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RESEARCH ARTICLE

Water Wave Optimization Algorithm-Based Dynamic Optimal Dispatch Considering a Day-Ahead Load Forecasting in a Microgrid

DUY C. HUYNH[1], (Senior Member, IEEE), LOC D. HO[1], HIEU M. PHAM[1], MATTHEW W. DUNNIGAN[2], AND CORINA BARBALATA[3], (Member, IEEE)

[1]Department of Electrical Engineering, HUTECH University, Ho Chi Minh City 70000, Vietnam
[2]Department of Electrical Engineering, Heriot-Watt University, EH14 4AS Edinburgh, U.K.
[3]Department of Mechanical and Industrial Engineering, Louisiana State University, Baton Rouge, LA 70803, USA

Corresponding author: Duy C. Huynh (hc.duy@hutech.edu.vn)

ABSTRACT A novel strategy is proposed to tackle an optimal dispatch of a microgrid in response to dynamic conditions, utilizing a water wave optimization (WWO) algorithm and considering a day-ahead load forecasting. Amongst meta-heuristic algorithms, the WWO algorithm stands out in terms of population size, parameter tuning, exploitation and exploration, convergence speed, as well as optimization mechanism. It leverages its ability to efficiently explore solution spaces and adapt to changing conditions. It is applied to the dynamic optimal dispatch of a microgrid with the uncertainty of load power considered and solved by day-ahead load forecasting. It dynamically adjusts the microgrid operation in response to these inputs, ensuring optimal decision-making in the face of varying load scenarios. With the competition of various day-ahead load forecasting techniques in the microgrid, a multi-variate linear regression (MLR) model shows its advantage features, being more transparent, more effective, and more robust than other techniques, especially transparent explainability, as well as simple and fast in model training. These are requirements to achieve the result of day-ahead load forecasting. Thus, the MLR model is proposed to forecast day-ahead load in the microgrid in this paper. The simulation results show that the percentage error (PE) between the MLR model-based forecasted and actual load powers is always less than 4.42%, the mean absolute percentage error (MAPE) of the forecasting result is 3.33%, and the execution time is 49 (s). These achievements meet the accurate and fast requirements. They are completely competitive with the results of using other techniques such as convolutional neural networks (CNN) and long short-term memory (LSTM), especially in the execution time. This has contributed to improving the efficiency of the dynamic optimal dispatch in the microgrid. Then, the diesel generation, battery energy storage, and total microgrid generation costs are 68.76 ($), 5.09 ($), and 73.85 ($) respectively by using the WWO algorithm which are better than those by using a genetic algorithm (GA), a non-dominated sorting genetic algorithm-II (NSGA-II), a particle swarm optimization (PSO) algorithm, and a transient search optimization (TSO) algorithm in the microgrid. The findings offer valuable insights for microgrid operators, energy planners, and policymakers seeking sustainable and cost-effective solutions for distributed energy resource management.

INDEX TERMS Dynamic optimal dispatch, day-ahead load forecasting, microgrid, water wave optimization algorithm.

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I. INTRODUCTION

Distributed energy resources (DERs), battery energy storage systems (BESS), and loads are incorporated into a scaled and decentralized energy system known as a microgrid, Fig. 1 [1], [2], [3]. Its purpose is to produce, store, and distribute electricity. Microgrids have the capability to function independently or in coordination with the main power system. They offer an energy solution that is more durable, catering to the energy demands of particular communities, campuses, industrial complexes, or localized regions. It has become an increasingly popular concept with many advantages relating to energy reliability and resilience; energy independence; efficient energy utilization; efficient management of peak demand; cost savings by reducing transmission and distribution costs and avoiding expensive grid upgrades; flexibility; and adaptability [4].

The integration of advanced optimization strategies has become of paramount importance in this area [5], [6]. A pioneering approach needs to address a dynamic optimal dispatch of a microgrid, with a particular focus on optimizing economic cost and enhancing energy efficiency.

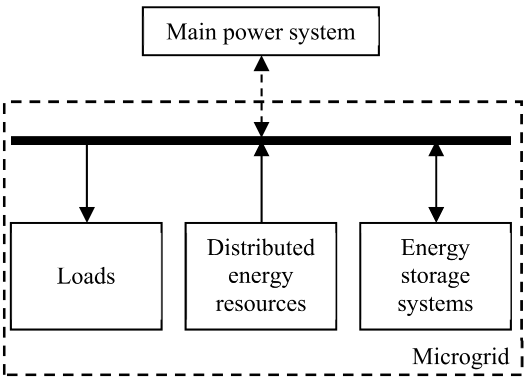

FIGURE 1. Microgrid.

The dynamic optimal dispatch of the microgrid refers to the real-time optimization of the scheduling of DERs under changing loads and storage conditions. Unlike a static optimal dispatch problem, which assumes fixed conditions for the entire scheduling period, the dynamic optimal dispatch adapts to the evolving and often unpredictable consumption within the microgrid. It is realized that the differences between static and dynamic optimal dispatch are time dependency, adaptability, and real-time considerations [7], [8].

For time dependency, the static optimal dispatch operates under the assumption of fixed parameters throughout the scheduling period, disregarding changes in load and generation conditions. Conversely, the dynamic optimal dispatch acknowledges the time-dependent nature of energy demand and supply, modifying the dispatch strategy in real-time to adapt to evolving conditions.

For adaptability, the static optimal dispatch is predetermined and lacks the ability to adjust to unexpected events or changes in the microgrid environment. Alternatively, the dynamic optimal dispatch is adaptive, responding to fluctuations in load, generation, and storage levels to ensure optimal performance in a dynamic and changing environment.

For real-time considerations, the static optimal dispatch relies on historical data and lacks responsiveness to real-time changes. In contrast, the dynamic optimal dispatch incorporates real-time data, including current load demand, enabling more precise and responsive decision-making in the microgrid operation.

A strategy of dynamic optimal dispatch is based on the proportional-integral-derivative control with an augmented Lagrangian approach in the microgrid, showing the difficulty and complexity of determining the appropriate proportional, integral, and derivative coefficients [7]. A distributed primal-dual continuous time consensus algorithm is the development of the primal-dual and consensus algorithms to be capable of solving the dynamic optimal dispatch in the microgrid. This leads to the complexity of implementing and obtaining the accurate and fast result of the dynamic optimal dispatch. Its convergence speed is also a concern which takes longer to reach a consensus [8].

Various optimization techniques are also employed to tackle optimization problems such as approximate dynamic programming and deep recurrent neural network learning [9], [10], equilibrium optimizer [11], and quadratic programming [12]. These techniques are complicated to obtain optimal solutions of the dynamic optimal dispatch in the microgrid.

Recently, there has been an increasing tendency to apply meta-heuristic algorithms for seeking optimal solutions to optimization problems. Specifically, in microgrids, the scheduling and allocation of energy from diverse sources, including renewables and storage systems have been optimized by genetic algorithms (GA) [13]. By using non-dominated sorting genetic algorithm-II (NSGA-II), an energy management system of a microgrid, as well as a configuration of a prosumer's energy storage system are optimized respectively [14], [15]. For the dispatch of optimal economics in microgrids, particle swarm optimization (PSO) algorithms have been applied [16], [17], [18]. Artificial bee colony (ABC) algorithms are employed for optimizing generation strategies [19], [20]. Cuckoo search (CS) algorithms are applied to validate optimal operation strategies as well as to enhance the reliability of microgrid operations [21], [22], [23].

Recently, grey wolf optimization (GWO) algorithms have been developed to schedule the optimal operation in a hybrid microgrid of various resources [24], as well as transient search optimization (TSO) algorithms are introduced to optimize operation costs and power outages for customers [25].

To realize the advantages and disadvantages of the above meta-heuristic algorithms, Table 1 shows the comparison of the GA, NSGA-II, PSO, ABC, CS, GWO, and TSO algorithms in the introduced optimization problems of microgrids [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25]. The main disadvantages of the mentioned algorithms are in the features of the population size, parameter tuning, exploitation and exploration, convergence speed, as well as optimization mechanism. The disadvantages

TABLE 1. Comparisons between usable algorithms in the optimization problems of microgrids.

Feature	Population size	Parameter tuning	Sensitivity to parameters	Scalability	Robustness	Exploitation and exploration balance	Convergence speed	Optimization mechanism
Genetic algorithm [13]	Large	Complicated	Moderate	Large	Moderate	Moderate	Moderate	Complicated
Non-dominated sorting genetic algorithm II [14]-[15]	Large	Complicated	Moderate	Large	More robust	Effective	Moderate	Complicated
Particle swarm optimization algorithm [16]-[18]	Large	Moderate	Moderate	Medium	Sensitive	Moderate	Fast	Simple
Artificial bee colony algorithm [19]-[20]	Medium	Moderate	Low	Medium	More robust	Effective	Moderate	Moderate
Cuckoo search algorithm [21]-[22]	Medium	Moderate	Moderate	Medium	Sensitive	Moderate	Moderate	Moderate
Grey wolf optimization algorithm [24]	Large	Moderate	Moderate	Large	More robust	Effective	Moderate	Moderate
Transient search optimization algorithm [25]	Large	Simple	Moderate	Large	More robust	Effective	Moderate	Moderate
Water wave optimization algorithm [26]	Small	Simple	Low	Large	More robust	Effective	Fast	Simple

directly affect the results of the dynamic optimal dispatch in the microgrid, especially in real-time considerations that need to be overcome to achieve the most accurate and fastest results. There are two approaches to solving this problem. The first way is to improve the mentioned algorithms. The second way is to propose another algorithm for overcoming the analysis disadvantages. In this paper, central to the second way is to propose and apply the WWO algorithm emulating the dynamics of water waves [3], [26]. It draws inspiration from the behaviours observed in ocean waves and seeks to replicate natural processes like wave propagation, interference, and refraction to enhance the optimization of solutions. When comparing the GA, NSGA-II, PSO, ABC, CS, GWO, TSO and WWO algorithms, the WWO algorithm exhibits potential advantages based on simulated wave interference and refraction mechanisms to effectively navigate the solution space and potentially avoid local optima, Table 1.

The WWO algorithm's nature-inspired approach, mirroring the dynamics of water waves, offers adaptability across a spectrum of optimization problems. This adaptability proves beneficial, particularly when dealing with intricate and diverse problems.

A distinctive feature of the WWO algorithm is its inherent ability to operate in parallel, leveraging the independent propagation of waves. This characteristic facilitates efficient parallelization and the utilization of parallel computing resources.

In certain instances, the WWO algorithm has demonstrated competitive convergence rates, achieving optimal or near-optimal solutions within a reasonable number of iterations. The efficiency in reaching solutions quickly is a crucial factor in evaluating the algorithm's overall performance. Therefore, it is appropriate to apply to the dynamic optimal dispatch, where it dynamically adjusts operational parameters based on real-time inputs, ensuring optimal decision-making in the face of anticipated load variations.

Otherwise, in the previous studies, the solutions of the dynamic optimal dispatch have not yet considered one of the very important inputs to this problem, which is load power demand [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25]. This is a factor that frequently changes and needs to be considered in the dynamic optimal dispatch. Microgrid operation is confronted with the challenge of managing distributed energy resources

TABLE 2. Comparisons between usable techniques to forecast day-ahead load in the microgrid.

Feature	Properties of input data	Management of non-linearity	Management of missing data	Complexity in model training	Management of multicollinearity	Management of outliers	Adaptability to real-time	Adaptability to large datasets
Time series analysis [26]	Data over time	Limited	Limited	Simple	Sensitive	Affected	Unavailable	Limited
Decision trees and random forests [27]	Structured and unstructure d data	Available	Effective	Simple	Robust	Robust	Effective	Effective
Gradient boosting model [28]	Various data	Effective	Effective	Complicated	Robust	Robust	Available	Effective
Neural network [29]-[30]	Diverse data	Available	Limited	Complicated	Available	Resilient	Available	Limited
Support vector regressio n [31]	Various data	Effective	Effective	Complicated	Robust	Robust	Available	Effective
Convolu tional neural network [32]	Diverse data	Effective	More robust	Complicated	Available	Robust	Effective	More effective
Long short-term memory [33]	Diverse data	Effective	More robust	Complicated	Available	Robust	Effective	More effective
Kalman filtering [34]	Time-dependent data	Unavailable	Robust	Relatively simple	Unavailable	Sensitive	Effective	Effective
Linear regressio n model [35]	Predictor data	Unavailable	Available	Simple	Sensitive	Sensitive	Limited	Effective
Multivar iate linear regressio n model [36]	Multiple predictor data	Effective	More robust	Simple	Available	Robust	Effective	More effective

and demand-side fluctuations, exacerbated by uncertainties introduced by day-ahead load forecasting. This is the motivation for researching, analyzing, and proposing an effective day-ahead load forecasting technique in this paper. The more accurate and faster the load demand is obtained, the more convenient the dynamic optimal dispatch as well as the more accurate the optimal result is achieved.

Several techniques are commonly used to forecast day-ahead load in the microgrid such as time series analysis (TSA) [27]; decision trees and random forests (DTRF) [28]; gradient boosting model (GBM) [29]; neural network (NN) with training algorithms of Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient [30], [31]; support vector regression (SVR) [32]; convolutional neural network (CNN) [33]; long short-term memory (LSTM) [34]; Kalman filtering (KF) [35]; and linear regression (LR) [36].

The comparison of these techniques used to forecast day-ahead load in the microgrid is shown in Table 2 through various specific features such as properties of input data, management of non-linearity, management of missing data, complexity in model training, management of multicollinearity, management of outliers, adaptability to real-time, and adaptability to large datasets [27], [28], [29], [30], [31], [32], [33], [34], [35], [36]. Amongst the above techniques, the CNN and LSTM techniques are more prominent than others. However, their model types are neural networks. Therefore, they must spend a lot of time on training models. It means that they sometimes cannot obtain good results. This is the feature of the complexity in model training showing a complicated feature in both the CNN and LSTM, Table 2.

To overcome the disadvantages of the mentioned techniques as well as to further refine day-ahead load forecasting, a multi-variate linear regression (MLR) model is proposed, providing a comprehensive understanding of load variations [37]. This model offers advantages when dealing with complex relationships involving multiple variables as well as providing a more flexible and comprehensive approach for modeling real-world phenomena with multiple influencing factors. The linear regression (LR) model involves only one independent variable and one dependent variable whereas the MLR model involves multiple independent variables and one dependent variable. Additionally, Table 2 shows that the MLR model is more transparent, more effective and more robust than other mentioned techniques, especially transparent explainability, as well as simple and fast in model training in day-ahead load forecasting of the microgrid. These are requirements to achieve the result of day-ahead load forecasting. Therefore, the MLR model-based technique is proposed to forecast day-ahead load in the microgrid in this paper. The result of this load forecasting is important to improve the effectiveness of the dynamic optimal dispatch in the microgrid.

The simulation results indicate the efficacy of the WWO algorithm with superior economic outcomes and enhanced reliability, solidifying its position as a leading contender for dynamic optimal dispatch in microgrids.

The primary aim of the proposed research is to achieve a dynamic optimal dispatch with the main contributions including:

- Proposal of the WWO algorithm to optimize the dynamic dispatch in the microgrid.
- Proposal of the MLR model-based technique for forecasting the day-ahead load in the microgrid. Accurate load forecasts are crucial for enhancing the efficiency of dynamic optimal dispatch.
- Proposal of the combination of the MLR model-based technique and the WWO algorithm for the dynamic optimal dispatch considering the day-ahead load forecasting in the microgrid.
- Optimization of the utilization of microgrid energy resources by giving priority to existing DERs, charging surplus energy to BESS, and discharging from BESS during peak demand periods. This approach aims to minimize the need for new investments in DERs to address temporary load power increases in the microgrid.
- Efficient management of DERs and BESSs by charging surplus energy to BESS after meeting initial load requirements and seamlessly discharging energy from BESS to compensate for any deficit in load requirements.
- Minimization of overall energy costs for the microgrid through the implementation of dynamic optimal dispatch strategies. This includes intelligent decision-making to ensure cost-effective energy usage and reduce the need for additional investments in energy infrastructure.

The paper is organised as follows. The dynamic optimal dispatch of the microgrid, employing the WWO algorithm is proposed in Section II. In Section III, the MLR model-based approach is introduced for the day-ahead load forecasting of the microgrid. Section IV provides simulation results for the dynamic optimal dispatch of the microgrid, taking into account the day-ahead load forecasting. These results are compared with outcomes from various algorithms, and the advantages of the proposed techniques are discussed. Finally, Section V presents the conclusion, affirming the proposed approach.

II. WWO ALGORITHM-BASED DYNAMIC OPTIMAL DISPATCH

A microgrid is considered with diesel generators (DG) and BESS. The BESS is utilized to enhance the efficiency of DGs during periods of underload or overload. Essentially, it helps the microgrid avoid investing in extra DG capacity when there are temporary increases in load demand during energy consumption. The dynamic optimal dispatch is detailed by their respective cost functions, and the proposed solution approach involves using the WWO algorithm to find the best solutions for optimizing the dynamic dispatch of the microgrid [38].

A. DIESEL GENERATOR

At time t, the i^{th} DG has its cost described by:

$$C_{Diesel,i}(t) = a_i P^2_{Diesel,i}(t) + b_i P_{Diesel,i}(t) + c_i \tag{1}$$

where

$P_{Diesel,i}(t)$: the power generated by the i^{th} DG;
a_i, b_i, and c_i: the cost coefficients of the i^{th} DG.

B. BATTERY ENERGY STORAGE SYSTEM

At time t, the j^{th} BESS has its cost described by:

$$C_{BESS,j}(t) = \frac{C_{capital,j}}{E_j \times L_j(t) \times DOD_j(t) \times \eta_j} \tag{2}$$

$$L_j(t) = 694 \times \left(DOD_j\right)^{-0.795} \tag{3}$$

$$DOD_j(t) = 1 - \frac{E_{BESS,j}(t)}{E_{BESS,j,\max}(t)} \tag{4}$$

where

$C_{capital,j}$: the initial cost of the j^{th} BESS;
E_j: the rated capacity of the j^{th} BESS;
$L_j(t)$: the lifecycle of the j^{th} BESS due to change in DOD;
$\text{DOD}_j(t)$: the depth of discharge;
$E_{BESS,j}(t)$: the charge level of the j^{th} BESS;
$E_{BESS,j,max}(t)$: the maximum charge level of the j^{th} BESS.

C. OBJECTIVE FUNCTION OF THE DYNAMIC OPTIMAL DISPATCH

The dynamic optimal dispatch of the microgrid is described through the objective function given by:

$$C_{Microgrid} = \sum_{t=1}^{T} \left[\sum_{i}^{n} C_{Diesel,i} + C_{BESS,j} \right] \tag{5}$$

where

n: the number of DGs;
T: the scheduling period.

It is realized that fast and accurate factors are important in the dynamic optimal dispatch of the microgrid. Therefore, simplifying the optimization problem in general and the objectives of the optimization problem in particular is necessary. This idea is implemented and shown in the flowcharts of Figs. 2 and 6.

D. CONSTRAINTS OF THE DYNAMIC OPTIMAL DISPATCH

In this paper on the dynamic optimal dispatch of the microgrid, the active power balance is prioritized over the reactive power balance. It is realized that the primary goal of this problem is to ensure a reliable and stable power supply to meet the power demand. The active power, representing the actual energy transferred to consumers, is important for maintaining the supply whereas the reactive power mainly affects voltages and power factors but does not contribute directly to energy transfer. In addition, the active power generation typically incurs higher costs compared to the reactive power generation. Thus, the dynamic optimal dispatch is prioritized to minimize the operation costs while meeting demand requirements. Furthermore, including the reactive power balance in the dynamic optimal dispatch increases the complexity to the optimization problem without significantly impacting the primary goal of meeting the energy demand. Therefore, the constraints of the dynamic optimal dispatch of the microgrid include:

The power balance in the microgrid:

$$\sum_{i=1}^{n} P_{Diesel,i}(t) + P_{Discharge}(t) = P_{load}(t) + P_{Charge}(t) \tag{6}$$

The generated power limitation of DGs in the microgrid:

$$P_{\min} \le P_{Diesel,i}(t) \le P_{\max} \tag{7}$$

The charging and discharging situation of BESSs in the microgrid:

$$E_{BESS,\min} \le E_{BESS,j}(t) \le E_{BESS,\max} \tag{8}$$

$$E_{BESS,j}(t) \le \begin{bmatrix} E_{BESS,j}(t-1) - \\ -E_{Discharge}U_{Discharge} + \\ +E_{Charge}U_{Charge} \end{bmatrix} \tag{9}$$

$$U_{Discharge} + U_{Charge} \le 1 \tag{10}$$

where

P_{max} and P_{min}: the generation power limitation of each DG;

$P_{load}(t)$: the demand load power at time t;

$E_{BESS,min}$ and $E_{BESS,max}$: the charge limitation of the BESS;

$P_{Discharge}$ and P_{Charge}: the discharged and charged power of the BESS;

$E_{Discharge}$ and E_{Charge}: the discharged and charged energy of the BESS;

$U_{Discharge}$: the discharged status of the BESS;

U_{Charge}: the charged status of the BESS.

The flowchart of determining the charge level of the BESS in the dynamic optimal dispatch of the microgrid is illustrated in Fig. 2.

E. DYNAMIC OPTIMAL DISPATCH USING WWO ALGORITHM

In the proposed WWO algorithm, the solution space, X is compared with an underwater area with the fitness of a point, x in X, being inversely related to its depth in the seabed. Effectively, points closer to the still water level have higher fitness [3], [26]. Then, x is a solution vector of $P_{Diesel,i}$ and $E_{BESS,j}$ with the objective function (5) and constraints (6)-(10). Each is a wave of height, h and length, λ; $h = h_{max}$ and λ =0.5 in the initial phase. In the WWO algorithm, propagation, refraction, and breaking are employed to manipulate waves and seek optimal solutions.

Each wave must propagate exactly once in each generation. The wave, x is transformed into a new wave, x' by shifting its dimension, d, through the propagation operator.

$$x'(d) = x(d) + rand(-1, 1) \times \lambda l(d) \tag{11}$$

where

$l(d)$: the length of the d^{th} dimension of the search space, $1 \le d \le n$.

As a wave transitions from deep water to shallow water, the wave experiences an increase in height and a decrease in length, Fig. 3.

Then, the fitness of x' is evaluated. If $f(x') > f(x)$, then x is replaced by x', and $h = h_{max}$. Conversely, if $f(x') < f(x)$, x remains, and $h = h - 1$. This reduction is considered a manifestation of energy dissipation caused by inertial resistance, vortex shedding, and bottom friction.

The wavelength is updated according to the following procedure.

$$\lambda = \lambda\alpha^{\frac{-(f(x)-f_{\min}+\varepsilon)}{(f_{\max}-f_{\min}+\varepsilon)}} \tag{12}$$

where

f_{max} and f_{min}: the fitness value limitation;

α: the coefficient of the wavelength decrease;

ε: the small positive number employed for avoiding zero in the denominator.

Fig. 4 shows that rays come together in shallow regions and spread apart in deep regions. Within the WWO algorithm, refraction is specifically implemented for waves whose heights diminish to zero.

Subsequently, the position is determined in the following manner after refraction.

$$x'(d) = N\left(\frac{x^*(d) + x(d)}{2}, \frac{|x^*(d) - x(d)|}{2}\right) \tag{13}$$

where

x^*: the best solution.

The wave height and length are then described as follows:

$$h' = h_{\max} \tag{14}$$

$$\lambda' = \lambda\frac{f(x)}{f(x')} \tag{15}$$

Upon reaching a location where the depth falls below a specific threshold, the velocity of the wave crest exceeds the wave velocity. This results in an elevation of the wave crest's steepness. Ultimately, the wave breaks into a sequence of solitary waves, Fig. 5.

The breaking only occurs for a wave, x, when it identifies a new optimal solution, x^*. Afterwards, the algorithm conducts

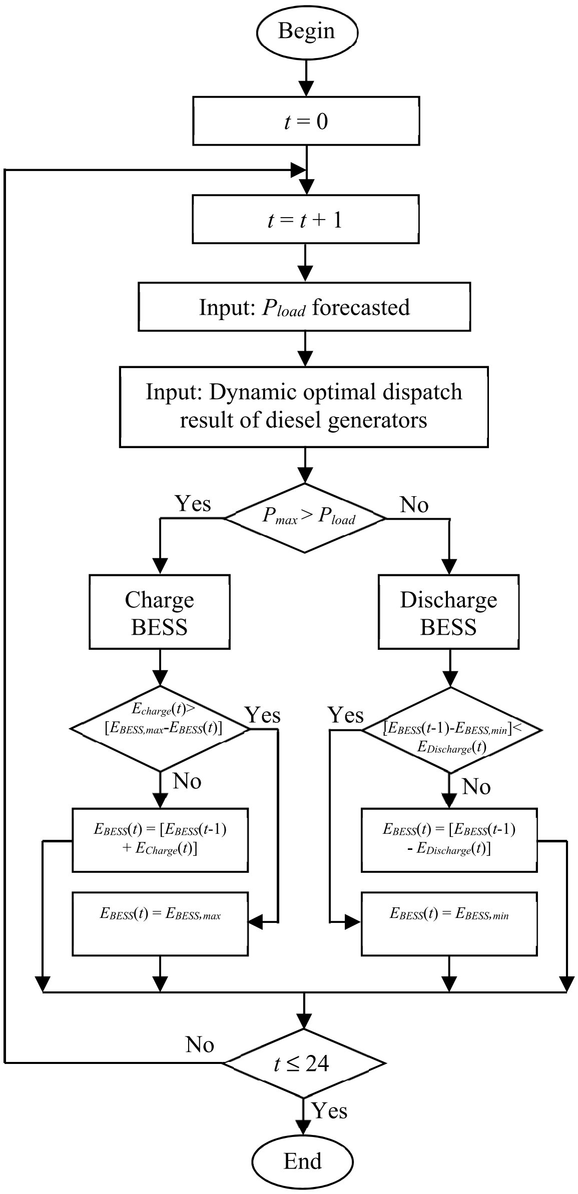

FIGURE 2. Flowchart of determining the charge level of the BESS in the dynamic optimal dispatch of the microgrid.

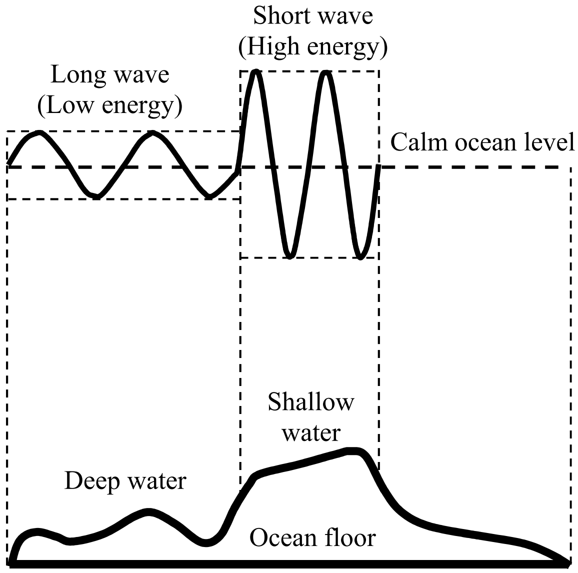

FIGURE 3. Shapes of the wave.

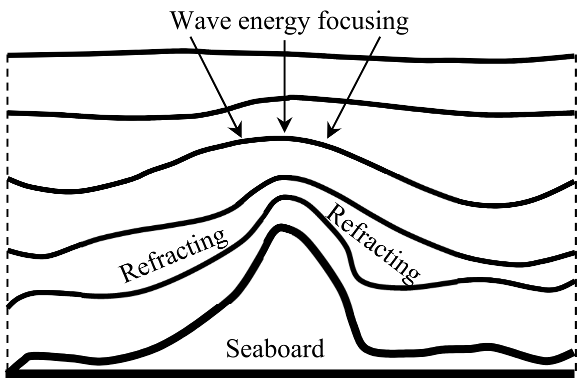

FIGURE 4. Wave refraction.

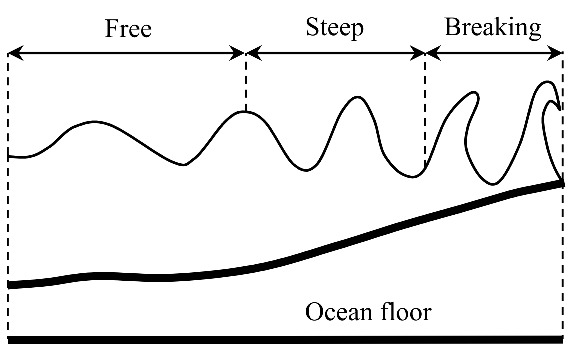

FIGURE 5. Wave breaking.

a local search around x^* to mimic wave breaking, resulting in the generation of a solitary wave, x', at dimension d, according to the following procedure.

$$x'(d) = x(d) + N(0, 1)\,\beta l(d) \tag{16}$$

where

β: the breaking coefficient.

If none of these individual waves surpasses x^*, x^* is preserved; however, if a fitter solitary wave emerges, it supplants x^* as the new optimal solution.

The flowchart for the WWO algorithm, designed for dynamically optimizing the dispatch of the microgrid, is depicted in Fig. 6.

Fig. 6 illustrates that the dynamic optimal dispatch process is implemented every hour throughout the day (24 hours). This process can be shorter or longer depending on the requirements of each dynamic optimal dispatch problem. For this reason, the data input for solving dynamic optimal dispatch needs to be updated every hour as well. One of the important data that significantly affects the results of dynamic optimal dispatch is the necessity of load data at each hour of the microgrid. The load demand of the microgrid is updated every hour for the dynamic optimal dispatch in this paper.

Additionally, the proposed optimization algorithm aims to address the dynamic optimal dispatch of the microgrid, not only requiring accurate dispatch results but also emphasizing the need to achieve these results quickly. This is considered one of the inherent prerequisites for the dynamic optimal dispatch of the microgrid. Comparing various optimization algorithms, Table 1 demonstrates that the WWO algorithm meets these requirements as well as outperforms the mentioned and compared optimization algorithms.

III. MLR MODEL-BASED DAY-AHEAD LOAD FORECASTING

A multivariate linear regression (MLR) model is proposed to forecast the day-ahead load of the microgrid. This strategy improves a linear regression (LR) model. A linear model is based on a linear regression. It is used to forecast a value as accurate to the actual value as possible [37], [39].

A dependent variable and several independent variables are modelled using the following MLR model.

$$y = r_0 + r_1x_1 + r_2x_2 + \ldots + r_kx_k + \varepsilon \tag{17}$$

where

y: the dependent variable;

x_i: the i^{th} independent variables, $i = 1, 2, \ldots, k$;

r_i: the regression coefficients;

ε: the error.

In the case of multiple observations, the model of the multiple linear regression is extended as follows:

$$\begin{aligned} y_1 &= r_0 + r_1x_{11} + r_2x_{12} + \ldots + r_kx_{1k} + \varepsilon_1 \\ y_2 &= r_0 + r_1x_{21} + r_2x_{22} + \ldots + r_kx_{2k} + \varepsilon_2 \\ &\ldots \\ y_k &= r_0 + r_1x_{n1} + r_2x_{n2} + \ldots + r_kx_{nk} + \varepsilon_k \end{aligned} \tag{18}$$

A matrix form of the model is also given by:

$$Y = RX + \varepsilon \tag{19}$$

where

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \ldots \\ y_k \end{bmatrix}; \quad X = \begin{bmatrix} 1 & x_{11} & x_{12} & \ldots & x_{1k} \\ 1 & x_{21} & x_{22} & \ldots & x_{2k} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 1 & x_{n1} & x_{n2} & \ldots & x_{nk} \end{bmatrix}; \quad R = \begin{bmatrix} r_0 \\ r_1 \\ \ldots \\ r_k \end{bmatrix}; \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \ldots \\ \varepsilon_k \end{bmatrix}.$$

It is realized that X and Y are the matrices consisting of information about the independent and dependent variables of all historical data respectively.

The regression coefficients, r_i, are unknown. These parameters are estimated from X and Y. It is assumed that $\hat{r}_i$, $i = 0, 1, 2, \ldots, k$ are the estimated regression coefficients of r_i.

Then, the forecasting of y, termed $\hat{y}$ is shown as follows:

$$\hat{y} = \hat{r}_0 + \hat{r}_1x_1 + \hat{r}_2x_2 + \ldots + \hat{r}_kx_k \tag{20}$$

By using the least square method, $\hat{R}$ is estimated as follows [40]:

$$\hat{R} = \begin{bmatrix} r_0 & r_1 & r_2 & \ldots & r_k \end{bmatrix}^T \tag{21}$$

$$\hat{R} = \left(X^TX\right)^{-1} X^TY \tag{22}$$

With the above-known regression coefficients, the load is forecasted from the multivariable linear regression model as follows:

$$\hat{Y} = \hat{R}X \tag{23}$$

In this application of load forecasting in the microgrid, it is assumed that there are samples of historical load power data of a current day, $P_m(d)$, a day from one day ago, $P_m(d\text{-}1)$, a day from two days ago, $P_m(d\text{-}2)$. Furthermore, it is realized that the temperature is one of the factors which significantly affects power consumption. When the temperature increases, the air conditioner is turned on. When the temperature decreases, the heater is turned on as well. Thus, there are samples of historical temperature data of a current day, $T_m(d)$, a day from one day ago, $T_m(d\text{-}1)$, a day from two days ago, $T_m(d\text{-}2)$ utilized in the MLR model. In addition, a variable, H is used to represent a special day such as weekends or holidays.

Then, at time t, the load power is forecasted by:

$$\begin{aligned} P_{mf} = {} & r_0 + r_1P(d) + r_2P(d-1) + r_3P(d-2) + \\ & + r_4T(d) + r_5T(d-1) + r_6T(d-2) + r_7H(d) \end{aligned} \tag{24}$$

where

P_{mf}: the forecasted load powers of a coming day;

$P_m(d)$: the load powers of a current day;

$P_m(d\text{-}1)$: the load powers of a day from one day ago;

$P_m(d\text{-}2)$: the load powers of a day from two days ago;

$T_m(d)$: the temperatures of a current day;

$T_m(d\text{-}1)$: the temperatures of a day from one day ago;

$T_m(d\text{-}2)$: the temperatures of a day from two days ago;

$H(t)$: the special or unspecial day of the current day;

m: the time of a day, $m = 1, 2, \ldots, 24$;

$r_0, r_1, \ldots, r_7$: the regression coefficients.

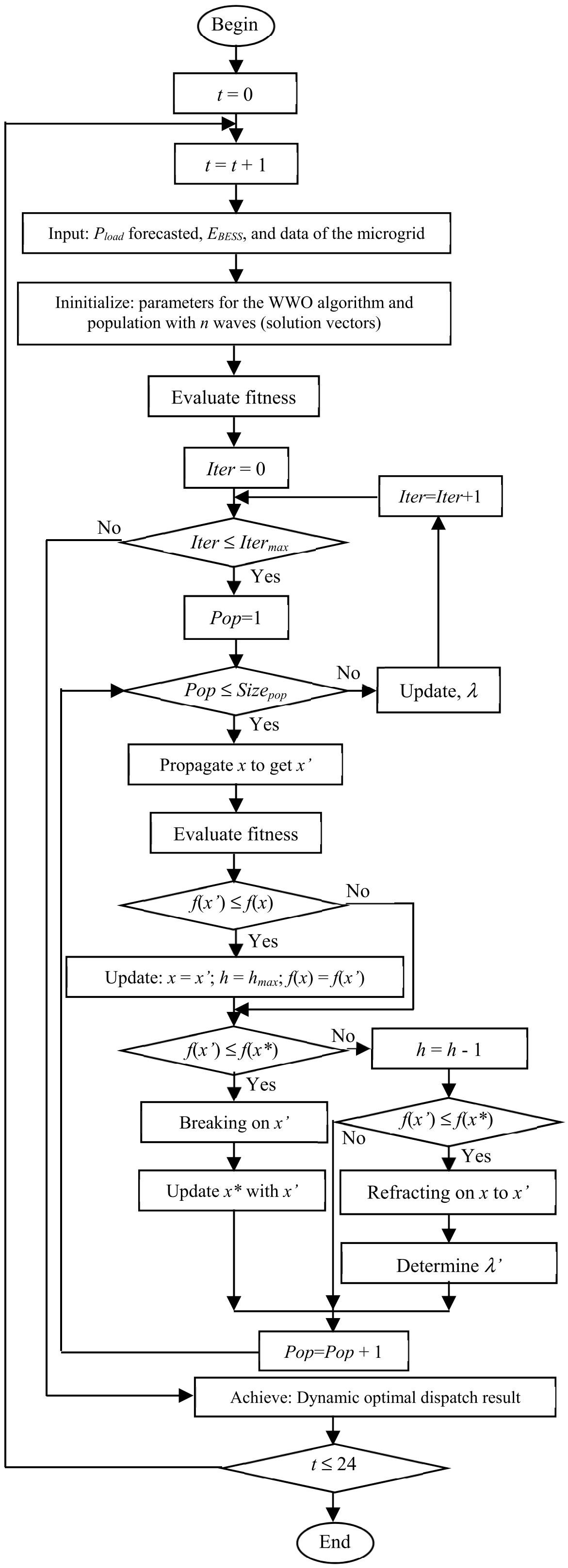

FIGURE 6. Flowchart of the WWO algorithm-based dynamic optimal dispatch of the microgrid.

To implement load forecasting in the microgrid with the proposed technique, data preprocessing is necessary through the following procedures.

Firstly, to overcome measurement noise and missing values for load forecasting in the microgrid, there is a data preprocessing to identify and remove outliers from load data as well as use a mean imputation technique for missing values before applying the least squares method. This data preprocessing is to limit the effects on the effectiveness of the proposed technique as well as improve the obtained results of load forecasting in the microgrid.

Secondly, the load data is checked the non-stationarity. If the load data exhibits the non-stationarity, the differencing is applied to make it stationary. Simultaneously, the detrending is also used to remove trends or long-term patterns from the load data, making the load data more stationary. To detrend, the differencing technique is applied with the first difference by subtracting each data point from its preceding point to remove a linear trend and the second difference by using the first difference again to remove quadratic trends. The load data also is checked the non-linearity. Then, the appropriate mathematical transformations are applied to linearize relationships. They are logarithm and square root in this paper.

During the multivariable linear regression applied for forecasting the load powers in the microgrid, there may be collinearity and overfitting. Therefore, the collinearity is checked among the forecasted load powers using the variance inflation factor. If the variance inflation factor is 1, there is no collinearity. If the variance inflation factor is greater than 1, there is a collinearity. The collinearity rises when the variance inflation factor increases. Then, the penalty term, $\alpha \sum_1^7 r_k^2$ is added to the objective function of the MLR model. The regularization parameter, α describes the strength of the regularization and controls the trade-off between fitting the data well and keeping the coefficients small. Through this procedure, the impact of collinearity is mitigated as well as the overfitting is prevented to ensure that the results of the load forecasting are accurate and robust.

To evaluate the forecasting results, a percentage error (PE), and a mean absolute percentage error (MAPE) are utilized and shown as follows:

$$PE = \left| \frac{P_{fi} - P_i}{P_i} \right| \times 100\% \tag{25}$$

$$MAPE = \frac{1}{k} \sum_{i=1}^{k} \left| \frac{P_{fi} - P_i}{P_i} \right| \times 100\% \tag{26}$$

where

P_{fi} and P_i: the forecasted and actual load powers.

IV. SIMULATION RESULTS

A microgrid is considered with three DGs and one BESS, Fig. 7. The specifications of the DGs and BESS are shown in Tables 3-4 [38].

The load power data of the microgrid is forecasted by using the MLR model. In this application, the dimension of the dataset is 204 with 7 independent variables. There are 24 load power data of a current day, 24 load power data of a day from one day ago, 24 load power data of a day from two days ago,

TABLE 3. Specification of the DGs.

DG	a_i ($/kW²h)	b_i ($/kWh)	c_i ($/h)	P_{min} (kW)	P_{max} (kW)
DG_1	0.0001	0.0417	0.2	0	30
DG_2	0.0001	0.0438	0.3	0	20
DG_3	0.0001	0.0469	0.3	0	5

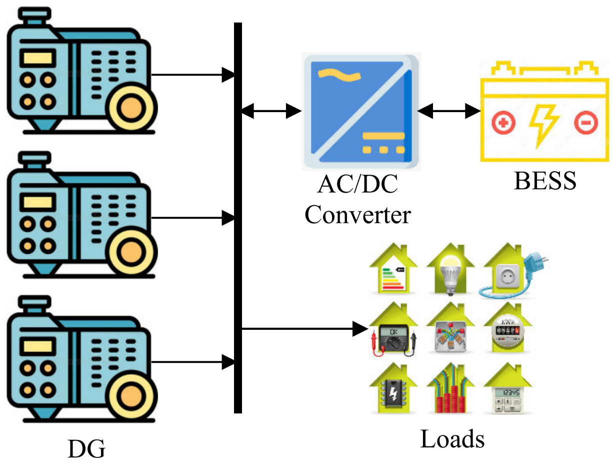

FIGURE 7. Microgrid with three DGs and one BESS.

TABLE 4. Specification of the BESS.

Specification	Value
$C_{capital}$ ($/kWh)	250
E_{BESS} (kWh)	50
$E_{BESS,max}$	$0.95\times E_{BESS}$
$E_{BESS,min}$	$0.15\times E_{BESS}$

24 temperature data of a current day, 24 temperature data of a day from one day ago, 24 temperature data of a day from two days ago, 52 weekends, and 8 assumed holidays.

Then, the load power of the microgrid is forecasted by using the MLR model-based technique, Table 5. Furthermore, it also indicates that the PE between the forecasted and actual load powers is always less than 4.42%. The PE is typically required to be less than 5%. This means that the accuracy of the load forecasting results is acceptable as well as the effectiveness of the MLR model-based load forecasting technique is confirmed in this paper. In addition, Table 6 shows the MAPE of the forecasting result, 3.33%. The lower PE and MAPE values indicate a more accurate forecasting model, Fig. 8.

On the other hand, the LSTM- and CNN-based techniques are also applied for forecasting load powers in the microgrid to compare with the MLR model-based technique, Table 5.

Fig. 9 illustrates the forecasted load powers by using the MLR model, LSTM and CNN compared with the actual load power of the microgrid. In addition, the comparison result shows that the MAPE of the LSTM- and CNN-based techniques, 2.86% and 2.91% respectively are better than that of the MLR model-based technique, 3.33%, Table 6. However, it is realized that the improvement of the MAPE, 0.47% and 0.42% are not significant. Meanwhile, the comparison of the execution time between the MLR model-, LSTM- and CNN-based techniques shows that the execution time of the MLR-based technique, 49 (s) is significantly better than that of LSTM- and CNN-based techniques, 185 (s) and 193 (s) respectively.

These quantitative analyses show that a compromise is necessary between the techniques in choosing the appropriate load forecasting technique for the dynamic optimal dispatch in the microgrid with its fast and accurate requirements. Then, it is realized that the MLR model-based technique is a suitable choice. This also re-validates the proposal of using the MLR model-based technique for day-ahead load forecasting in the dynamic optimal dispatch in the microgrid.

The MLR model-based forecasting load powers are shown in Figs. 8-9 which validates the expected forecasting accuracy as well as the expected best result for the dynamic optimal dispatch in the microgrid.

The load power is one of the required inputs of the dynamic optimal dispatch in the microgrid. Therefore, the accuracy of load forecasting results is crucial for optimizing the dynamic dispatch of the microgrid. The more precise the load forecasting, the more effectively the dynamic optimal dispatch is executed.

The forecasted load power by using the MLR model-based technique is obtained and utilized for the dynamic optimal dispatch in the microgrid.

TABLE 5. Forecasted load power using LSTM, CNN and MLR model.

t (h)	P (kW)	LSTM		CNN		MLR model	
		P_f (kW)	PE (%)	P_f (kW)	PE (%)	P_f (kW)	PE (%)
1	26.97	27.76	2.92	27.78	2.99	27.88	3.36
2	25.95	25.23	2.77	25.22	2.81	25.09	3.31
3	23.98	24.67	2.89	24.66	2.85	24.75	3.23
4	26.96	27.75	2.93	27.76	2.97	27.87	3.38
5	35.04	36.01	2.78	36.04	2.87	36.09	3.01
6	39.06	40.21	2.95	40.20	2.92	40.23	3.00
7	48.07	46.71	2.83	46.69	2.87	46.49	3.29
8	56.08	57.74	2.95	57.72	2.92	57.73	2.93
9	61.07	62.86	2.94	62.87	2.95	63.10	3.33
10	63.57	65.26	2.66	65.38	2.85	60.76	4.42
11	66.93	65.06	2.80	64.95	2.96	64.81	3.17
12	61.94	63.73	2.89	63.73	2.89	64.15	3.57
13	54.95	56.53	2.88	56.57	2.96	56.82	3.41
14	46.05	47.42	2.98	47.40	2.94	47.53	3.22
15	42.04	43.21	2.78	43.25	2.87	40.54	3.57
16	40.05	41.17	2.79	41.21	2.89	41.31	3.14
17	41.07	39.90	2.84	39.86	2.94	42.32	3.05
18	50.05	48.67	2.76	48.59	2.92	51.73	3.36
19	55.94	54.32	2.90	54.33	2.89	54.07	3.35
20	56.93	58.56	2.87	58.60	2.94	59.01	3.66
21	47.95	49.32	2.85	49.34	2.89	49.53	3.29
22	43.04	44.31	2.94	44.29	2.90	44.37	3.08
23	31.03	31.89	2.77	31.92	2.86	32.02	3.19
24	29.01	29.83	2.84	29.86	2.94	27.97	3.57

The dynamic optimal dispatch is based on the proposed WWO algorithm to determine the best solution for the dynamic optimal dispatch in the microgrid. The best solution

TABLE 6. Evaluation index of load forecasting of the microgrid using techniques of LSTM and MLR model.

Technique	MAPE (%)	RMSE	Execution time (s)
LSTM	2.86	1.33	185
CNN	2.91	1.36	193
MLR model	3.33	1.56	49

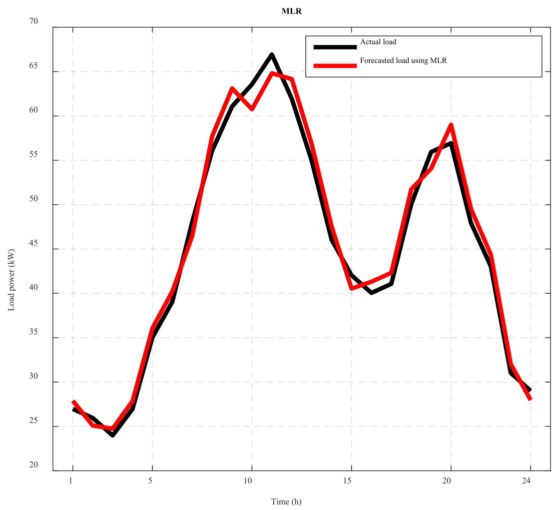

FIGURE 8. Actual and forecasted load powers using MLR model.

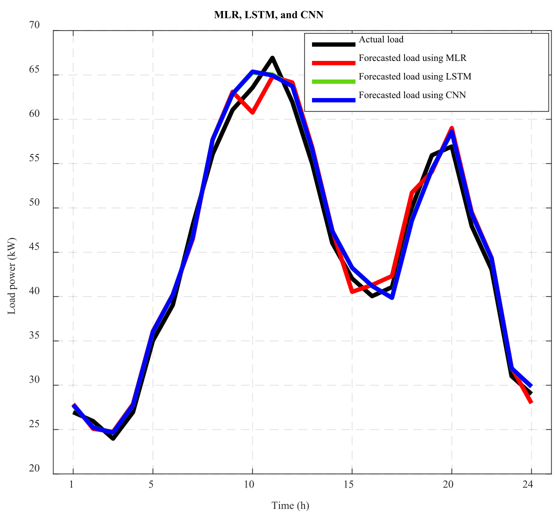

FIGURE 9. Actual and forecasted load powers using CNN, LSTM, and MLR models.

is determined through the optimal solution vector of the optimal generation powers of three DGs, P_1, P_2, and P_3; and the optimal capacity of one BESS, E_{BESS}.

Table 7 shows the proposed WWO algorithm's parameters to perform the dynamic optimal dispatch. The GA, NSGA-II, PSO, and TSO algorithms with their parameters in Tables 8-11 are used for comparison to validate the WWO algorithm-based proposal [24], [25], [41], [42], [43], [44], [45].

Selecting optimal parameters for meta-heuristic algorithms of the GA, NSGA-II, PSO, TSO, and WWO algorithms is crucial for achieving high-quality solutions. There are two main approaches of parameter tuning and parameter control for setting algorithm parameters. In this paper, parameter tuning, specifically, is utilized to determine the best parameters for the optimization algorithms, tailored to the requirements of the dynamic optimal dispatch in the microgrid. This process involves identifying the optimal parameters before applying the algorithms. Once set, these parameters remain fixed through operation. The task of finding the best tuning parameters for these algorithms can be framed as an optimization problem, given that they are all optimization algorithms. This process is referred to as meta-optimization. This paper suggests solving this meta-optimization problem using meta-heuristic algorithms, creating a meta-meta-heuristic approach with two levels of the meta- and base-levels. At the meta-level, meta-heuristic algorithms work with populations of solutions to optimize the parameters of the optimization algorithms. Each solution at the meta-level corresponds to an independent meta-heuristic at the base level. It operates on populations of solutions for the original optimization problem, with a particular focus on the dynamic optimal dispatch in the microgrid [46], [47].

TABLE 7. WWO algorithm's parameters.

Parameter	Value
Population size	6
Maximum iteration	300
Wavelength reduction coefficient	1.01
Breaking coefficient	0.01
Maximum number of breaking directions	0.5
Wavelength	0.5

TABLE 8. GA's parameters.

Parameter	Value
Population size	60
Maximum iteration	300
Crossover rate	0.8
Crossover	Uniform
Mutation rate	0.005
Mutation	Bit inversion
Selection	Roulette wheel

TABLE 9. NSGA-II's parameters.

Parameter	Value
Population size	60
Maximum iteration	300
Crossover rate	0.8
Crossover	Arithmetic
Mutation rate	0.05
Mutation	Gaussian
Selection	Tournament

The population size of the proposed WWO algorithm, 6 is less than that of the GA, NSGA-II, PSO, and TSO algorithms, 60. This shows that the proposed WWO algorithm does not

TABLE 10. PSO algorithm's parameters.

Parameter	Value
Population size	60
Maximum iteration	300
Inertia weight	0.94
Cognitive coefficient	2
Social coefficient	2

TABLE 11. TSO algorithm's parameters.

Parameter	Value
Population size	60
Maximum iteration	300
Constant in exploration and exploitation behaviours	2
Variable decreasing linearly in exploration and exploitation behaviours	[2, 0]

require a large population size. Moreover, the number of the parameter tuning of the proposed WWO algorithm is also less than that of the GA and NSGA-II. These are the advantages of the WWO algorithm allowing improvement of the solution quality of the dynamic optimal dispatch in the microgrid.

By using the WWO algorithm, the result of the dynamic optimal dispatch in the microgrid is achieved and presented in Table 12 with the generation powers of DG_1, DG_2, DG_3, and the storage energy of BESS. It is realized that the capability of DG_1 and DG_2 meets the demand load power from $t = 1$ (h) to $t = 6$ (h). During this period, the excess energy is charged into the BESS to ensure the operation efficiency of the microgrid. The BESS achieves very high charging efficiency, up to 98%.

At $t = 7$ (h), the microgrid begins its peak hour, and DG_3 starts to join into the microgrid to generate power. The peak hours of the microgrid take place from $t = 8$ (h) until $t = 13$ (h). It is obvious that the BESS has performed its role very well with a high discharging efficiency of 77%.

Similarly, from $t = 14$ (h) to $t = 19$ (h), DG_1, DG_2, and DG_3 are operated to satisfy the demand load power of the microgrid. The excess energy is also charged into the BESS during this period.

At $t = 20$ (h), the microgrid is in a peak hour once again. The BESS is activated to support the microgrid.

From $t = 21$ (h) to $t = 22$ (h), the demand load power is decreased in the microgrid. This leads to the generation power of DG_1, DG_2, and DG_3 being decreased, especially the power of DG_3 being gradually reduced until it completely shuts down at $t = 23$ (h).

From $t = 21$ (h) to $t = 24$ (h), the BESS maintains charging the excess energy of the DGs to ensure optimal efficiency of the microgrid.

Then, the power generation cost of DGs and energy storage cost of BESS using the WWO algorithm are 68.76 (\$) and 5.09 (\$) respectively in a day (24 hours) of the microgrid.

Fig. 10 visually illustrates the operation of the microgrid during a day through the demand load power, the total

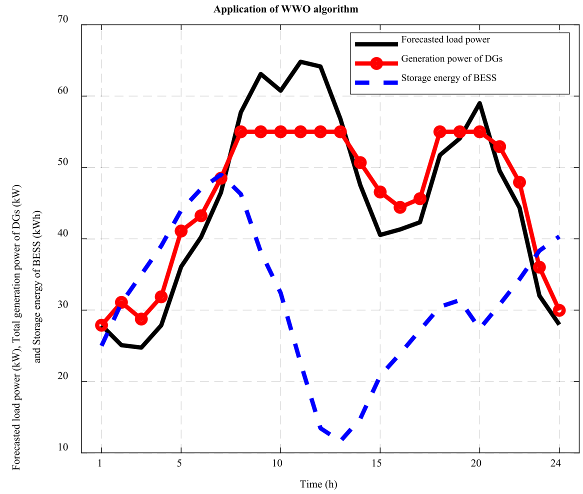

FIGURE 10. Forecasted load power, total generation power of the DGs, and storage energy of the BESS during a day using the WWO algorithm.

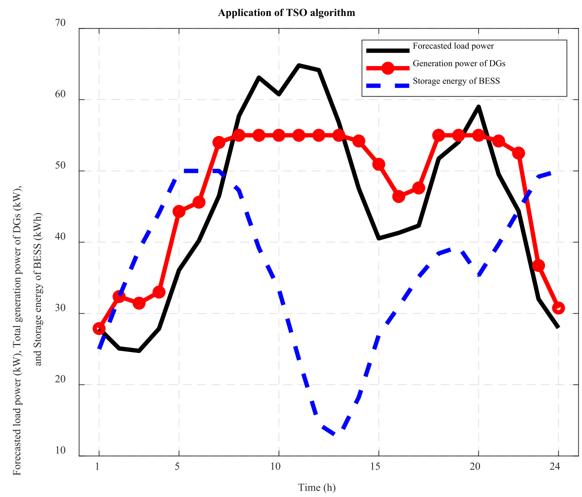

FIGURE 11. Forecasted load power, total generation power of the DGs, and storage energy of the BESS during a day using the TSO.

generation power of the DGs, and the storage energy of the BESS by using the WWO algorithm. The simulation results show that the proposal allows the time-dependent nature of energy demand and supply; adapts despite changes and fluctuations in load, generation, and storage levels; as well as incorporates real-time load demand forecasted by using the MLR model-based technique from $t = 1$ (h) to $t = 6$ (h), at $t = 7$ (h), from $t = 8$ (h) to $t = 13$ (h), from $t = 14$ (h) to $t = 19$ (h), at $t = 20$ (h), and from $t = 21$ (h) to $t = 24$ (h). This allows more precise and responsive decision-making in the microgrid operation.

To validate the proposed application of the WWO algorithm, the GA, NSGA-II, PSO, and TSO algorithms are utilized to optimize the dynamic dispatch in the microgrid.

The results of the dynamic optimal dispatch in the microgrid are obtained in Tables 12-16 with the generation powers of DG_1, DG_2, DG_3, and the energy storage of BESS by

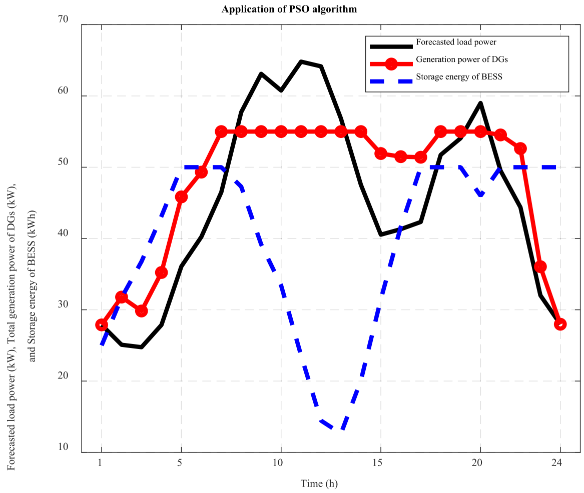

FIGURE 12. Forecasted load power, total generation power of the DGs, and storage energy of the BESS during a day using the PSO.

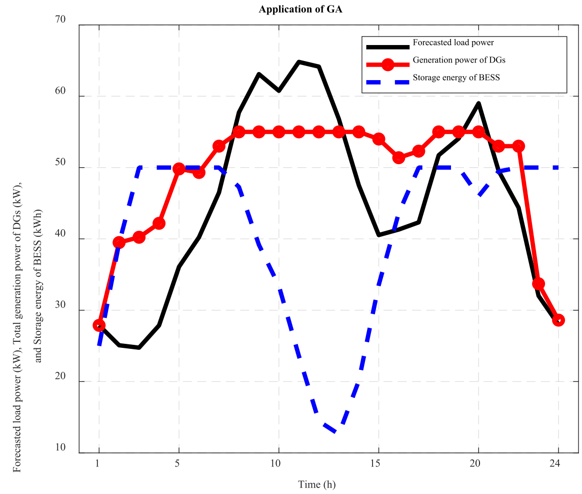

FIGURE 14. Forecasted load power, total generation power of the DGs, and storage energy of the BESS during a day using the GA.

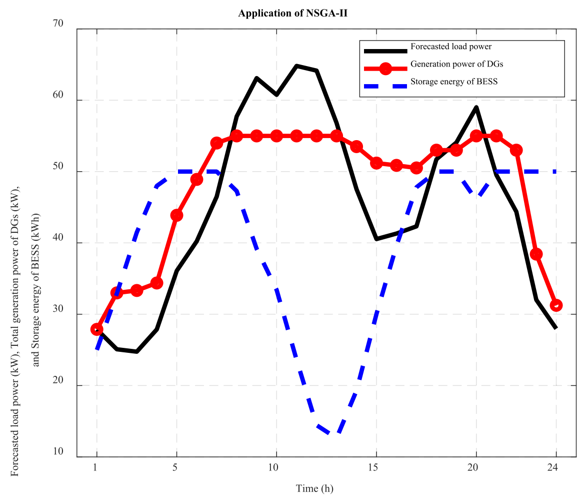

FIGURE 13. Forecasted load power, the total generation power of the DGs, and the storage energy of the BESS during a day using the NSGA-II.

using the WWO, TSO, PSO, NSGA-II, and GA algorithms respectively.

The behaviours of the microgrid consisting of DGs and BESS for load powers are shown in Figs. 11-14 using the TSO, PSO, NSGA-II, and GA algorithms, respectively. The algorithms have allowed the dynamic optimal dispatch in the microgrid within 24 hours. However, the power generation cost of DGs and the energy storage cost of BESS are different depending on each algorithm. The comparisons of these achievable costs are implemented between the algorithms to validate the most suitable algorithm for achieving the solution of the dynamic optimal dispatch in the microgrid, Table 17.

Table 17 shows that the power generation cost of DGs and energy storage cost of BESS are 68.76 ($) and 5.09 ($) respectively using the WWO algorithm, whereas they are 70.43 ($) and 6.12 ($) respectively using the TSO algorithm; 71.12 ($) and 7.23 ($) respectively using the PSO algorithm; 71.05 ($) and 7.06 ($) respectively using the NSGA-II; as well as 72.37 ($) and 8.19 ($) respectively using the GA in a day (24 hours) of the microgrid.

The power generation cost of the DGs with the WWO algorithm has improved by 2.43%, 3.43%, 3.33%, and 5.25%, compared to the TSO, PSO, NSGA-II, and GA algorithms respectively. Furthermore, the energy storage cost of the BESS by utilizing the WWO algorithm has been enhanced by 20.24%, 42.04%, 38.70%, and 60.90%, compared to the TSO, PSO, NSGA-II and GA algorithms respectively. This results in the improvement of the total power supplying cost in the microgrid by using the WWO algorithm, 3.66%, 6.09%, 5.77%, and 9.09% compared with that by using the TSO, PSO, NSGA-II, and GA algorithms respectively.

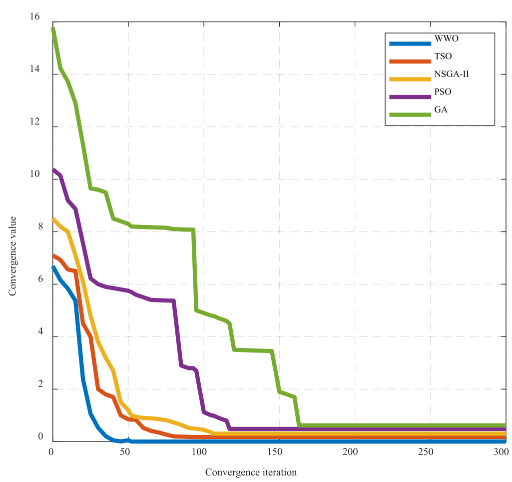

FIGURE 15. Convergence of the algorithms in the dynamic optimal dispatch.

Additionally, regarding the performance of the optimization algorithms applied in this paper, Table 18 shows that the convergence of the WWO algorithm is better than that of the

TABLE 12. Dynamic optimal dispatch of three DGs and one BESS using the WWO algorithm.

Time (h)	Load (kW)	P_1 (kW)	P_2 (kW)	P_3 (kW)	E_{BESS} (kWh)
1	27.88	19.38	8.50	0.00	25.00
2	25.09	20.09	11.00	0.00	31.00
3	24.75	19.50	9.25	0.00	35.00
4	27.87	21.12	10.75	0.00	39.00
5	36.09	25.09	16.00	0.00	44.00
6	40.23	26.15	17.08	0.00	47.00
7	46.49	28.19	17.30	3.00	49.00
8	57.73	30.00	20.00	5.00	46.27
9	63.10	30.00	20.00	5.00	38.17
10	60.76	30.00	20.00	5.00	32.41
11	64.81	30.00	20.00	5.00	22.60
12	64.15	30.00	20.00	5.00	13.45
13	56.82	30.00	20.00	5.00	11.63
14	47.53	29.13	18.40	3.15	14.78
15	40.54	27.32	17.32	1.92	20.80
16	41.31	27.15	16.16	1.10	23.90
17	42.32	27.17	17.15	1.30	27.20
18	51.73	30.00	20.00	5.00	30.47
19	54.07	30.00	20.00	5.00	31.40
20	59.01	30.00	20.00	5.00	27.39
21	49.53	29.76	19.26	3.90	30.78
22	44.37	28.13	17.54	2.25	34.33
23	32.02	23.01	13.01	0.00	38.33
24	27.97	20.35	9.62	0.00	40.33

TABLE 13. Dynamic optimal dispatch of three DGs and one BESS using the TSO algorithm.

Time (h)	Load (kW)	P_1 (kW)	P_2 (kW)	P_3 (kW)	E_{BESS} (kWh)
1	27.88	18.58	9.30	0.00	25.00
2	25.09	21.14	11.23	0.00	32.28
3	24.75	21.18	10.26	0.00	38.97
4	27.87	21.25	11.75	0.00	44.10
5	36.09	27.16	17.15	0.00	50.00
6	40.23	28.05	17.56	0.00	50.00
7	46.49	30.00	20.00	4.00	50.00
8	57.73	30.00	20.00	5.00	47.27
9	63.10	30.00	20.00	5.00	39.17
10	60.76	30.00	20.00	5.00	33.41
11	64.81	30.00	20.00	5.00	23.60
12	64.15	30.00	20.00	5.00	14.45
13	56.82	30.00	20.00	5.00	12.63
14	47.53	30.00	20.00	4.20	18.25
15	40.54	29.68	18.65	2.60	26.96
16	41.31	27.75	16.46	2.20	30.96
17	42.32	27.85	17.36	2.40	35.15
18	51.73	30.00	20.00	5.00	38.42
19	54.07	30.00	20.00	5.00	39.35
20	59.01	30.00	20.00	5.00	35.34
21	49.53	30.00	20.00	4.20	39.71
22	44.37	30.00	20.00	2.50	44.49
23	32.02	23.06	13.67	0.00	49.20
24	27.97	20.87	9.89	0.00	50.00

TABLE 14. Dynamic optimal dispatch of three DGs and one BESS using the PSO algorithm.

Time (h)	Load (kW)	P_1 (kW)	P_2 (kW)	P_3 (kW)	E_{BESS} (kWh)
1	27.88	15.18	12.70	0.00	25.00
2	25.09	15.07	16.71	0.00	31.69
3	24.75	14.46	15.37	0.00	36.77
4	27.87	19.17	16.06	0.00	43.13
5	36.09	26.03	19.81	0.00	50.00
6	40.23	30.00	19.31	0.00	50.00
7	46.49	30.00	20.00	5.00	50.00
8	57.73	30.00	20.00	5.00	47.27
9	63.10	30.00	20.00	5.00	39.17
10	60.76	30.00	20.00	5.00	33.41
11	64.81	30.00	20.00	5.00	23.60
12	64.15	30.00	20.00	5.00	14.45
13	56.82	30.00	20.00	5.00	12.63
14	47.53	30.00	20.00	5.00	20.10
15	40.54	30.00	19.00	2.92	31.48
16	41.31	30.00	19.38	2.10	41.65
17	42.32	29.45	19.65	2.30	50.00
18	51.73	30.00	20.00	5.00	50.00
19	54.07	30.00	20.00	5.00	50.00
20	59.01	30.00	20.00	5.00	45.99
21	49.53	30.00	19.53	3.90	50.00
22	44.37	30.00	19.37	2.25	50.00
23	32.02	25.35	10.70	0.00	50.00
24	27.97	19.71	8.26	0.00	50.00

TABLE 15. Dynamic optimal dispatch of three DGs and one BESS using the NSGA-II.

Time (h)	Load (kW)	P_1 (kW)	P_2 (kW)	P_3 (kW)	E_{BESS} (kWh)
1	27.88	18.29	9.59	0.00	25.00
2	25.09	21.23	11.76	0.00	39.40
3	24.75	21.45	11.88	0.00	50.00
4	27.87	22.29	12.09	0.00	50.00
5	36.09	25.60	18.27	0.00	50.00
6	40.23	29.12	19.78	0.00	50.00
7	46.49	30.00	20.00	4.00	50.00
8	57.73	30.00	20.00	5.00	47.27
9	63.10	30.00	20.00	5.00	39.17
10	60.76	30.00	20.00	5.00	33.41
11	64.81	30.00	20.00	5.00	23.60
12	64.15	30.00	20.00	5.00	14.45
13	56.82	30.00	20.00	5.00	12.63
14	47.53	30.00	20.00	3.50	20.10
15	40.54	29.83	18.86	2.50	33.56
16	41.31	28.62	19.05	3.20	43.63
17	42.32	28.85	19.16	2.50	50.00
18	51.73	30.00	20.00	3.00	50.00
19	54.07	30.00	20.00	3.00	50.00
20	59.01	30.00	20.00	5.00	45.99
21	49.53	30.00	20.00	5.00	49.46
22	44.37	30.00	20.00	3.00	50.00
23	32.02	23.18	15.25	0.00	50.00
24	27.97	20.95	10.30	0.00	50.00

TSO, PSO, NSGA, and GA algorithms in the application of the dynamic optimal dispatch in the microgrid. The convergence value of the WWO algorithm, 0.0028, is better than that of the TSO, PSO, NSGA-II and GA algorithms, 0.1743, 0.4832, 0.3051, and 0.6198 respectively. Simultaneously, the convergence iteration of the WWO algorithm, 52, is also better than that of the TSO, PSO, NSGA, and GA algorithms, 93, 117, 106, and 163, respectively.

Fig. 15 provides a visualization, indicating that the GA and PSO algorithm have struggled to maintain an effective search for optimal solutions globally.

Meanwhile, the TSO and NSGA-II algorithms are better than the PSO and GA algorithms through the convergence

TABLE 16. Dynamic optimal dispatch of three DGs and one BESS using the GA.

Time (h)	Load (kW)	P_1 (kW)	P_2 (kW)	P_3 (kW)	E_{BESS} (kWh)
1	27.88	24.13	3.75	0.00	25.00
2	23.78	21.78	15.71	0.00	32.90
3	24.75	23.05	17.18	0.00	41.48
4	27.87	24.12	18.06	0.00	47.99
5	36.09	30.00	19.81	0.00	50.00
6	40.23	30.00	19.31	0.00	50.00
7	46.49	30.00	20.00	3.00	50.00
8	57.73	30.00	20.00	5.00	47.27
9	63.10	30.00	20.00	5.00	39.17
10	60.76	30.00	20.00	5.00	33.41
11	64.81	30.00	20.00	5.00	23.60
12	64.15	30.00	20.00	5.00	14.45
13	56.82	30.00	20.00	5.00	12.63
14	47.53	30.00	20.00	5.00	19.30
15	40.54	30.00	19.00	5.00	30.05
16	41.31	30.00	19.38	2.00	39.61
17	42.32	30.00	20.00	2.30	47.80
18	51.73	30.00	20.00	5.00	50.00
19	54.07	30.00	20.00	5.00	50.00
20	59.01	30.00	20.00	5.00	45.99
21	49.53	30.00	20.00	3.00	50.00
22	44.37	30.00	20.00	3.00	50.00
23	32.02	23.01	10.70	0.00	50.00
24	27.97	20.35	8.26	0.00	50.00

TABLE 17. Power generation cost of DGs and energy storage cost of bess using various algorithms in a day of 24 hours.

Cost	C_{Diesel} (\$)	C_{BESS} (\$)	$C_{Microgrid}$ (\$)
WWO	68.76	5.09	73.85
TSO	70.43	6.12	76.55
PSO	71.12	7.23	78.35
NSGA-II	71.05	7.06	78.11
GA	72.37	8.19	80.56

TABLE 18. Convergence comparison of the algorithms in the dynamic optimal dispatch.

Convergence	Convergence value	Convergence iteration
WWO	0.0028	52
TSO	0.1743	93
PSO	0.4832	117
NSGA-II	0.3051	106
GA	0.6198	163

values and iterations. However, they still require more iterations to achieve globally optimal solutions compared to the WWO algorithm; as well as their convergence values are worse than that of the WWO algorithm. This leads to poor results of the dynamic optimal dispatch in the microgrid. In other words, the total costs of supplying power from the microgrid to the load by using the TSO, PSO, NSGA-II, and GA algorithms are always more than that by using the WWO algorithm. The total costs are reduced by up to 9.09% by using the WWO algorithm.

V. CONCLUSION

This paper has investigated microgrid optimization, specifically focusing on achieving dynamic optimal dispatch involving real-time adjustments to operational parameters based on accurate day-ahead load forecasts.

The proposed MLR model-based technique demonstrates its efficacy in forecasting day-ahead load for the microgrid, providing accurate predictions crucial for the success of the dynamic optimal dispatch. The PE between the forecasted load powers by the MLR model and the actual values consistently remains less than 4.42%, demonstrating high accuracy. Additionally, the MAPE for the forecasted results is 3.33%, further emphasizing the precision of the proposal. Moreover, the execution time for the forecasting process is impressive at 49 (s), meeting both accurate and fast requirements. These achievements not only fulfil the criteria for precise and fast predictions but also prove to be highly competitive as compared to CNN and LSTM, particularly in terms of execution time. The precision of load forecasting directly influences the overall performance of the microgrid, affecting its ability to adapt to changing conditions and make informed decisions in real-time.

The WWO algorithm is introduced as a novel approach to solving the dynamic optimal dispatch problem. The algorithm's unique features include the population size, parameter tuning, exploitation and exploration, convergence speed, as well as optimization mechanism.

Simulation results, comparing the proposed WWO algorithm with established optimization techniques such as the TSO, PSO, NSGA-II and GA algorithms, demonstrate the superior performance of the WWO algorithm. The diesel generation, battery energy storage, and microgrid generation costs are 68.76 (\$), 5.09 (\$), and 73.85 (\$) respectively using the WWO algorithm which are better than those by using the GA, NSGA-II, PSO, and TSO algorithms in the microgrid. It not only achieves better cost outcomes in terms of diesel generation, battery energy storage, and microgrid generation costs but also exhibits improved efficiency of the convergence values and iteration.

Furthermore, the paper contributes valuable insights into the practical implementation of dynamic optimal dispatch, emphasizing the prioritization of existing DERs and BESSs to minimize the need for additional investments during temporary load increases. The proposed approach efficiently manages DERs and BESSs, optimizing their utilization and reducing overall energy costs for the microgrid.

The research findings have implications for microgrid operators, energy planners, and policymakers, offering a robust methodology for sustainable and cost-effective solutions in the evolving landscape of modern energy systems. By combining the MLR model for accurate load forecasting and the WWO algorithm for dynamic optimal dispatch, the paper provides actionable strategies to enhance the reliability, economic efficiency, and overall performance of microgrid operations.

The proposed methodology is a significant step forward in the quest for efficient and sustainable microgrid management, contributing to the broader knowledge base in the field of microgrid optimization.

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DUY C. HUYNH (Senior Member, IEEE) received the B.E. and M.E. degrees in electrical engineering from the University of Technology, Vietnam National University of Ho Chi Minh City, Vietnam, in 2001 and 2005, respectively, and the Ph.D. degree in electrical engineering from Heriot-Watt University, Edinburgh, U.K., in 2010. He is currently an Associate Professor of electrical engineering. His research interests include the areas of energy-efficient control and parameter estimation for induction machine drive systems, power systems, renewable energy systems, microgrids, and smart grids.

LOC D. HO received the B.Sc. degree in electrical engineering from the National Technical University, Kharkiv Polytechnic Institute, Ukraine, in 1991, the D.Eng. degree in automation engineering from the Igor Sikorsky Kyiv Polytechnic Institute, National Technical University of Ukraine, Ukraine, in 1994, and the Dr.Sc. degree in automation engineering from the National Research University, Moscow Power Engineering Institute, Russia, in 2002. He is currently a Professor and the President of the HUTECH University, Vietnam. His research interests include control and operation in power systems, microgrids, and smart grids; stability analysis in control systems; soft computing techniques such as neural networks, and fuzzy logics; meta-heuristic algorithms such as genetic algorithms, and particle swarm optimization algorithms; and cloud computing techniques.

HIEU M. PHAM received the B.E. degree in electrical engineering from the University of Technology, Vietnam National University of Ho Chi Minh City, Vietnam, in 2001, and the M.E. degree in electrical engineering from HUTECH University, Vietnam, in 2018, where he is currently pursuing the Ph.D. degree in electrical engineering. His research interests include optimal operation and configuration determination of microgrids and smart grids considering renewable energy sources.

MATTHEW W. DUNNIGAN received the B.Sc. degree (Hons.) in electrical and electronic engineering from Glasgow University, Glasgow, U.K., in 1985, and the M.Sc. and Ph.D. degrees from Heriot-Watt University, Edinburgh, U.K., in 1989 and 1994, respectively. From 1985 to 1988, he was with Ferranti, as a Development Engineer in the design of power supplies and control systems for moving optical assemblies and device temperature stabilization. In 1989, he became a Lecturer with Heriot-Watt University, where he was concerned with the evaluation and reduction of the dynamic coupling between a robotic manipulator and an underwater vehicle. He is currently an Associate Professor and his research grants and interests include the areas of hybrid position/force control of an underwater manipulator, coupled control of manipulator-vehicle systems, nonlinear position/speed control and parameter estimation methods in vector control of induction machines, frequency domain self-tuning/adaptive filter control methods for random vibration, and shock testing using electrodynamic actuators.

CORINA BARBALATA (Member, IEEE) received the B.E. degree in electrical engineering from Transilvania University, Brasov, Romania, in 2011, the joint M.Sc. degree in computer vision and robotics from Heriot-Watt University, Edinburgh, U.K., and the University of Burgundy, Dijon, France, in 2013, and the Ph.D. degree in electrical engineering from Heriot-Watt University, in 2017. She is currently an Assistant Professor with Louisiana State University, Baron Rouge, LA, USA. Her research interests include marine robot systems, autonomous mobile-manipulation, cooperative robotics, multi-body control and planning theory, and underwater perception systems and algorithms.