demand management, respectively. |
| $\mu^{Off}, \mu^{On}$ | DG's binary variable, On=1 and Off=0 |

systems are their ability to provide a more stable and reliable energy supply. By combining different sources of energy, these systems can ensure that power is always available, even when one source is not producing energy. This can help to prevent blackouts and other disruptions to the energy supply [3]. Energy hybrid systems not only enhance reliability but also contribute to cost savings for consumers. By integrating various renewable energy sources like solar and wind, these systems can decrease energy expenses and lessen dependence on costly fossil fuels. This can help to make energy more affordable for consumers while also reducing greenhouse gas emissions and other environmental impacts. The latest advancements in energy systems are highlighted by these systems, which make use of communication links connecting consumers and generation resources to enhance and simplify consumer participation in load profile transformation. The modifications to the load profile significantly influence the efficient distribution of energy, leading to a more flexible system that lowers generation expenses, decreases emissions, and enhances dependability. Additionally, through the utilization of ideal resource dimensions, energy production can be significantly decreased in energy markets, all the while promoting collaboration between energy providers and consumers to regulate demand and prevent the necessity for extra units. The increasing diversity of hybrid loads will undoubtedly require careful consideration of optimal sizing, which will play a crucial role in future energy management [3][4].

Several research studies have been carried out on different aspects of microgrid energy systems. The study highlighted in reference [5] emphasizes the importance of optimal scheduling for an energy system, with a specific focus on considering risk constraints. The optimal energy management approach for micro-scale energy hybrid presented in [6] takes into account various factors including availability and demand. By employing an algorithm, this approach aims to minimize costs effectively. The examination of the scheduling issue within the energy hybrid system, utilizing step modeling and optimal sizing through various methods, is discussed in reference [7]. The emphasis in [8] is on optimizing the operation of the system using optimization techniques in order to maximize the profit of the energy hybrid system. The scheduling strategy proposed in [9] focuses on the energy hybrid system, taking into account conditional risk and highlighting the importance of optimal sizing modeling in order to minimize generation costs efficiently. A novel approach for energy management has been introduced in [10] to

Int. Journal of Integrated Engineering Vol. 16 No. 9 (2024) p. 385-397

improve the security of load supply. Furthermore, the study in reference [11] delves into the energy transfer process aimed at minimizing overall energy expenses within an energy hybrid setup. The study in [12] presents an analysis of an energy system optimization model, which considers load clipping of thermal and cost reduction.

The assessment of energy flow within energy networks of energy systems involves conducting power flow analysis to optimize the energy system, as outlined in [13]. Additionally, the study in [14] presents an efficient scheduling framework for the energy system, taking into account the constrained optimization of energy sources in order to reduce investment expenses. The paper in [15] introduces a variety of techniques for energy management, focusing on essential methods for demand-side management and load forecasting aggregation. The study in [16] delves into the examination of maximizing anticipated advantages within an energy system, taking into account energy market prices and uncertainties related to wind generation, by means of stochastic optimization analysis. The research conducted in [17] focuses on the stochastic optimization framework within the energy system, incorporating risk modeling approaches. The framework for an energy system, as proposed in [18], is established on energy pricing through decision theory. The study in [19] delves into the development of an energy system for sizing, taking into account the variability of energy sources through the utilization of Benders algorithm. The research carried out in [20] centers on investigating how the weight sum method can be used to optimize energy usage, operational costs, and reduce emission pollution. In [21] and [22], an assessment is conducted on a multi-objective issue that takes into consideration economic aspects to enhance the operation of the system. In [23], the focus is on examining the most suitable design for the energy hybrid system, with a careful consideration of economic factors impacts.

Figure 1 depicts the architecture of an AES. In this illustration, DERs denote diesel generators (DGs) that produce electricity by utilizing fuel. The main energy users within AESs is the consumers. Consumers have the ability to achieve efficient energy use by adopting demand-side management (DSM) strategies. Effective collaboration among participants, aligned with established goals focused on enhancing economic and technical metrics, is a crucial element in assessing the operator's capabilities.

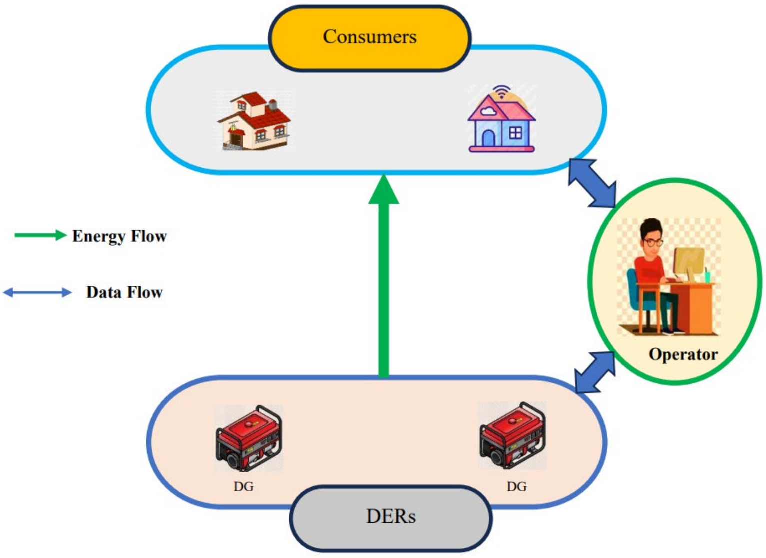


**Fig. 1** *The AES structure*

This paper presents a scheduling strategy for AESs, employing a multi-objective approach that balances technical and economic factors for day-ahead planning. The process of multi-objective decision-making focuses on reducing operational costs while enhancing the voltage index. Furthermore, this research introduces load management via reduction modeling. The objectives are optimized by employing the Particle Swarm Optimization (PSO) algorithm, all while considering constraints. Additionally, the max-min method with fuzzy approach is employed to select the best answer from the set of non-dominated solutions.

## 2. Modeling of DSM

The DSM is modeled based biding price by operator as follow [23]:

$$C_{DM} = \sum_{n=1}^{N} \sum_{t=1}^{T} \Theta_{DM} \times D_{DM}(t) \times \theta_{DM}(t) \qquad \forall n \tag{1}$$

$$a_{DM}(t)-b_{DM}(t)=\theta_{DM}(t)-\theta_{DM}(t-1) \qquad \forall n,t \tag{2}$$

$$\theta_{DM}(t)=\begin{cases}1 & a_{DM}(t)>b_{DM}(t)\\ 0 & a_{DM}(t)<b_{DM}(t)\end{cases} \qquad \forall t \tag{3}$$

The expenses associated with DSM are represented by equation (1). Equation (2) outlines the initial and final times for DSM. Equation (3) clarifies that the initial and final times for demand management do not happen at the same time.

## 3. Modeling Objectives

The objectives considered in this study are as follows:

### 3.1 First Objective

The operation cost modeling is minimized as follow:

$$\min f_1=\sum_{t=1}^{T}\left[\sum_{d=1}^{D}C_d(t,d)+\sum_{n=1}^{N}C_{DM}(t,n)\right] \tag{4}$$

Where:

$$C_d(t,d)=\left\{\mathrm{N}P_d^2(t,d)+\Omega P_d(t,d)+\Upsilon\right\}+\left\{C_{SU}\times\mu^{on}(t,d)\right\} \\ +\left\{C_{SD}\times\mu^{off}(t,d)\right\} \tag{5}$$

The cost of the DGs is outlined in equation (5).

### 3.2 Second Objective

Enhancing the voltage profile is second objective, which is modeled as follow:

$$\min f_2=\left|\sum_{i,j\in\Lambda}V_\Lambda(\Lambda)-V_{ref}\right| \tag{6}$$

## 4. Modeling Constraints

The optimization of the objectives is carried out while taking into account the following constraints:

### 4.1 Power Balance Constraint

The power balance constraint is as follow:

$$\sum_{d=1}^{D}P_d(t,d)-\left[D_{eq}(t)-D_{DM}(t)\right]=\sum_{i,j\in\Lambda}V_i(t,i)\times V_j(t,j)\times Y_{i,j} \\ \times\cos\left[\theta_{i,j}+\delta_j(t,j)-\delta_i(t,i)\right] \qquad \forall t,\Lambda \tag{7}$$

$$\sum_{d=1}^{D} Q_d(t,d) - \left[QD_{eq}(t) - QD_{DM}(t)\right] = \sum_{i,j\in\Lambda} V_i(t,i)\times V_j(t,j)\times Y_{i,j} \times \sin\left[\theta_{i,j} + \delta_j(t,j) - \delta_i(t,i)\right] \qquad \forall t,\Lambda \tag{8}$$

## 4.2 Constraint of DG

Where (9) and (10) are employed to define the boundaries for both active and reactive generation by DGs. Furthermore, the ramp rate limitations, which encompass the ramp-up and down capabilities of DGs, are established through constraints (11) and (12), respectively.

$$0 \le P_d(t,d) \le P_d^{\max} \qquad \forall t,d \tag{9}$$

$$0 \le Q_d(t,d) \le Q_d^{\max} \qquad \forall t,d \tag{10}$$

$$P_d(t,d) - P_d(t-1,d) \le RU \qquad \forall t,d \tag{11}$$

$$P_d(t-1,d) - P_d(t,d) \le RD \qquad \forall t,d \tag{12}$$

## 4.3 Grid Constraint

The voltage threshold in buses is defined by constraint (13).

$$V_\Lambda^{\min} \le V_\Lambda(t,\Lambda) \le V_\Lambda^{\max} \qquad \forall t,\Lambda \tag{13}$$

## 5. Methodology

In the PSO algorithm, particles are organized into groups. The formulation of the PSO algorithm involves two key variables: v, representing particle velocity, and x, denoting particle position. Each particle's optimal position is determined by its performance in the objective function, referred to as p_best, while the best position across the entire group is known as g_best. To ensure the convergence of the PSO algorithm, it is essential to utilize a parameter known as the contraction coefficient for optimal adjustment of the algorithm's parameters. Consequently, the velocity and position of a particle, influenced by the contraction coefficient, can be expressed as follows [24]:

$$v_{d+1} = \alpha(w \times v_d + \varphi_1 \times rand(p\_best - x_d) + \varphi_2 \times rand(g\_best - x_d)) \tag{14}$$

$$x_{d+1} = x_d + v_{d+1} \tag{15}$$

Where $d$ is the repetition counter, $x_d$ is the particle position in repetition, $x_{d+1}$ is particle position in repetition $v_d$, and $d+1$ is particle velocity in repetition $d$. The $w$ is inertia weight, $\phi_1$ and $\phi_2$ are acceleration coefficient each of particle. Rand is generation functions for random number with a monotonous disperse in range of [0,1]. The $\alpha$ is a function of $\phi_1$ and $\phi_2$ for more convergence of the PSO algorithm. The suitable choice of $w$ has caused balance in local and global search space. Generally, $w$ for a better and optimize function of algorithm will dynamically change:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \tag{16}$$

Where *iter* shows the current iteration. For decreasing the steps of search, particle velocity will be limited by amount of $v_{max}$:

$$v \in [-v_{\max} v_{\max}] \tag{17}$$

Where $v_{max}$ will improve the local search.

In this study, objectives are optimized concurrently, leading to the acquisition of frontier solutions. The energy operator is tasked with identifying the optimal solution for these objectives within the frontier solutions, acting as the decision maker. According to equation (18), all frontier solutions must be normalized using the max-min fuzzy method to establish the optimal solution as follows [25][26]:

$$\Gamma\left(f_z(\vartheta)\right) = \begin{cases} 0 & otherwise \\ \dfrac{f_z^{\max} - f_z(\vartheta)}{f_z^{\max} - f_z^{\min}} & f_z^{\min} \le f_z(\vartheta) \le f_z^{\max} \\ 1 & f_z^{\min} \ge f_z(\vartheta) \end{cases} \tag{18}$$

The optimal solution is defined by a high rate of the minimum solution.

$$\max\left\{\min \Gamma\left(f_z(\vartheta)\right)\right\} \tag{19}$$

## 6. Case Studies

To assess the effectiveness and reliability of the modeling, several case studies related to the suggested DSM have been examined, as detailed below.
Case A) Modeling system without DSM.
Case B) Modeling system with DMS.

Figure 2 illustrates the 33-bus system known as AESs. Detailed data about this test system is available in reference [27]-[32]. To forecast the load demand for the day-ahead, the Monte Carlo method is employed. Figure 3 showcases the load demand forecast achieved through the generation of random variables using the Monte Carlo method. The data of DGs are extracted from references [33]-[40]. Additionally, Figure 4 depicts the bid price that the operator presents to consumers for executing demand management.

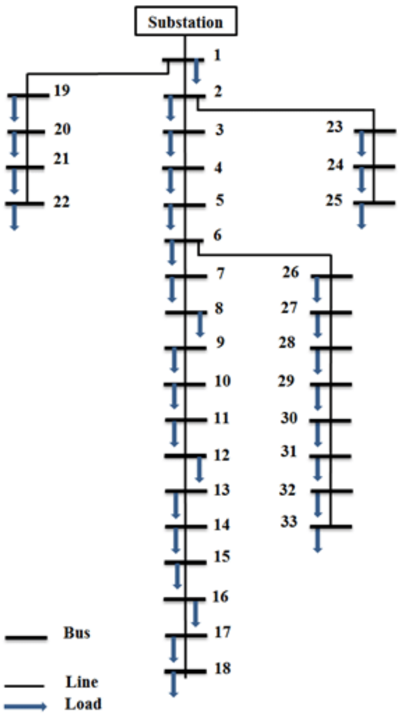


**Fig. 2** *33-bus test system*

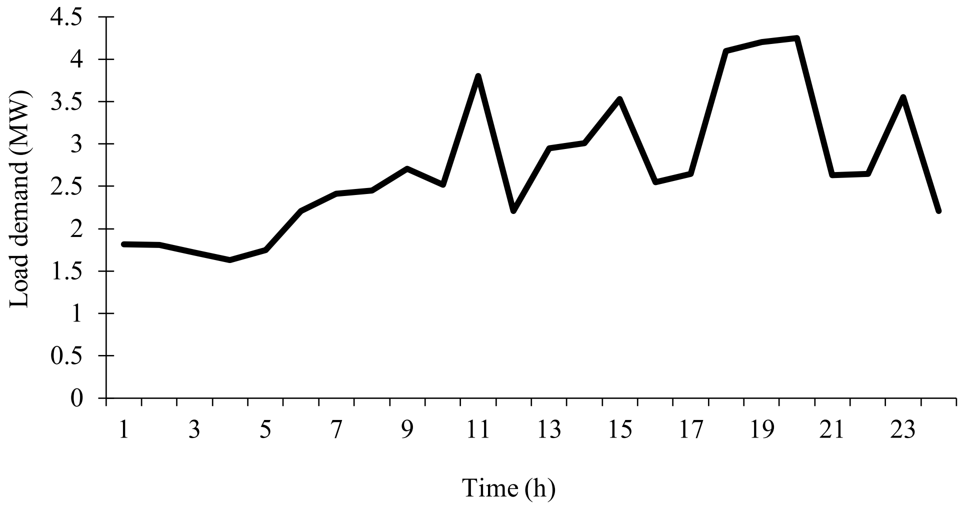


**Fig. 3** *Demand of AES*

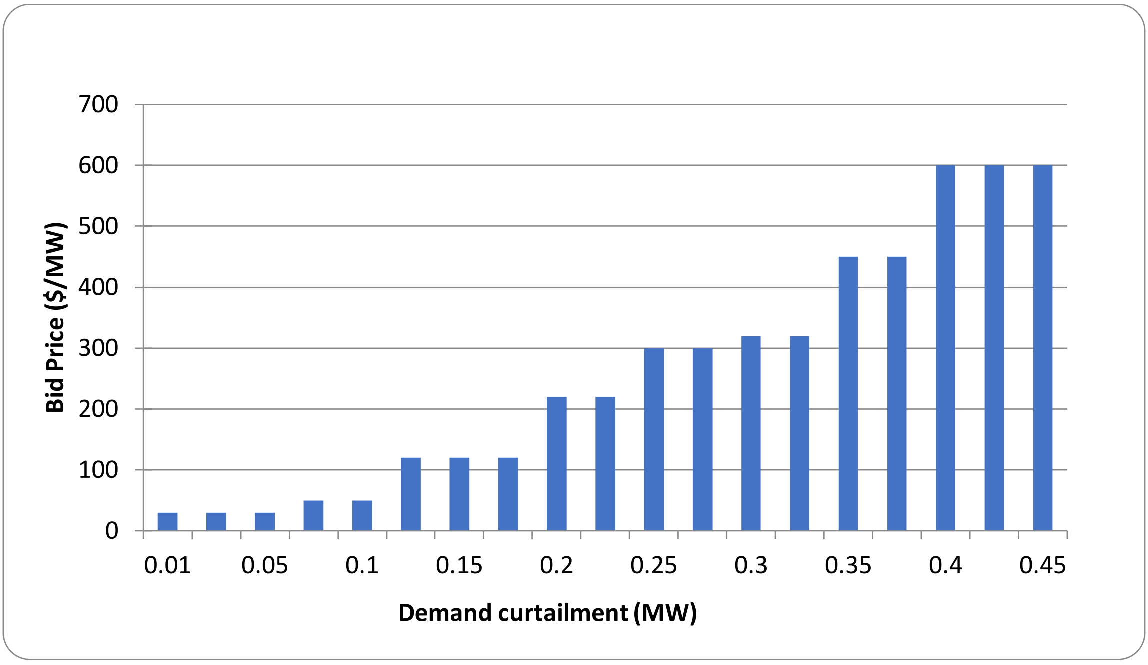


**Fig. 4** *Bid price for DSM*

## 6.1 Results

This section presents the findings from the previously mentioned case studies. Furthermore, a comparative analysis of the proposed modeling is carried out by discussing the cases to demonstrate its advantages. The cases are organized as follows:

Case A) This case study examines the operation of AES without the implementation of DSM. The operator is the primary decision maker responsible for enhancing pre-defined objectives within the AESs. Figure 5 illustrates the non-dominated solutions for the objectives in Case A, as well as the optimal solution. The optimal solution was achieved using the Fuzzy max-min decision-making method. The optimal solution highlighted in red in Fig. 5 demonstrates operation costs of $14,365.3 and voltage levels of 7.65 pu.

Table 1 illustrates the electrical power distribution for Case A. It is evident that DGs 2 and 3, which incur lower fuel expenses compared to DG 1, are employed consistently across all hours. Figure 6 displays the voltage index. The voltage buses deviate from the reference voltage by 7.65 pu. The highest voltage drop is observed at bus 18, measuring 0.58 pu. This voltage drop is influenced by deficiencies in power delivery and peak consumption levels.

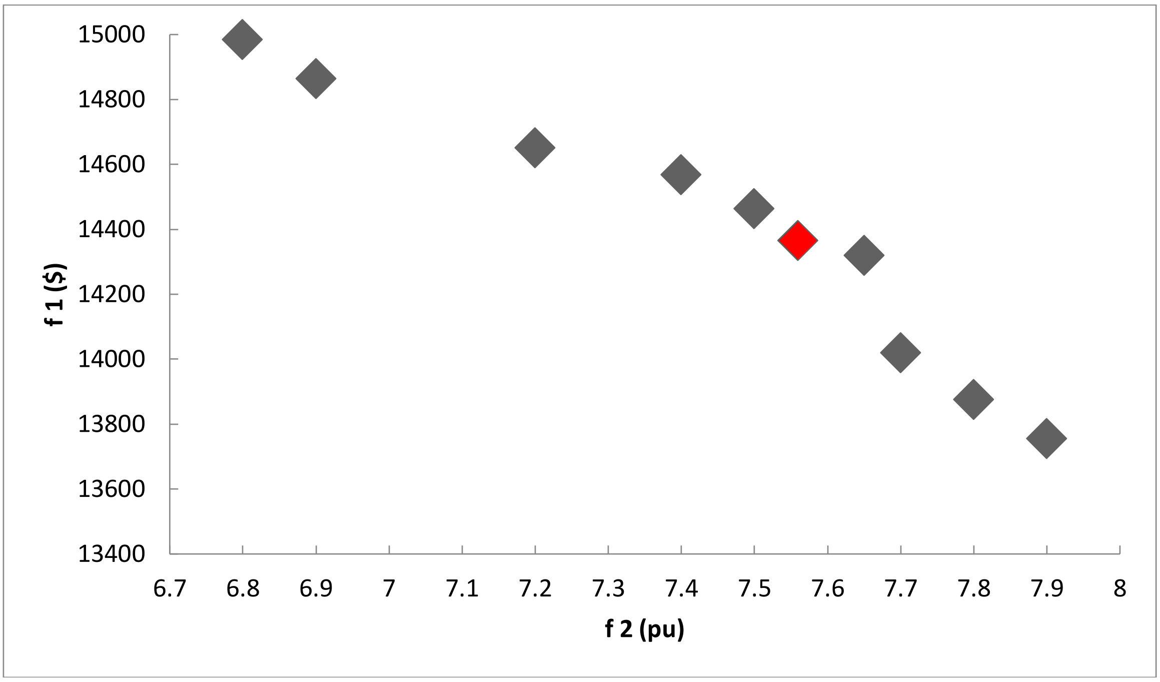


**Fig. 5** *Non-dominated solutions in Case A*

**Table 1** *Energy of the DGs in Case A*

| Hour | DG 1 (MW) | DG 2 (MW) | DG 3 (MW) |
|---|---|---|---|
| 1 | 0 | 0.85 | 0.73 |
| 2 | 0 | 0.79 | 0.66 |
| 3 | 0 | 0.68 | 0.56 |
| 4 | 0 | 0.74 | 0.63 |
| 5 | 0 | 0.76 | 0.65 |
| 6 | 0 | 0.95 | 0.84 |
| 7 | 0.09 | 0.95 | 0.95 |
| 8 | 0.7 | 0.74 | 0.55 |
| 9 | 0.72 | 0.82 | 0.76 |
| 10 | 0.68 | 0.8 | 0.67 |
| 11 | 0.91 | 0.95 | 0.85 |
| 12 | 0.5 | 0.8 | 0.5 |
| 13 | 0.78 | 0.88 | 0.73 |
| 14 | 0.81 | 0.9 | 0.76 |
| 15 | 0.91 | 0.95 | 1 |
| 16 | 0.66 | 0.76 | 0.7 |
| 17 | 0.71 | 0.79 | 0.66 |
| 18 | 0.95 | 0.95 | 1 |
| 19 | 0.92 | 0.95 | 1 |
| 20 | 0.91 | 0.95 | 1 |
| 21 | 0.78 | 0.87 | 0.78 |
| 22 | 0.78 | 0.88 | 0.76 |
| 23 | 0.93 | 0.95 | 1 |
| 24 | 0.1 | 0.9 | 1 |


**Fig. 6** *Voltage of buses in Case A*

Case B) In Case B, the AES is operated with the participation of load management. This case study assumes that all consumers are subject to bid price for demand management under load management. Fig. 7 compares the original load demand with the implementation of load management. The figure shows a reduction in load demand during hours 6-23, with a total reduction of 6.01 MW compared to the original demand. The non-dominated solutions obtained through the implementation of PSO algorithm in Case B are depicted in Fig.8. The optimal solution, with a maximum rate of 0.52, has been selected, wherein the operation cost and voltage deviation are valued at $13486.2 and 6.83pu, respectively. Notably, in Case B, the total operation cost has been reduced by 6.12% as compared to Case A.

Table 2 illustrates the power generation of DGs in Case B. The implementation of demand management strategies results in a reduction of peak hour demand, allowing for the scheduling of optimal power generation to meet demand.

Fig.9 illustrates the voltage index for all case studies. Notably, Case B exhibits an improved voltage profile compared to Case A, attributed to the successful implementation of load management by consumers across all buses. The utilization of load management techniques has resulted in a reduction in voltage drop in bus 18, relative to the reference voltage.

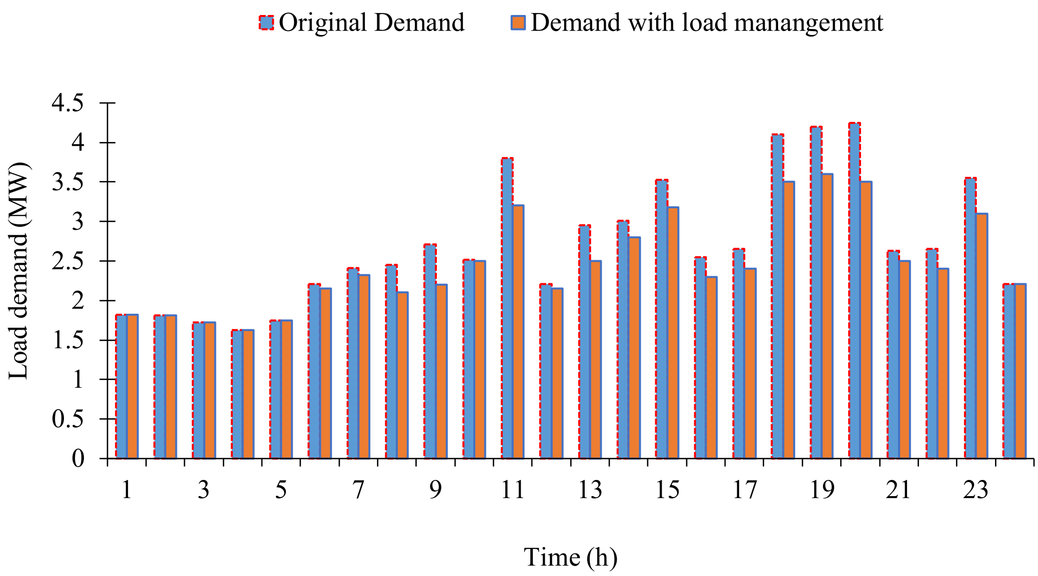


**Fig. 7** *Load demand with management*

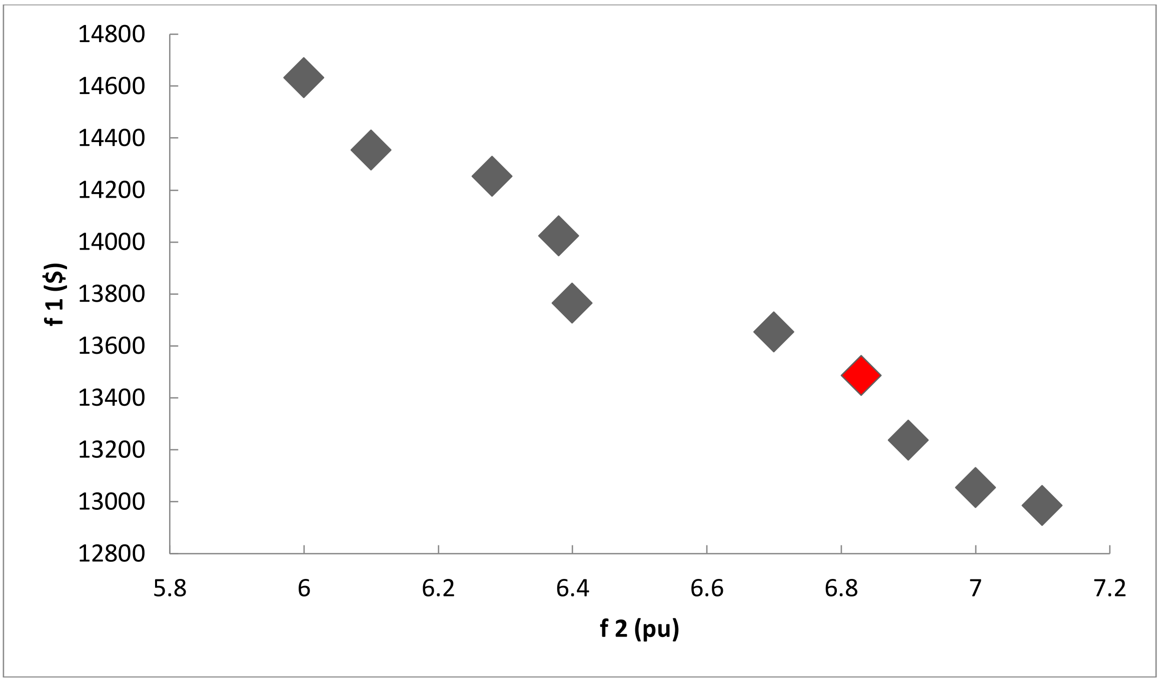


**Fig. 8** *Non-dominated solutions in Case B*

**Table 2** *Energy of the DGs in Case B*

| Hour | DG 1 (MW) | DG 2 (MW) | DG 3 (MW) |
|---|---|---|---|
| 1 | 0 | 0.65 | 1 |
| 2 | 0 | 0.79 | 0.66 |
| 3 | 0 | 0.68 | 0.56 |
| 4 | 0 | 0.74 | 0.63 |
| 5 | 0 | 0.76 | 0.65 |
| 6 | 0 | 0.93 | 0.84 |
| 7 | 0 | 0.9 | 1 |
| 8 | 0 | 0.93 | 1 |
| 9 | 0 | 0.82 | 1 |
| 10 | 0.45 | 0.8 | 0.63 |
| 11 | 0.86 | 0.95 | 0.88 |
| 12 | 0.73 | 0.8 | 0.65 |
| 13 | 0.38 | 0.88 | 0.73 |
| 14 | 0.68 | 0.9 | 0.76 |
| 15 | 0.7 | 0.95 | 1 |
| 16 | 0.3 | 0.95 | 1 |
| 17 | 0.4 | 0.79 | 0.75 |
| 18 | 0.5 | 0.95 | 1 |
| 19 | 0.8 | 0.95 | 1 |
| 20 | 0.6 | 0.95 | 1 |
| 21 | 0.7 | 0.9 | 0.73 |
| 22 | 0.43 | 0.93 | 0.9 |
| 23 | 0.93 | 0.95 | 1 |
| 24 | 0 | 0.9 | 1 |

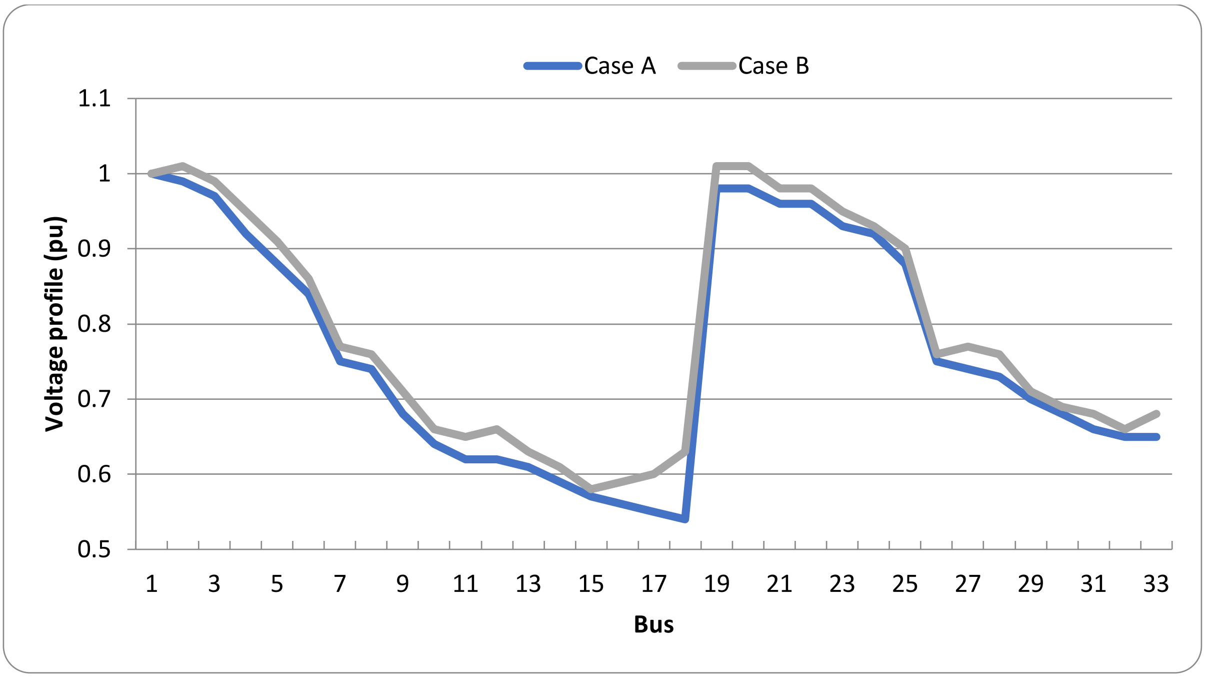


**Fig. 9** *Voltage of buses in Case B*

## 7. Conclusion

This research paper introduces a novel model that aims to optimize the multi-objective functions of AES, while taking into consideration both technical and economic indices. The model focuses on two specific objective functions: operational cost and the improvement of the voltage index in AES. To achieve the desired objective functions, the study proposes the implementation of load management techniques, which involve consumers responding to bid prices from the operator in order to reduce demand. The proposed methodology utilizes the PSO algorithm and a fuzzy decision-making approach to optimize the model. This allows for the selection of the most optimal solution from a set of non-dominated solutions, based on the desired objectives. The results of the study demonstrate that the implementation of the proposed load management strategy by consumers in AES leads to an increase in generation capacity, thereby improving both technical and economic objectives. To validate the effectiveness of the proposed strategy, two case studies are implemented. With implementing demand management, operational cost is minimized by 6.12% and voltage indices is improved by 9.65% than without implementing demand management.

## Acknowledgement

The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University for funding this work through large group Research Project under grant number RGP2/403/45

## Conflict of Interest

The authors declare that they have no known competing interests.

## Author Contribution

Paul Rodrigues, Ashish Singh, Vikas Kaushik, Jasgurpreet Singh Chohan, Mustafa Adnan Abdulrahman, Layth Hussein, Y.S Romaní have equal contributions reviewing and editing the writing, formal analysis, software development and conceptualization.

## References

[1] Malik, G. H., Al Jasimee, K. H., & Alhasan, G. A. K. (2019). Investigating the Effect of Using Activity Based Costing (ABC) on Captive Product Pricing System in Internet Supply Chain Services. Int. J Sup. Chain. Mgt Vol, 8(1), 400.

[2] Al Jasimee, K. H., & Blanco-Encomienda, F. J. (2024). Decoding task uncertainty: moderating effects on participative budgeting and budgetary slack dynamics. Total Quality Management & Business Excellence, 1-19.

[3] Kunelbayev, M. ., Mansurova, M. ., Tyulepberdinova, G. ., Sarsembayeva, T. ., Issabayeva, S. ., & Issabayeva, D. (2024). Comparison of the parameters of a flat solar collector with a tubular collector to ensure energy flexibility in smart buildings. International Journal of Innovative Research and Scientific Studies, 7(1), 240–250. https://doi.org/10.53894/ijirss.v7i1.2605.

[4] Stamatiou, P. . (2024). Quality of life: The role of tourism and renewable energy. International Journal of Applied Economics, Finance and Accounting, 18(1), 43–52. https://doi.org/10.33094/ijaefa.v18i1.1286.

[5] Uckun-Ozkan, A. . (2024). The impact of investor attention on green bond returns: How do market uncertainties and investment performances of clean energy and oil and gas markets affect the connectedness between investor attention and green bond?. Asian Journal of Economic Modelling, 12(1), 53–75. https://doi.org/10.55493/5009.v12i1.4986.

[6] Hussan, B. K., Rashid, Z. N., Zeebaree, S. R., & Zebari, R. R. (2023). Optimal Deep Belief Network Enabled Vulnerability Detection on Smart Environment. Journal of Smart Internet of Things, 2022(1), 146-162.

[7] Hagh, S. F., Amngostar, P., Zylka, A., Zimmerman, M., Cresanti, L., Karins, S., O'Neil-Dunne, J. P., Ritz, K., Williams, C. J., Morales-Williams, A. M., Huston, D., & Xia, T. (2024). Autonomous UAV-Mounted LoRaWAN System for Real-Time Monitoring of Harmful Algal Blooms (HABs) and Water Quality. IEEE Sensors Journal, 24(7), 11414-11424. https://doi.org/10.1109/JSEN.2024.3364142.

[8] Panahi, S., & Cheraghifar, F & Talebian, Sh. (2018). An Investigation on Painting and Imagery in Zen, Modern Applied Science; Vol. 12, No. 9; 2018, 200-208.

[9] Emdadi Derabi, M., Sangsefidi, M., & Rahmani, O. (2021). The effect of thickness on the multiwalled carbon nanotubes performance in glass/epoxy composite laminates under dynamic loading. Polymer Composites, 42(11), 5789-5800. https://doi.org/10.1002/pc.26260

[10] Shabani, S., Majkut, M., Dykas, S., Smołka, K., & Cai, X. (2022). Liquid Phase Identification in Wet Steam Transonic Flows by Means of Measurement Methods. Journal of Physics: Conference Series, 2367(1), 012013. https://doi.org/10.1088/1742-6596/2367/1/012013

[11] Hagh, S. F., Amngostar, P., Chen, W., Sheridan, J., Williams, C. J., Morales-Williams, A. M., Huston, D., & Xia, T. (2024). A Low-Cost LoRa Optical Fluorometer–Nephelometer for Wireless Monitoring of Water Quality Parameters in Real Time. IEEE Sensors Journal, 24(13), 21511-21519. https://doi.org/10.1109/JSEN.2024.3403416

[12] Naseri, S., Eshraghi, S., & Talebian, S. (2024). "Innovative Sustainable Architecture A Lesson Learned from Amphibious House in the UK". Current Opinion, 4(4), 766–777. https://doi.org/10.52845/currentopinion.v4i4.318

[13] Shabani, S., & Majkut, M. (2024). CFD approach for determining the losses in two-phase flows through the last stage of condensing steam turbine. Applied Thermal Engineering, 123809. https://doi.org/10.1016/j.applthermaleng.2024.123809

[14] Shokrollahi, H., Emdadi Derabi, M. (2024). Deformation of an Open Sandwich Cylindrical Shell with CNT Reinforced Faces Using HDQ Method. Arabian Journal for Science and Engineering. https://doi.org/10.1007/s13369-024-09339-1

[15] Kiani, S., Salmanpour, A., Hamzeh, M., & Kebriaei, H. (2024). Learning Robust Model Predictive Control for Voltage Control of Islanded Microgrid. IEEE Transactions on Automation Science and Engineering. doi: 10.1109/TASE.2024.3388018

[16] Shabani, S., Majkut, M., Dykas, S., Smołka, K., Lakzian, E., Ghodrati, M., & Zhang, G. (2024). Evaluation of a New Droplet Growth Model for Small Droplets in Condensing Steam Flows. Energies, 17(5), 1135. https://doi.org/10.3390/en17051135.

[17] Seifi, N. and Al-Mamun, A. (2024) Optimizing Memory Access Efficiency in CUDA Kernel via Data Layout Technique. Journal of Computer and Communications, 12, 124-139. doi: 10.4236/jcc.2024.125009.

[18] H Chamandoust et al. Tri-objective optimal scheduling of smart energy hub system with schedulable loads. Journal of Cleaner Production. 236. 117584. 2019. https://doi.org/10.1016/j.jclepro.2019.07.059.

[19] H Chamandoust et al. Multi-objective performance of smart hybrid energy system with Multi-optimal participation of customers in day-ahead energy market. Energy & Buildings. 216. 109964. 2020. https://doi.org/10.1016/j.enbuild.2020.109964.

[20] H Chamandoust et al. Multi-objectives Optimal Scheduling in Smart Energy Hub System with Electrical and Thermal Responsive Loads. Environmental and Climate Technologies. 24. 209-232. 2020. https://doi.org/10.2478/rtuect-2020-0013.

[21] H Chamandoust et al. Tri-objective scheduling of residential smart electrical distribution grids with optimal joint of responsive loads with renewable energy sources. Journal of Energy Storage. 27. 2020. 101112. https://doi.org/10.1016/j.est.2019.101112.

[22] H Chamandoust et al. Multi-objective operation of smart stand-alone microgrid with the optimal performance of customers to improve economic and technical indices. Journal of Energy Storage. 31. 2020. 101738. https://doi.org/10.1016/j.est.2020.101738.

[23] H Chamandoust et al. Energy management of a smart autonomous electrical grid with a hydrogen storage system. International journal of hydrogen energy. 46. 17608-17626. 2021. https://doi.org/10.1016/j.ijhydene.2021.02.174.

[24] H Chamandoust et al. Day-ahead scheduling problem of smart micro-grid with high penetration of wind energy and demand side management strategies. Sustainable Energy Technologies and Assessments. 40.100747. 2020. https://doi.org/10.1016/j.seta.2020.100747.

[25] H Chamandoust et al. Optimal hybrid participation of customers in a smart micro-grid based on day-ahead electrical market. Artificial Intelligence Review. 2022. In press. https://doi.org/10.1007/s10462-022-10154-z.

[26] H Chamandoust et al. Energy Economic Management of Hybrid Energy System Based on Short-term Generation and Demand Response. Environmental and Climate Technologies. 24. 653–668.2020. https://doi.org/10.2478/rtuect-2020-0040.

[27] Chamandoust H., Hashemi A., Derakhshan G., Abdi B. Optimal Hybrid System Design Based on Renewable Energy Resources. IEEE Smart Grid Conference (SGC), Dec 2017. https://doi.org/10.1109/SGC.2017.8308878.

[28] Chamandoust H. et al. Scheduling of Smart Micro Grid Considering Reserve and Demand Side Management. IEEE Smart Grid Conference (SGC), 2018. https://doi.org/10.1109/SGC.2018.8777926.

[29] Xu, J., Liu, S., & Ming, X. (2024). Reduced order calculation method of subsynchronous oscillation mode of PMSG based wind farm connected with power grid based on Arnoldi method. Science and Technology for Energy Transition, 79, 47.

[30] Jiang, S., Shu, N., Liang, T., Cao, X., Chen, S., Yang, P., ... & Sun, H. (2024). Control strategy and capacity optimization of energy-storage-based railway power conditioner. *Science and Technology for Energy Transition*, *79*, 46.

[31] Pavan, G., & Babu, A. R. (2024). Enhanced Randomized Harris Hawk Optimization of PI controller for power flow control in the microgrid with the PV-wind-battery system. *Science and Technology for Energy Transition*, *79*, 45.

[32] Adeleye, S. A., Adebanji, B., & Awogbemi, O. (2024). Renewable energy sources acceptability for decentralized energy system in Nigeria: Issues, challenges and prospects. *Science and Technology for Energy Transition*, *79*, 44.

[33] Liu, C., Tang, X., Yu, F., Zhang, D., Wang, Y., & Li, J. (2024). Carbon emission measurement method of regional power system based on LSTM-Attention model. *Science and Technology for Energy Transition*, *79*, 43.

[34] Du, X., Yang, Y., & Guo, H. (2024). Economic energy scheduling of electrical microgrid considering optimal participation of the electric vehicles. *Science and Technology for Energy Transition*, *79*, 42.

[35] Kaur, S., Bala, A., & Parashar, A. (2024). A multi-step electricity prediction model for residential buildings based on ensemble Empirical Mode Decomposition technique. *Science and Technology for Energy Transition*, *79*, 7.

[36] Saurabh, S., & Kumar, R. (2024). Optimizing PV integration: Addressing energy fluctuations through BIPV and rooftop PV synergy. *Science and Technology for Energy Transition*, *79*, 6.

[37] Ergul, M., & Selimli, S. (2024). An applied study on energy analysis of a coke oven. *Science and Technology for Energy Transition*, *79*, 1.

[38] Özgür, C., Uludamar, E., Soyhan, H. S., & Shah, R. M. R. A. (2024). Optimisation of exhaust emissions, vibration, and noise of unmodified diesel engine fuelled with canola biodiesel-diesel blends with natural gas addition by using response surface methodology. *Science and Technology for Energy Transition*, *79*, 37.

[39] Anand, M., Chatterjee, D., & Goswami, S. K. (2024). Optimal frequency determination for wind–hydro hybrid unit using Telegrapher's method for low-frequency transmission lines. *Science and Technology for Energy Transition*, *79*, 40.

[40] Manzoor, A., Akram, W., Judge, M. A., Khan, N., & Khattak, H. A. (2024). Efficient economic energy scheduling in smart cities using distributed energy resources. *Science and Technology for Energy Transition*, *79*, 29.