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Development of an Optimal Energy Management System for Grid-Connected Micro Grid

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ABSTRACT

This paper developed an optimal energy management system (EMS) for a grid-connected microgrid (MG) integrating distributed generation (DG) to minimize operational costs of the MG, which consisted solar PV, micro turbine, wind turbine, combined heat and power, electricity energy storage, and fuel cells. The parameters were optimized using particle swarm optimization (PSO) algorithms and implemented by MATLAB/SIMulink 2023a. With 100% investment in energy efficiency, operational costs decreased from approximately $218 to $207, representing a 5.31% reduction in the operational cost of the system. The challenges were addressed through the new methodologies, improved results were compared to mixed integer non-linear programming (MINLP) used in the base paper.

1. INTRODUCTION

In recent years, the grid has become the most sustainable renewable energy sources worldwide as compared to other energy generation sources (Tze-Zhang Ang, et al., 2022). The integration of distributed renewable energy resources (DERs) into the conventional electricity distribution grid aims to reduce power cost for consumers, eliminate environmental pollution, increase production capacity, lower maintenance costs, and ensure the global availability of the parts, making it a reliable alternative power supply in the electricity industry (Subhasis, et al., 2022). With the emerging technologies, the structure of power system was changed from one-way communication to two-way communication in the MG with high flexibility of power system (Montinur, et al., 2024). This concept has some integral elements such as Distributed Generations (DGs), Demand Response Programs (DRPs) and energy storage (EESSs) systems to facilitate the operational objectives. The EESSs played vital roles in MG in terms of cost reduction and quick investment return rate in energy management program (EMP) (Junjie, et al., 2024). One of the interesting and relevant problems for the MG was the evaluation of the operation of EESSs in the day ahead of generation scheduling problem (Dorahaki et al., 2020). The energy management model was developed considering the EESSs and thermal storages in the residential energy systems (Boyko et al., 2024).

Nowadays, the MG operations are challenged by the integration of more DGs (Abhay et al., 2024). Furthermore, the operation of MGs would depend on the power exchange level between a MG and the main grid (Yousi et al., 2022). Therefore, it was important to apply energy management in order to optimize the operation of the MGs with the aim of providing power consumption with the lowest operation cost. The challenges and opportunities which are related to energy management system in the MG have been investigated (Shahimol et al., 2023). The paper offered a comprehensive overview of DGs and their application in the MG system. The structure was proposed to solve the optimal energy market management and optimal energy pricing in the grid power system (Dorahaki et al., 2020). Therefore, the control-theoretic approaches were developed to provide feasible solutions for optimal energy market management and dynamic energy pricing. Furthermore, the EESSs and DGs have been considered to demonstrate the grid environment (Dorahaki et al., 2020). A method for monitoring and implementation of MGs was presented and the main objective was to offer a model for the long-term implementation and planning of the MG (Kayode et al., 2025). A probabilistic energy management of the MGs was proposed with wind, solar, fuel cell, electrical and thermal energy storages. The uncertainty was considered in the energy management when dealing with the data from wind and solar energy and the main contribution was to apply point estimation method in the MGs (Shamugaraia et al., 2022). The economic analysis and energy management of the grid-connected was provided for MG in Thailand (Vikas et al., 2023). The review between the electrical, thermal storages were investigated and the results showed that proper utilization and appropriate sizing of electrical and thermal storage provided substantial economic benefits. The Demand Side Management (DSM) programs are realized as virtual power plant (Dorahaki et al., 2020). This is why the results of the DSM programs on the short-term and long-term load demands are significant because any increase in DSM programs would lead to reduction in the cost of power systems as well as greenhouse emissions. The DSM programs are categorized into Demand Response Programs (DRPs) and the Energy Efficiency Programs (EEPs) (Hossein et al., 2022).

In this study, the EEPs and DRPs were vital tools in the MG environment to ensure energy management efficiency. The EEPs was used as economic tool to decrease the planning cost and increase the social benefits. This paper considers the EEPs policy as effective tool to achieve the energy conservation targets (Dorahaki et al., 2020). The outcome of EEPs on the load demand was the same with respect to time while on the contrary, the DRPs effects were changing with time. Moreover, the EEPs in the power system are categorized to the generation side EEPs and the demand side EEPs. In the generation side EEPs, the system operator of the MG tries to use the energy efficient resources to decrease the operation cost of the system as well as the greenhouse gas emissions. Therefore, this would significantly raise the total energy productivity index of the MG. In this research work, demand side EEPs would be considered as a virtual demand side power plant to lowering the electrical and thermal demand by raising the energy efficiency of the consumer's appliances (Dorahaki et al., 2020). The generation units with increasing operation cost are decommitted with significant consideration for demand side EEPs. Consequently, the total operation cost of the MG would be reduced and from the customer viewpoint, billing cost would be equally reduced resulting in efficient investment returns (Dorahaki et al., 2020). In this research work, demand side EEPs would be considered as a virtual demand side power plant to lowering the electrical and thermal demand by raising the energy efficiency of the consumer's appliances (Dorahaki et al., 2020). The generation units with increasing operation cost are decommitted with significant consideration for demand side EEPs. Consequently, the total operation cost of the MG would be reduced and from the customer viewpoint, billing cost would be equally reduced resulting in efficient investment returns (Dorahaki et al., 2020).). This research was conducted to reduce the operational cost of energy management by considering EEPs and EESSs within MG environment. In this study, uncertainties related to combined CHP systems and boilers were not considered. The developed energy management approach aims to enhance cost efficiency in power generation for consumers through the implementation of EEPs and EESSs components in the MG. A Particle Swarm Optimization (PSO) algorithm was applied and MATLAB software achieve this goal.

2. THE PROPOSED FRAMEWORK OF ENERGY MANAGEMENT PROGRAM CONSIDERING EEPS AND EESSS MODEL $(\boldsymbol{EMP_{EESS}^{EEP}})$.

MGs effectively integrate DGs, EESSs, and demand side management programs, with DGs being the primary elements. EESSs are optional but incorporate advanced technologies that can be costly. System operators must thoroughly assess the technical and financial implications of EESSs before implementation. Additionally, demand side management programs, particularly EEPs, represent a viable investment avenue for enhancing energy efficiency. A novel framework for analyzing the impacts of EEPs and EESSs on energy management programs in MG is proposed. This framework aims to facilitate better decision-making for system operators, promoting efficiency and optimization within the energy management landscape. Figure 1, show the proposed framework of the MGs.

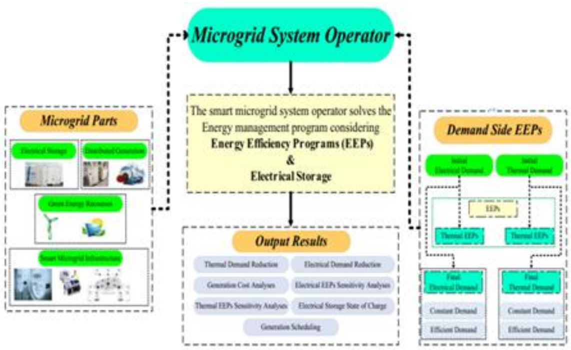

Figure 1. The proposed framework of the MGs

Figure 1, left side illustrates key MG components: electrical storage, DGs, green energy resources, and MG infrastructure submitted to operators. The demand model of MGs, depicted in Figure 1, categorizes demand into electrical and thermal components. Each component is split into a constant part, represented by a dashed line, and a variable part that participates in EEPs. This model is submitted to the MG system operator for management and optimization. The dual categorization aids in understanding and addressing the demands effectively.

2.1 Solar PV system

The PV cell model includes a photocurrent, diode, parallel resistor for leakage current, and series resistor, as shown in Figure 2. Its current can be described using Kirchhoff's circuit laws, represented by equation (1).

$$I_{pv} = I_{ph} - I_d - I_p = I_{ph} - I_0\left(e^{\frac{V_{pv}+R_sI_{pv}}{n_sV_tQ_d}} - 1\right) \quad (1)$$

where; $V_{pv} = PV - module$, I_{pv}= PV Module Current, I_{pv}= Light current in (A), I_{pv}= Diode reverse saturation current, Q_d= Diode idealistic factor, R_p= Shun Resistance, R_s= series resistance, n_s = number of cells, $V_t = \frac{KT_c}{q}$ is the thermal voltage (V), k is Boltzmann's constant, T_c is the cell temperature, and q is the charge of an electron respectively.

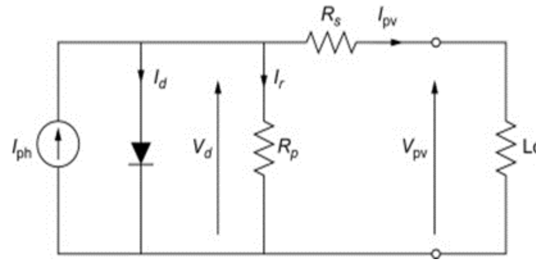

Figure 2: PV Model Electrical equivalent circuit

2.2 Energy storage system

The Battery energy storage systems (BESS) feature high energy density and rapid access, crucial for storing large energy amounts. They enable balanced use of generation facilities by storing excess energy during off-peak hours for later use during peak times. The rise of intermittent renewable sources, such as wind and solar, highlights the need for small-scale storage solutions. Batteries provide efficient electrochemical storage, offering quick power delivery or sustained energy over time, with increased capacity through module connections.

The battery ensures RES operates effectively, providing constant power; its transfer function model is described as a first-order equation by Das et al. (2011) as given in (2).

$$SOC(t) = SOC(t_0) - \frac{1}{C_n}\int_{t_0}^{t} I(\tau)dr \quad (2)$$

where K_{BESS}, ΔP_{BESS}, and ΔU_{BESS} are the gain constant, the time constant (in seconds), the power output (in p.u.) and the associated input of the BESS unit, respectively.

2.3 Wind turbine system

The Wind energy is rapidly growing as a renewable electricity source. Wind turbines operate remotely and face harsh weather variations, including severe winds, heat, and cold. These conditions create fluctuating loads on the turbines, resulting in significant mechanical stress due to variable operational states (Shankar & Mukherjee, 2016).

A wind farm was model using Homer software environment. The power captured from wind P_m can be expressed mathematically as in (3).

$$P_m = 0.5\rho\pi r^2 {V_w}^3 C_p(\lambda, \beta) \tag{3}$$

where ρ equals air density, r represents blade radius, V_w represents wind speed, λ equal tip speed ratio, β is blade pitch angle, R is radius of WT rotor, ω_B equals blade speed and the power coefficient C_p is given by (5) (Hasanien & El-Fergany, 2019).

$$\lambda = \frac{\omega_B R}{V_w}, \lambda_i = \frac{3600R}{1609\lambda} \tag{4}$$

$$C_p = 0.5(\lambda_i - 0.022\beta^2 - 5.6)e^{-0.17\lambda_i} \tag{5}$$

2.4 Electrical and thermal demand

In Figure 3, the peak electrical demand occurs between 15:00 and 17:00, while the peak thermal demand happens between 23:00 and 2:00. The microgrid (MG) is operating in grid-connected mode, making power exchange prices crucial. With this data, the grid operator can effectively buy and sell energy. Figure 4 illustrates the power exchange prices, including both the selling price and the buying price.

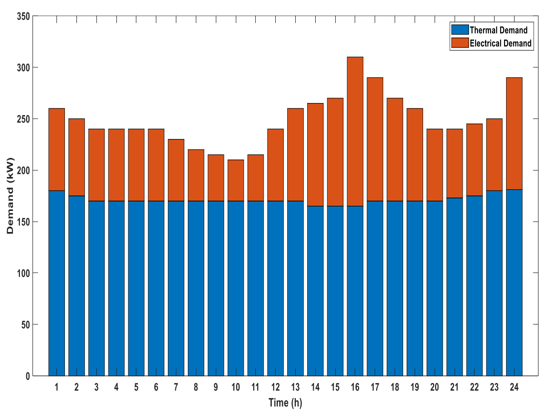

Figure 3: MG Electrical and Thermal Demand (Dorahaki et al., 2020)

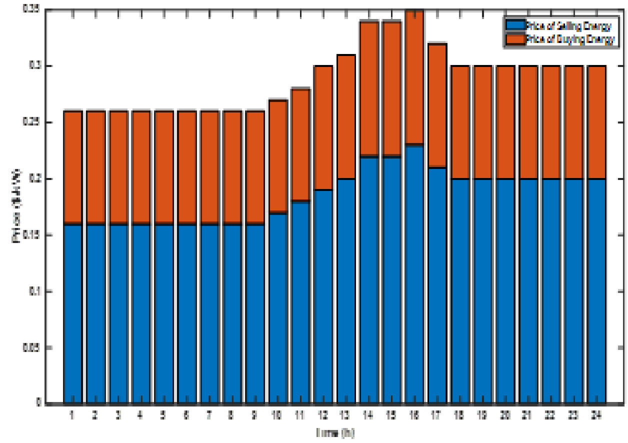

Figure 4: Exchange Power Hourly Price (Dorahaki et al., 2020)

3. METHODOLOGY

1.1 Formulation of objective function

Within the context of economic challenges in energy management program, the overall objective is to reduce the operational cost as defined in equation (6).

$$F(cost) = \sum_{t=1}^{T} \Big(C_{CHP}(t) + C_{wind}(t) + C_{boiler}(t) + C_{pv}(t) + C_{buy}(t) + C_{ES}(t) + C_{MT}(t) - C_{sell}(t)\Big) \tag{6}$$

where F(cost) is the total generation cost, $C_{CHP}(t)$ is the cost of the CHP′s unit, $C_{wind}(t)$ is the cost of wind unit, $C_{boiler}(t)$ is the cost of boiler unit, t is time, $C_{PV}(t)$ is the cost of solar unit, $C_{buy}(t)$ the cost incurred by purchasing power, $C_{sell}(t)$ the income of power sales, $C_{ES}(t)$ the cost of the electric storage unit and $C_{MT}(t)$ cost of the microturbine unit. The cost functions are in dollars ($).

Equation (7) shows the output cost of the CHP's unit as in (7);

$$C_{CHP}(t) = \frac{C_{fuel} \cdot P_{CHP}(t) \cdot \theta}{\eta_{CHP}} + C_{op-chp} . P_{CHP}(t) \cdot \theta + C_{m-chp} \tag{7}$$

where C_{fuel} is the fuel price, $P_{CHP}(t)$ is the CHP output power, θ is the time frame, n_{CHP} is the CHP efficiency rate, C_{op-chp} the variable cost of CHP in ($;/kW) and C_{m-chp} is the fixed cost of CHP unit. All power units are in kW. Equation (8) shows the cost of the wind unit,

$$C_{wind}(t) = C_{op-wt} \cdot P_{wt}(t) \cdot \theta + C_{cons-wt} \quad (8)$$

where C_{op-wt} is the variable cost of wind in($;/kW), $P_{wt}(t)$ is the output wind power, and $C_{cons-wt}$ the fixed cost of wind unit. Equation (9) represents the output cost of the boiler unit.

$$C_{boiler}(t) = \frac{C_{fuel} \cdot P_{boiler}(t) \cdot \theta}{\eta_{boiler}} + C_{op-boiler} \cdot P_{boiler}(t) \cdot \theta + C_{m-boiler} \quad (9)$$

where $P_{boiler}(t)$ is the thermal power of the boiler unit, n_{boiler} is the boiler efficiency rate, $C_{op-boiler}$ is the variable cost of boiler in ($;/kW) and $C_{m-boiler}$ the fixed cost of boiler unit. The output cost of the solar unit is described in equation (10);

$$C_{PV}(t) = C_{op-pv} \cdot P_{pv}(t) \cdot \theta + C_{cons-p} \quad (10)$$

where Cop−pv is the variable cost of the solar unit in ($;/kW), Ppv(t) solar output power and Ccons−pv the fixed cost of the PV unit. Since MG could exchange power with the main grid during operation with the aim of buying when the generated power is low and sell excess when generated power exceeds demand, equations (11) and (12) stated these two scenarios of exchange power cost as follows,

$$C_{buy}(t) = c_{buy} \cdot P_{buy}(t) \cdot \theta \quad (11)$$

$$C_{sell}(t) = c_{sell} \cdot P_{sell}(t) \cdot \theta \quad (12)$$

where $C_{buy}(t)$ is the price of buying power from the grid in ($;/kW), $C_{sell}(t)$ is the price of selling power to the grid in ($;/kW), $P_{buy}(t)$ is the amount of power to buy from the grid and $P_{sell}(t)$ is the amount of power to be sold to the grid.

The cost of the electrical storages is presented in equation (13).

$$C_{ES}(t) = C_{op-ES} \cdot P_{ES}(t) \cdot \theta + C_{m-ES} \quad (13)$$

where C_{op-ES} is the variable cost of EESSs in ($;/kW), C_{m-ES} is the fixed cost of the EESS and P_{ES} is the electrical storage output power. Equation (14) described the cost of micro turbine unit.

$$C_{MT} = \frac{C_{fuel} \cdot P_{MT}(t) \cdot \theta}{\eta_{MT}} + C_{op-MT} \cdot P_{MT}(t) + C_{m-MT} \quad (14)$$

where $P_{MT}(t)$ is the output power of microturbine unit, n_{MT} the micro turbine efficiency rate, C_{op-MT} is the variable cost of microturbine unit in ($;/kW) and C_{m-MT} is the fixed cost of microturbine unit.

3.2 Constraints

Constraints limit the objective function and solution space; Equation (15) details the electric power balance constraint.

$$P_{wt}(t) + P_{pvt}(t) + P_{Mt}(t) + P_{CHP}(t) + P_{ES}(t) + P_{buy}(t) - P_{sell}(t) = E_{LD}(t).(1-\gamma) + \gamma E_{LD}(t)\left(1 + \rho \frac{(ELEEI - ELEEI_0)}{ELEEI_0}\right) \quad (15)$$

where $E_{LD}(t)$ is the electrical load in (kW), γ is the penetration rate of electrical EEPs in (%), ρ is the electrical load elasticity of energy efficiency, ELEEI is the improved electrical energy efficiency rate in (%) and ELEEIo is the current percentage of investment electrical energy efficiency. The generated power by DGs must match consumer demand, enabling investment in energy efficiency, which subsequently decreases demand, as expressed in equation (15).

In the equation (16), the thermal load equilibrium is shown with the generated heat energy.

$$P_{boiler}(t) + P_{CHP}(t).TF_{CHP} = T_{LD}(t).(1-\beta) + \beta T_{LD}(t)\left(1 + \delta \frac{(ThEEI - ThEEI_0)}{ThEEI_0}\right) \quad (16)$$

where TF_{CHP} is the coefficient between the electrical power and thermal output of CHP, $T_{LD}(t)$ is the thermal load in (kW), β is the penetration rate of thermal EEPs in (%) δ is the thermal elasticity of energy efficiency, ThEEI is the improved thermal energy efficiency rate (%) and ThEEIo is the current percentage of investment on thermal energy efficiency (%).

The relationship in equation (16) shows the existence of thermal investment elasticity of load, it further describes a decrease in thermal demand with a corresponding investment in energy efficiency.

The limit of the CHP's unit constraint is represented in equation (17),

$$0 \leq P_{CHP} \leq P_{CHP}^{max} \tag{17}$$

Equation (18) described the constraint in thermal generation capacity of the boiler between the minimum and maximum value,

$$0 \leq P_{boiler} \leq P_{boiler}^{max} \tag{18}$$

Equation (19) stated the constraint in output power of micro turbine,

$$0 \leq P_{MT} \leq P_{MT}^{max} \tag{19}$$

Equations (20) and (21) showed the limited output power in solar and wind units respectively,

$$0 \leq P_{PV} \leq P_{PV}^{max} \tag{20}$$

$$0 \leq P_{WT} \leq P_{WT}^{max} \tag{21}$$

Equation (22) described the power exchange with the main grid and the transmission line limits,

$$P_{buy}(t)\ or\ P_{sell}(t) \leq P_{line} \tag{22}$$

Equations (23) to (26) represented the modeled storage EESSs.

$$P_{ES}(t) \leq P_{dech}^{max}\ for\ disch\ (P_{ES}(t) > 0 \tag{23}$$

$$-P_{ES}(t) \leq P_{ch}^{max}\ for\ ch\ (P_{ES}(t) < 0 \tag{24}$$

$$P_{ES}(t) = E_s(t) - E_s(t-1) \tag{25}$$

$$E_s^{min} \leq E_s(t) \leq E_s^{max} \tag{26}$$

3.3 Proposed optimization algorithm

The aim of the suggested energy management is to implement secure 24-hour-ahead hourly choices for the economic operations of the microgrid. The EMS takes into account the fluctuations in renewables, electric demand, and electricity rates, employing suitable predictions for these factors.

The PSO was utilized in this paper to address the EMS optimization issue as shown in the figure 5, Particle Swarm Optimization algorithm is a stochastic optimization technique inspired by the behavior of bird flocks or fish schools. Initiated with a population of random particles, it searches for optimal solutions. Each particle moves through the search space, tracking its best-known position (Pbest) and the global best (Gbest). The particles adjust their speeds toward both Pbest and Gbest locations, enhancing the efficiency of the search process in finding optimal solutions within a specified problem space (Kumarakrishnan et al., 2020). PSO features equations for particles' speed and position as shown in (27-28).

$$\mathrm{v_{i+1}}^{\mathrm{k}} = \omega \mathrm{v_i^k} + \mathrm{c_l r_l}\left(\mathrm{d_{best}^k} - \mathrm{d_i^k}\right) + \mathrm{c_g r_g}\left(\mathrm{G} - \mathrm{d_i^k}\right) \tag{27}$$

$$\mathrm{d_{i+1}}^{\mathrm{k}} = \mathrm{d_i^k} + \mathrm{v_{i+1}^k} \tag{28}$$

Where ω is the inertia weight, c_l and c_g are the acceleration parameters or self-experience and social experience parameters, respectively. d_{best}^k is the personal best solution or the best private solution of particle k, G is the global best position, k is a counter that represents the particle number k = [1, 2, ... SS], SS is the swarm-size, and r_l and r_g are random values in between [0 1], the counter i is a counter represents the iteration number where its value varies between 1 to maximum iteration number. Figure 5 illustrates the PSO algorithm flowchart.

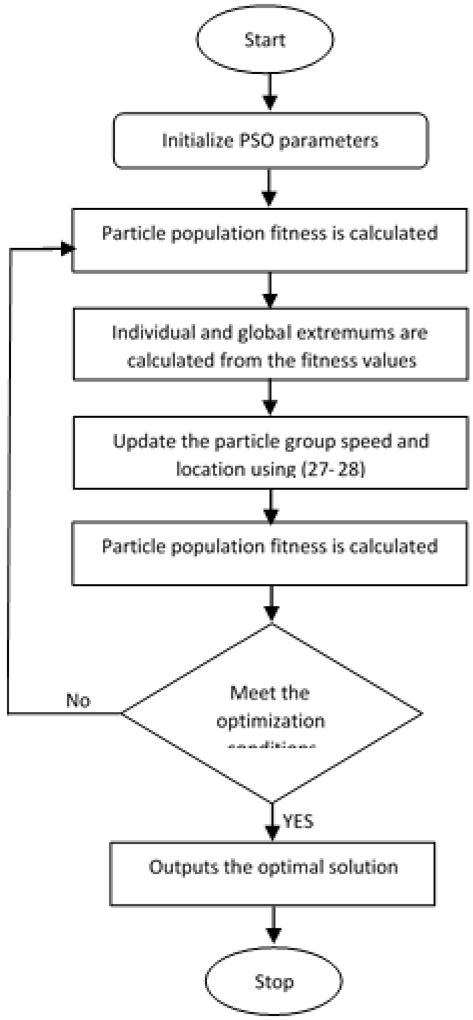

Figure 5: Flowchart of the Particle Swarm Optimization (PSO) algorithm

In this work, the parameters of a SunPower SPR-330E-WHT-D PV module are used for simulation. The solar cell is modeled and simulated using MATLAB software. The simulation is based on the datasheet of the SunPower SPR-330E-WHT-D module. The parameters of this solar module are given in Table 1.

Table 1: SunPower SPR-330E-WHT-D PV module Electrical Characteristic

Parameters	Values
Maximum Power (P_{max})	330.303W
Voltage at P_{max} (V_{mp})	64V
Current at P_{max} (I_{mp})	5.49A
Open-circuit voltage (V_{oc})	85.3V
Short-circuit current (I_{sc})	5.87A

Table 2 shows the annual average wind speed of 8.5 m/s indicates a strong wind resource suitable for efficient wind power generation. With a wind shear exponent of 0.20, wind speeds increase moderately with height, favoring taller hub designs. The turbine is engineered to withstand an extreme wind speed of 42.5 m/s and a survival limit of 59.5 m/s, ensuring structural safety during storms. Operational controls include an automatic stop at 20 m/s to prevent mechanical stress, with a re-cut-in at 18 m/s once conditions stabilize. A turbulence intensity of 16% suggests moderate gustiness, which must be factored into turbine loading and fatigue design. The maximum in-flow angle of 8° ensures optimal aerodynamic performance and protects against off-angle winds. Overall, these parameters confirm the site's suitability for wind energy while highlighting the turbine's operational safety margins.

Table 2: Wind Data parameter

Parameters	Values
Annual average wind speed	8.5 m/s
Wind shear 0.20	0.2
Extreme wind speed	42.5 m/s (10 min. average)
Survival wind speed	59.5 m/s (3 sec. average)
Automatic stop limit	20 m/s (10 min. average)
Re-cut in	18 m/s (10 min. average)
Characteristic turbulence intensity	16% (including wind farm turbulence)
Maximum in-flow angle	8°

4. RESULT AND DISCUSSION

This section provides the detailed results and discussion of the analysis carried out based on the methodologies in the preceding section.

Figures 6 and 7 illustrate the effects of a 20% investment in energy efficiency, revealing a significant reduction in electrical demand and thermal load within the microgrid.

The decrease in electrical load minimizes reliance on expensive operational units, while the lowered thermal load allows the system operator to effectively meet thermal demand.

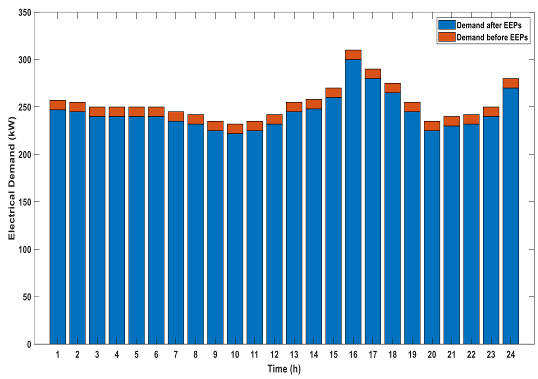

Figure 6: Electrical demand before and after Electrical EEPs

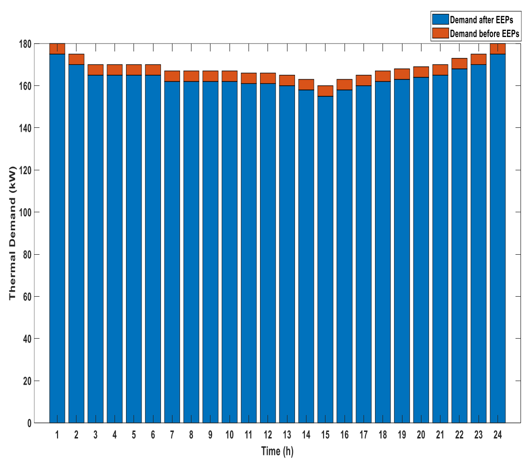

Figure 7: Thermal demand before and after Thermal EEPs

The Figure 8 shows higher power sales from the MG to the main grid in the electrical EEPs scenario than without EEPs. Energy Efficiency and Storage Systems (EESSs) boost power sales in both cases, while EEPs decrease power purchases from the grid, enhancing the MG's self-sufficiency.

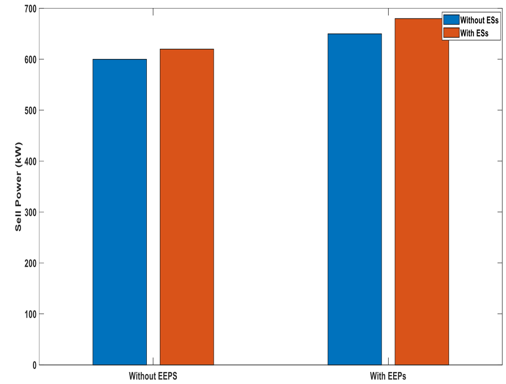

Figure 8: Sell power to grid with and without EEPs

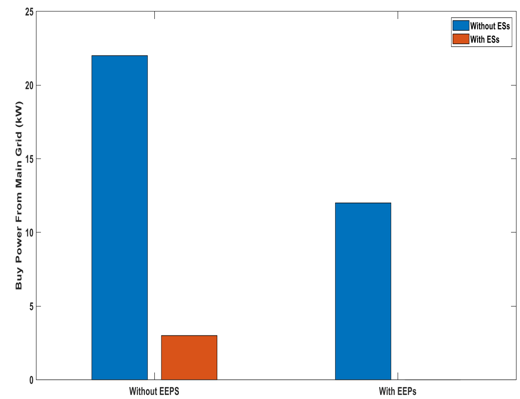

Figure 9: Buy power from grid with and without EEPs

Figure 8 is the power sold to grid with and without EEPs while figure 9 showed the power purchased from the main grid in various scenarios, indicating reduced operational costs for the microgrid and protection from price fluctuations. Additionally, Figure 9 demonstrated how Energy Efficiency and Storage Systems (EESSs) enhance the microgrid's self-sufficiency by lowering grid power purchases.

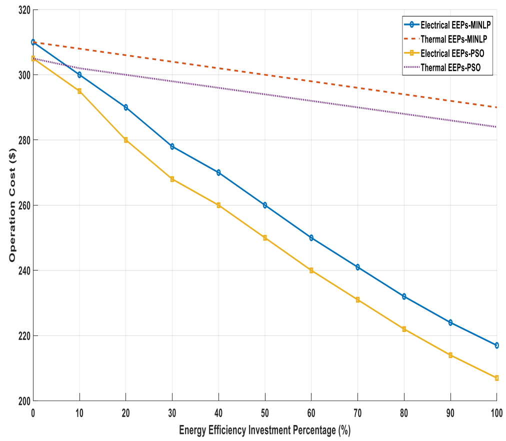

Figure 10: Comparative Analysis of the Effect of EEPs Investment Percentage on the Operation Cost

In figure 10, the slope for electrical EEPs is steeper than for thermal EEPs, indicating a greater impact on MG operational costs. Additionally, PSO outperforms MNLP regarding operational cost, as evidenced in Table 1.

Thermal and electrical demand EEPs reduced operation costs significantly; however, Table 3 indicates that electrical EEPs outperform thermal EEPs in effectiveness.

Energy Efficiency Investment percentage (%)	MINLP	PSO	% REDUCTION
10	300	295	1.69
20	295	280	5.35
30	280	268	4.48
40	270	260	3.85
50	260	250	4.00
60	250	240	4.17
70	241	231	4.33
80	238	222	7.21
90	225	214	5.14
100	218	207	5.31

Table 3: Comparative analysis of Operational Costs

5. CONCLUSION

In this paper, an improved energy management system (EMS) of the microgrid. using the electrical energy storage systems (EESSs) and demand-side energy efficiency programs (EEPs) was developed. The parameters of MG were optimized using PSO and simulated on MATLAB software 2023a. The proposed EMS ensures efficient scheduling of distributed energy resources (DERs), storage systems, and controllable loads to achieve cost-effective, reliable, and sustainable operation. By prioritizing the utilization of renewable sources such as solar and wind, the system enhances clean energy penetration while minimizing dependency on the main grid and reducing greenhouse gas emissions. The results showed that using EESSs alone (without electrical and thermal EEPs) reduces the operational cost of the MG by approximately 5.35% as shown in figure 8 to 9, and table 3 respectively. Additionally, the power sold to the main grid significantly increases when EESSs are used in grid-connected MGs. Moreover, the use of EESSs in the MG helps decrease power purchases from the main grid, thereby enhancing the MG's self-sufficiency.

REFERENCES

[1] Abhay Sanatan, Sthitapragyan Mohanty and Asit Mohanty, Emerging Technologies, Opportunities and Challenges for Microgrid Stability and Control, https://doi.org/10.1016/j.egyr.2024.03.026.

[2] Chibuike Peter Ohanu, Salihu Ahmed Rufai and Ugbe Christiana Oluchi, A Comprehensive Review of Recent Developments In Smart Grid Through Renewable Energy Resources Integration (2024) https://doi.org/10.1016/j.heliyon.2024.e25705.

[3] Dorahaki Sobhan, Rahman Dashti and Hamid Reza Shaker "The Optimal Energy Management in the Microgrid Considering Demand Response Program and Energy Storage" 978-1-7281-3729-2/19/$31.00 ©2019 IEEE.https://doi.org/10.1109/ISAECT47714.2019.9069722.

[4] Fahim Ansari, Padmanabh Thakur, Parvesh Saini "Particle Swarm Optimization Technique for Photovoltaic System" International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-5, January 2020. http://doi.org/10.35940/ijrte.E5774.018520.

[5] Feroz Ali, Rafiqul Islam Sheikh, Rubaiya Akter (2025) "Grid-connected hybrid microgrids with PV/wind/battery" https://doi.org/10.1016/j.rineng.2024.103774.

[6] Hossein Azarinfar, Mohsen Khosravi, Reza Ranjkeshan and Ehsan Akbari "Modelling of demand response programs in energy management of combined cooling, heat and power-

based microgrids considering resiliency" 2022, https://doi.org/10.1049/rpg2.12648.

[7] Junjie Zhao, Fan Wang, Qidong Ruan and Yong Wu, "Hybrid Energy Storage Systems for fast-developing Renewable Energy Plant" September 20246(4) DOI:10.1088/2515-7655/ad6fd4.

[8] Kayode Ebenezer Ojo, Akshay Kumar Saha and Viranjay Mohan Srivastava, Microgrids' Control Strategies and Real-Time Monitoring Systems: A Comprehensive Review: Energies 2025, 18(13), 3576; https://doi.org/10.3390/en18133576.

[9] Manoj Gupta and Annapurna Bhargava, Optimal design of hybrid renewable-energy microgrid, system: a techno–economic–environment–social–reliability perspective, (2024), https://doi.org/10.1093/ce/zkad069.

[10] Motinur Rahman, Saikot Hossain, Miao He, and Michael Giesselmann, An Overview of Power System Flexibility: High Renewable Energy Penetration Scenarios, Energies 2024, 17(24), 6393; https://doi.org/10.3390/en17246393.

[11] Murty, V. V. S. N., & Kumar, A. (2020). Multi-objective energy management in microgrids with hybrid energy sources and battery energy storage systems. Protection and Control of Modern Power Systems, 5(1). http://doi.org/10.1186/s41601-019-0147-z.

[12] Musa Terkes and Alpaslan Demirci, (2023) "Optimal Energy Management in Microgrids Considering Supply Demand Rate and Battery Discharge Depth" DOI 10.29121/granthaalayah.v11.i10.2023.5336.

[13] Philipo, G. H., Chande Jande, Y. A., & Kivevele, T. (2020). Demand-Side Management of Solar Microgrid Operation: Effect of Time-of-Use Pricing and Incentives. Journal of Renewable Energy, 2020, 1–12. https://doi.org/10.1155/2020/6956214.

[14] Sengthavy Phommixay, Mamadou Lamine Doumbia and David Lupien St-Pierre "Review on the cost optimization of microgrids via particle swarm optimization" International Journal of Energy and Environmental Engineering (2020) 11:73–89 https://doi.org/10.1007/s40095-019-00332-1.

[15] Shahimol Basheer and Sindhu Thampatty, Analysis of Protection Challenges in DG Integrated Microgrids: 2023 IEEE International Conference, DOI: 10.1109/PESGRE58662.2023.10404285.

[16] Shanmugarajah Vinothine, Lidula, and N. Widanagama, Microgrid "Energy Management and Methods for Managing Forecast Uncertainties" (2022), 15(22),8525; https://doi.org/10.3390/en15228525.

[17] Subhasis Panda, Sarthak Mohanty and Pravat Kumar, An Insight into the Integration of Distributed Energy Resources and Energy Storage Systems with Smart Distribution Networks Using Demand-Side Management, Appl. Sci. 2022, 12(17), 8914; https://doi.org/10.3390/app12178914.

[18] Tze-Zhang Ang, Mohamed Salem, Mohamad Kamarol, Himadry Shekhar, Mohammad Alhuyi Nazari and Natarajan Prabaharan, A Comprehensive Study of Renewable Energy Sources: Classifications, Challenges and Suggestions, (2022): https://doi.org/10.1016/j.esr.2022.100939.

[19] Vikas Khare and Pradyumn Chaturvedi, Design, control, reliability, economic and energy management of microgrid: A review (2023): https://doi.org/10.1016/j.prime.2023.100239.

[20] Yousri, Ahmed Osama and Yomna Shaker, Managing the Exchange of Energy between Microgrid Elements base on Multi-Objective Enhanced Marine Predators Algorithm, (2022): Alexandria Engineering Journal 61(11), DOI:10.1016/j.aej.2022.02.008.