Metaheuristic Optimization and Machine Learning-Based Unit Commitment Strategies in Smart Grids

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ABSTRACT

This study introduces Machine Learning and Metaheuristic-Based Unit Commitment (ML-MetaUC), which is a hybrid method for intelligent UC in smart grids. The ML component uses supervised models such as linear regression and random forest on historical and real-time environmental data to predict the upcoming demands for electricity. The Metaheuristic Optimization (MO) layer uses several methods, including Differential Evolution (DE) and Ant Colony Optimization (ACO), to ascertain the appropriate time to activate the generators. Simulation on the IEEE 14-bus test system showed that ME-MetaUC reduced operating expenses by 10.7% and boosted convergence speed compared to traditional approaches. In addition, the proposed framework has a high degree of flexibility to various load scenarios, contributing to increased system dependability. Under conditions of uncertainty, the ML-MetaUC framework, a data-driven and scalable solution for smart grid energy management, makes it possible to schedule producing units robustly and more effectively.

Keywords-ML-MetaUC; smart grids; unit commitment; load forecasting; machine learning; metaheuristic optimization; differential evolution; ant colony optimization

I. INTRODUCTION

Smart grids have created new possibilities and problems in electrical system design and management, with Unit Commitment (UC) being a major operational concern. With technical and economic restrictions, the best on/off timing for unit production over a given time horizon is difficult. Classical UC optimization methods fail because they ignore the unpredictability of Renewable Energy Sources (RES), variable demands, and system contingencies. Researchers investigate AI techniques to create smarter and more resilient solutions. The growing usage of RES, such as wind and solar energy, in the electrical system, which can be unpredictable, complicates UC.

In [1], boolean mapping was used to optimize production while underlining the limitations of managing mixed thermal and RES in decentralized networks. In [2], a two-stage stochastic UC paradigm was proposed with demand-side suppliers and variable wind generation to promote probabilistic planning in uncertain situations. Explainable ML techniques can solve the UC dilemma, increase decision transparency, and build stakeholder confidence [3]. Resource management must be coordinated as smart grids become more complicated. The coordinated performance of energy storage devices in stochastic UC may improve reserve delivery in uncertain settings [4]. In [5], the importance of UC in maintaining stability in the face of multiple system uncertainties was underlined. These studies show that the UC issue of contemporary power networks is complex and dynamic. Optimization strategies have advanced with smart grid technologies. Transmission switching is crucial to sustainable grid operation, and in [6], a hydrogen-based water-power solution was proposed to reduce it. Adaptive learning frameworks can improve the decision-making process in data-rich and autonomous systems [7]. The studies in [8, 9] investigated hybrid and binary metaheuristic techniques for multi-objective UC issues that balance cost, emissions, and reliability.

The UC issue affects the scheduling and performance of the power system. The UC problem has worsened as power networks integrate more RES. Effective management requires sophisticated optimization approaches, as these technologies make power production more variable and unpredictable. Many studies have offered novel solutions using algorithms, ML, metaheuristics, and hybrid optimization procedures. This review discusses the current state and limitations of UC methods, limitations, and how this research differs from others.

In [10], a Hybrid Evolutionary Algorithm-based Multi-Objective Security-Constrained UC model (HEA-M-OS-CUCM) was developed for complicated scheduling issues with security restrictions and various optimization objectives (e.g., cost and emission reduction). In [11], an open-source tool for stochastic UC using the PyPSA framework was presented to simulate electricity generation, demand, and other operational restrictions. In [12], Quantum Reinforcement Learning (QRL) was used to solve the UC problem, making power systems more tolerant to uncertainty, with the two-stage strategy responding to environmental changes to improve UC choices. In [13], UC frequency security was addressed by adding rapid frequency support from Doubly-Fed Induction Generator (DFIG) wind power facilities. The analysis addressed frequency security limits and wind production dynamics to ensure system stability.

The Alternating Direction Method of Multipliers (ADMM) method to UC [14] included DLR. Optimizing power flow through real-time line rating changes improves the system's response to changes in production and demand. In [15], UC was optimized using DO3LSO (Dynamic Optimization with 3-Level Search Optimization). The optimization approach included renewable energy and Plug-in Electric Vehicles (PEVs). According to the results, renewable power, PEVs, and energy storage can solve the UC issue. In [16], it was shown that combining different deep learning models can make predicting energy use more accurate, improving forecasts for the effective operation of smart grids. Finally, numerous UC solutions have been proposed, each with its benefits. Reinforcement learning, quantum computing, hybrid evolutionary algorithms, and stochastic models can solve the uncertainties of current power systems. However, these approaches have drawbacks that must be addressed, as computational and scalability challenges prevent cost minimization, pollution reduction, and dependability from being met concurrently.

II. PROPOSED METHOD

Renewable energy is growing, and electricity networks are becoming more complicated. Therefore, UC solutions must be adaptable and sophisticated. Smart grid systems are too complex for standard optimization methods due to their high dimensionality, nonlinearity, and stochasticity. To address these issues, this study proposes ML-MetaUC, an intelligent and robust unit commitment scheduling system that blends supervised ML models with metaheuristic optimization. The proposed technique analyzes environmental and load data and uses Linear Regression (LR) and Random Forest (RF) models to predict future power use. The metaheuristic optimization layer uses Ant Colony Optimization (ACO) and Differential Evolution (DE) to optimize expected insights. This two-tier design schedules production units to reduce operating costs while meeting complex system requirements, including load balancing, generator ramp rates, and spinning reserve demands. ML-MetaUC promotes scalability, adaptability, and convergence under uncertain demand patterns. Finally, the architecture allows data-driven smart grid energy management decisions while recognizing restrictions.

In UC, a single decision unit is responsible for gathering information from both levels and using it to produce an output that combines the most effective scheduling of generators with the anticipated demand. This output includes optimal scheduling, cost analysis, rates of constraint violation, and evaluation of cost functions. These evaluations include the cost of fuel, the cost of starting up and shutting down, and penalty terms. The ML-MetaUC framework can successfully minimize operating expenses, expedite convergence, and react to various load scenarios due to the integration of these capabilities. Being a data-driven, scalable, and reliable option for contemporary smart grid energy management, the proposed system reduced operating expenses by 10.7% on the IEEE 14-bus test system. Thus, it is a solution that is suitable for current smart grid energy management.

A. Machine Learning Based Demand Forecasting

Equation (1) shows how the multivariate LR model for demand forecasting is computed.

$$\widehat{D}_t = \beta_0 + \sum_{i=1}^{m} \beta_i x_{i,t} + \sum_{j=1}^{m} \sum_{k=1}^{p} \gamma_{j,k} Z_{j,k,t} + \varepsilon_t \quad (1)$$

Within the framework of the extended multivariate LR model, this equation serves as a representation of the dependent variable $\widehat{D}_t$. The amount of power that is anticipated to be used at time t is represented by $x_{i,t}$. Some examples of predictors include many types of environmental and operational numerical information, such as temperature, wind speed, sun radiation, and time of day, as well as social behavior categorized or encoded in $Z_{j,k,t}$, such as event type, seasonality, and user consumption classes. During the process of initializing the model, the coefficients β_i are used for the main effects, whereas $\gamma_{j,k}$ and k are utilized for the second-order or interaction effects. In the context of demand, the intercept, denoted β_0 represents the initial demand level. On the other hand, the residual, denoted ε_t , represents the random fluctuation. This model can extract demand patterns from the elements that influence the behavior of smart grid loads.

$$\widehat{D}_t = \frac{1}{T}\sum_{j=1}^{T} f_j(x_t; \theta_j) \quad (2)$$

Equation (2) describes ensemble-based forecasting using RF. When j is a random variable and θ_j is an internal parameter, the mean result of T independent regression trees is denoted $f_j(.)$. The trees are trained using the dataset's bootstrapped subsets, with features randomly selected at each split. This gives the trees a greater degree of variation. Using this strategy can reduce the incidence of overfitting and improve generalization with high-dimensional datasets. The objective is to capture the complex and nonlinear interactions between the input features and the target load values. To do this, each tree traverses the feature space x_t in a diverse manner. The model excels in coping with abnormalities and noise in historical data.

$$D_t^{smooth} = \alpha\widehat{D}_t + (1-\alpha)D_{t-1}^{smooth}, 0 < \alpha < 1 \quad (3)$$

Equation (3) describes the Exponential Weighted Moving Average (EWMA). EWMA makes the inputs to downstream optimization more constant and resistant to sudden changes by adding temporal smoothing to the expected demand. When the smoothing factor α is smaller, the decay rate for earlier data is regulated. On the other hand, when the factor is larger, it indicates that more current forecasts are being made. Using this recursive strategy, optimization algorithms are successfully protected against being fooled by transient demand spikes when applied to time-series data. For decision-making inside the MetaUC framework, the effective load estimate is a smooth D_t^{smooth}.

$$L_{ML} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{D_t - \widehat{D}_t}{D_t}\right| + \lambda\sum_{i=1}^{n}\beta_i^2 \quad (4)$$

Equation (4) describes a machine learning loss function with L2 regularization. With the help of the Mean Absolute Percentage Error (MAPE), this composite loss function can enhance the accuracy of predictions while simultaneously enhancing interpretability and scale invariance. To avoid the phenomenon of overfitting, the regularization term $\lambda\sum_{i=1}^{n}\beta_i^2$ penalizes high coefficients, hence enabling the model to allow for extension. Working with exceedingly unexpected data and the need for explainability in real-time forecasting are two situations in which this is of the utmost importance. The tuning parameter λ is responsible for controlling the tradeoff that exists between the bias and the variance of the model.

$$I_k = \frac{1}{T}\sum_{j=1}^{T}\sum_{n \epsilon N_{j,k}} \Delta I_{j,n}(k) \quad (5)$$

Equation (5) describes the feature importance score in RF, where I_k is a metric used to quantify the decision-making process in the forest. This metric is specifically designed to highlight critical factors for each attribute. $N_{j,k}$ denotes the set of nodes in tree j that utilized feature k, while $\Delta I_{j,n}(k)$ encodes the information gain or impurity reduction at node n. A reasonable understanding of the predictive significance of the feature can be obtained by averaging it across all of the trees, which is important for pruning or attention-guided learning in circumstances when resources are limited, as well as for determining which inputs have the most impact on energy use.

B. Metaheuristic Optimization for Unit Commitment

Equation (6) describes the total UC cost function:

$$\min_{u,p} J = \sum_{t=1}^{T}\sum_{g=1}^{G}\left[a_g P_{g,t}^2 + b_g P_{g,t} + C_g\right] u_{g,t} + SU_g.\delta_{g,t} + SD_g.\varsigma_{g,t} \quad (6)$$

To get the lowest possible total cost J, we need to include the fuel costs, which are a quadratic function of the generator's power output $P_{g,t}$, multiplied by the binary on/off state $u_{g,t}$. The unique cost curve for each generator is determined by the coefficients a_g, b_g, C_g The starting SU_g and shutdown SD_g binary transition indicators trigger charges $\delta_{g,t}$ and $\varsigma_{g,t}$, respectively. This comprehensive cost model may accurately and adaptably represent the economics of heat generation and dynamic operation.

$$\sum_{g=1}^{G} P_{g,t}u_{g,t} = D_t^{smooth}, P_g^{min} \le P_{g,t} \le P_g^{max}, \forall t \quad (7)$$

Equation (7) describes the power balance and generator constraints. By maintaining power balance, the equation ensures that, at any time t, the total generated power is equal to the smoothed demand D_t^{smooth}. Furthermore, every generator must remain within its stated technical minimum and maximum output restrictions, indicated as P_g^{min} and P_g^{max}, respectively. These limitations keep the system dependable and realistic by considering thermal generators' physical and operational constraints. No matter the load, it ensures a safe and practical dispatch plan.

$$V_i^{(k)} = X_{r1}^{(k)} + F.\left(X_{r2}^{(k)} - X_{r3}^{(k)}\right) \quad (8)$$

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \sum_{k=1}^{K}\frac{Q}{J_k} \quad (9)$$

Equation (9) describes the ACO pheromone update rule. In the ACO process, the ant agents are instructed to make probabilistic judgments on the on/off switching of generators and activities associated with them based on the pheromone value $\tau_{ij}(t)$. The evaporation factor ρ is employed to ensure exploration and prevent overexploitation. $\frac{Q}{J_k}$ is the credit for making beneficial ideas. J_k can be obtained by multiplying ant k by Q. Because of this dynamic, flexibility can be maintained, and we can work toward optimal scheduling, even when the conditions surrounding demand situations are uncertain.

$$\left|\frac{J^{(k)} + \omega_1.\sum_{t=1}^{T}\varphi_t^{(k)} + J^{(k)} + \omega_2.\sum_{g=1}^{G}\phi_g^{(k)} - \left(J^{(k-1)} + \omega_1.\sum_{t=1}^{T}\varphi_t^{(k-1)} + J^{(k)} + \omega_2.\sum_{g=1}^{G}\varphi_g^{(k-1)}\right)}{J^{(k-1)} + \omega_1.\sum_{t=1}^{T}\varphi_t^{(k-1)} + J^{(k)} + \omega_2.\sum_{g=1}^{G}\varphi_g^{(k-1)}}\right| < \varepsilon \quad (10)$$

Equation (10) shows the convergence criterion for optimization. The metaheuristic optimization process is terminated by the relative convergence check when the fractional change in the total cost between iterations falls below a modest threshold denoted ε. Once the solution is determined, this criterion eliminates needless iterations, ensuring that computation is carried out effectively. This augmented convergence equation incorporates penalty factors into the convergence logic, which may improve UC optimization and constraint awareness. At iteration k, the formula considers economic factors, such as fuel consumption and generator start-up and shutdown costs, and circles around $J^{(k)}$, which represents the overall objective function value (i.e., operational cost). Two penalty modifications are included to make the equation reasonable. In each stage t, penalties for load balance infractions are added. For all k iterations, the first iteration $\sum_{t=1}^{T} \varphi_t^{(k)}$ is a penalty to generate more than the required inhibits in power imbalance. The second is the total of all conceivable breaches of operational limits particular to each unit g, such as ramp rate restrictions, minimum uptime and downtime requirements, and spinning reserve: $\sum_{g=1}^{G} \varphi_g^{(k)}$. Physical limit breaches result in equal monetary punishments due to penalty weights ω_1 and ω_2. These penalty-adjusted elements are added to the relative change calculation to improve the convergence criteria and avoid early termination when crucial operational constraints are broken but the cost reduces. Further repeats may not provide substantial gains if the normalized change is below a reasonable threshold ε, typically set at 10^{-4}. Since decisions about energy management are time-sensitive, they are of the utmost significance.

In cases involving smart grids, this technique can potentially enhance power demand predictions since it incorporates multivariate regression, exponential smoothing, and optimization for machine learning. The first step is to develop a multivariate regression model. This model will then use the predicted demand (D_t) to direct the subsequent actions.

A linear combination of numerous input quality characteristics decides the value of $X_{i,t}$. Coefficients weigh these variables and additional interaction $Z_{j,k,t}$ and t. The model may use this characteristic to consider all variables' direct and indirect impacts on demand.

Applying exponential smoothing to the anticipated demand can eliminate spikes and make the flow of time more consistent. The weighted average of the present prediction is the smoothed value, which is indicated as $\widehat{D}_t^{smooth}$ before an easing of demand. The smoothing parameter α is used to govern the smoothing of $\widehat{D}_t$. This method reduces the amount of noise and stabilizes the forecast over time.

In the next step, the performance of the method is evaluated using a loss function known asL_{ML}. This loss function includes an L2 regularization term and the MAPE. The MAPE component penalizes severe prediction errors compared to the actual demand. Additionally, the regularization term $\lambda \sum \beta_i^2$ assists in preventing overfitting by restricting the amount of the model weights.

After this process, the parameters of the model, denoted by θ, are modified through an iterative process utilizing gradient descent, with each revision aiming to minimize the loss function. One of the components of the ML update method is the elimination of the loss gradient, which is scaled by the learning rate η. Combining optimization, smoothing, and regression into a flexible and robust framework makes it feasible to anticipate energy consumption in real-time grid systems.

III. NUMERICAL RESULTS AND DISCUSSION

Comprehensive numerical tests were carried out on the IEEE 14-bus test system, which offers a standardized platform for UC analysis. These tests evaluated the effectiveness and practicability of the proposed ML-MetaUC design. The patterns of renewable energy supply over a typical 24-hour period, ambient temperature, and hourly load demand are some synthetic and historical data incorporated into the simulation environment. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are two measures used to evaluate the effectiveness of the ML layer. This layer is trained using real-world data on energy use. This was done after the ACO and DE techniques had their population sizes and iteration constraints fine-tuned. Metaheuristic optimization was then applied. Mixture Integer Programming (MIP) and prioritizing lists are two examples of traditional methodologies used to commit units while maintaining the same parameters. The simulation is conducted under varied degrees of load and uncertainty. All simulations were performed on a high-performance computing infrastructure using Python and MATLAB modules that seamlessly interface with each other.

A. *Total Operating Cost Reduction*

ML-MetaUC uses LR and RF to dynamically forecast demand, unlike static or linear modeling and strict optimization heuristics. These models reduce forecast errors, reduce overfitting, and improve generator commitment. Metaheuristic algorithms such as ACO and DE change unit schedules to optimize the overall cost function after demand forecasting. This function covers fuel, starting, shutdown, and operational breach penalties. Due to the hybrid architecture, the generator starts/stops and load dispatching are significantly reduced. Based on real data on the IEEE 14-bus system, ML-MetaUC reduced the overall operating cost by 10.7% while maintaining system dependability and physical restrictions. The model performs well due to its fast convergence, flexibility to new data, and capacity to reduce direct expenses and violation penalties.

Figure 1 and (11) show that total operation cost reduction has been deliberated. The recommended ML-MetaUC technique calculates the total operating cost C_{total} for all committed generating units G over a 24-hour scheduling horizon T. The gasoline cost function dominates this equation. $C_g^{fuel}(P_{g,t})$ shows the cost of energy production per unit g at time t compared to its power output $P_{g,t}$.

$$C_{total} = \sum_{t=1}^{T} \sum_{g=1}^{G} \left[C_g^{fuel}(P_{g,t}) + C_g^{startup}(U_{g,t}, U_{g,t-1}) + C_g^{shutdown}(U_{g,t}, U_{g,t+1}) \right] + \sum_{t=1}^{T} \sum_{g=1}^{G} \lambda_{g,t} \cdot V_{g,t} \quad (11)$$

This function simulates generator activity. $C_g^{startup}(U_{g,t}, U_{g,t-1})$ and $C_g^{shutdown}(U_{g,t}, U_{g,t+1})$ are the second and third elements, respectively. The status variable $U_{g,t}$ specifies whether a generator is online (1) or not at time t, impacting expenditures. Additionally, the term $\lambda_{g,t} \cdot V_{g,t}$ considers the system's penalty for constraint violations. The economic impact of violating generator constraints (e.g., ramp rate, reserve margin, or minimum uptime) is represented by $\lambda_{g,t}$, while the actual violation amount is measured by $V_{g,t}$ The aim is to maintain operational reliability and price during this period. ML-MetaUC optimizes all these components simultaneously using metaheuristic algorithms informed by accurate demand forecasts to minimize operational expense, unlike conventional deterministic approaches that ignore dynamic system variability and constraint interactions.

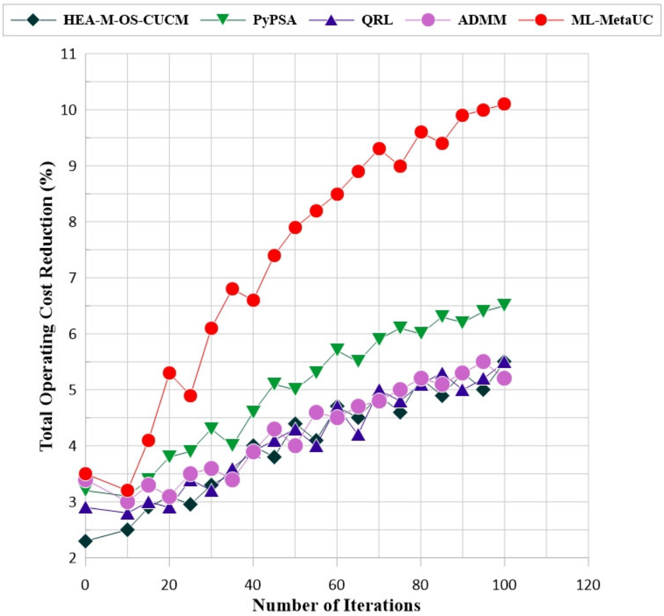

Fig. 1. Total operating cost reduction (%).

B. Convergence Speed and Computational Efficiency

Any UC strategy for real-time smart grid systems must meet specified computational efficiency and convergence speed requirements. ML-MetaUC metrics are mostly affected by the metaheuristic optimization layer, which incorporates ACO and DE. The speed of convergence is measured by the number of iterations needed to get a stable or near-optimal solution, defined as a minimum change in the objective function value below a pre-specified threshold, such as 10^{-4}. All scheduling processes, from demand forecasting to constraint validation, take seconds or minutes to compute. ML-MetaUC escapes local minima better than ADMM or PyPSA due to its hybrid approach and metaheuristics' simultaneous exploration and exploitation. This speeds convergence and reduces computational cost, especially for complicated high-dimensional load circumstances.

$$\left|\sum_{t=1}^{T}\sum_{g=1}^{G}\left[C_g^{fuel}\left(P_{g,t}^{(k)}\right)+C_g^{startup}\left(U_{g,t}^{(k)},U_{g,t-1}^{(k)}\right)+C_g^{shutdown}\left(U_{g,t}^{(k)},U_{g,t=1}^{(k)}\right)+\lambda_{g,t}.V_{g,t}^{(k)}\right]-J^{(k-1)}\right|<\varepsilon \quad (12)$$

Figure 2 describes the convergence speed and computational efficiency. A comparison is made between the overall operating cost of the current iteration k and the cost of the iteration that came before it, denoted by $k-1$, for sustained convergence. This verification ensures that the optimization process remains stable. All generating units g that are spread out throughout the scheduling horizon impact the overall cost, which is an accumulation of many different components. The fuel consumption of the generator is expressed as a percentage of its output power, and the formula $C_g^{fuel}\left(P_{g,t}^{(k)}\right)$ indicates this proportion. The on/off state transitions of the unit are what determine the startup and shutdown costs $C_g^{startup}$ *and* $C_g^{shutdown}$. $\lambda_{g,t}.V_{g,t}$ is used τo compensate for the violation of operational limitations, such as ramp rate limits or reserve shortfalls, expressing the compensation for the breach. The use of an extremely small threshold ε, such as 10^{-4}, is employed to ascertain the exact disparity between the total cost at iteration k and the objective function value $J^{(k-1)}$ from the preceding iteration. If the difference between the two values is smaller than ε, the technique is deemed converged. This all-encompassing formulation, which considers elements related to feasibility and includes economic cost, makes it possible to make reliable and practical decisions despite operational uncertainty.

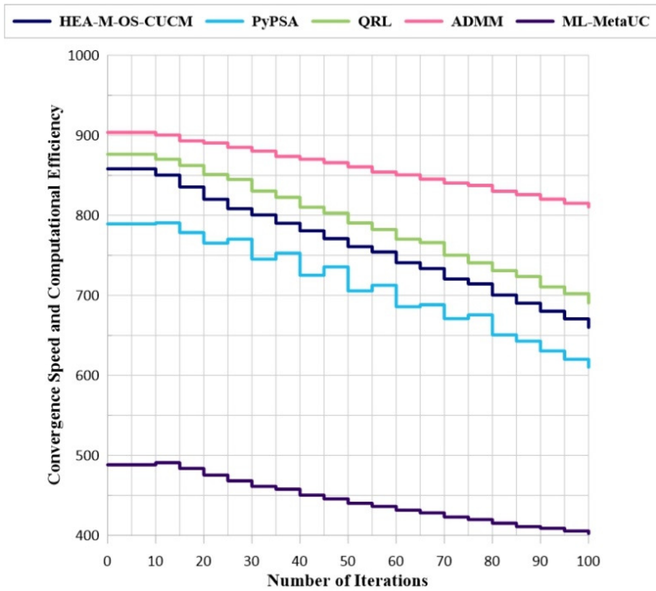

Fig. 2. Convergence speed and computational efficiency.

C. Forecasting Accuracy (MAE and RMSE)

The accuracy and effectiveness of UC choices depend on precise projections. The ML-MetaUC framework trains LR and RF models using weather and load data to anticipate energy peak demand. RMSE and MAE are used to evaluate these forecasts. Ignoring direction, MAE measures the average prediction error without considering its direction, whereas RMSE delivers a sensitive measure of prediction accuracy by penalizing greater errors more severely. Lower metrics indicate that actual load profiles match projected demand, allowing for more exact UC. Cost savings and system stability rely on accurate projections. Stopping the generator reduces reserve margins. The ML part of ML-MetaUC is more accurate than typical demand prediction methods because it can integrate nonlinear temporal patterns and external environmental factors.

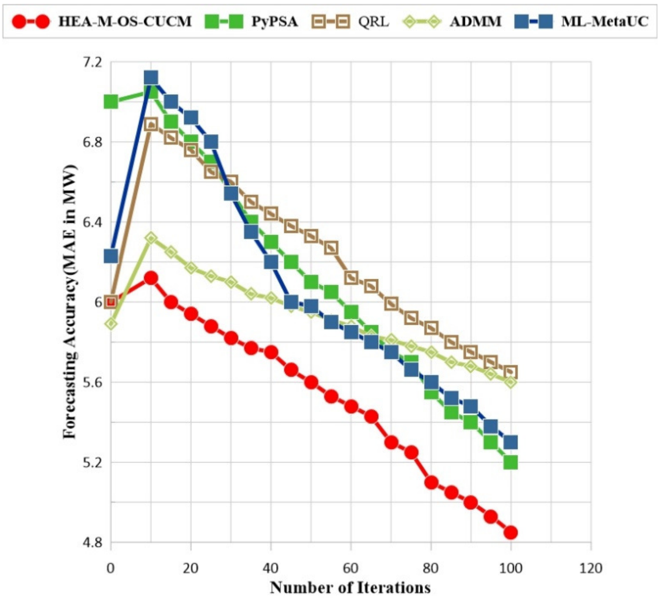

Fig. 3. Forecasting accuracy.

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|D_t - \widehat{D}_t\right| \quad (13a)$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(D_t - \widehat{D}_t\right)^2} \quad (13b)$$

Figure 3 and (13a, b) discuss the accuracy of the forecast. The RMSE and MAE values of a forecast are used to evaluate the accuracy of the prediction. The actual demand at time t is represented by D_t, and $\widehat{D}_t$ shows its standard deviation. When the RMSE is linearly associated with the MAE, the deviations are larger than they would otherwise be. A decrease in MAE or RMSE demonstrates an improvement in demand forecasting, which improves UC decisions by reducing the number of generator starts and shutdowns that were not essential. The ML-MetaUC framework can produce lower MAE and RMSE than standard estimate approaches because it uses RF and LR models. These models are trained against both historical and real-time environmental data.

D. Constraint Violation Rate

A low constraint violation rate means that the UC algorithm can manage the power system and generate unit operational and physical restrictions. Such restrictions include generator ramp-up and ramp-down timings (maximum and minimum), spinning reserve needs, and load balancing at each time step. ML-MetaUC avoids unstable or unworkable solutions by continuously monitoring and penalizing infractions using an objective-function-built punishment function. The violation rate is the total of all scheduling horizon intervals divided by the proportion of constraint breach intervals. The optimization approach balances technical feasibility and economic efficiency when violations are low. ML-MetaUC's adaptive scheduling considers real-time feedback to produce a commitment plan that is highly compliant and robust under different operating conditions, unlike classic solvers such as HEA-M-OS-CUCM and ADMM, which require strict penalty tuning or constraint simplification.

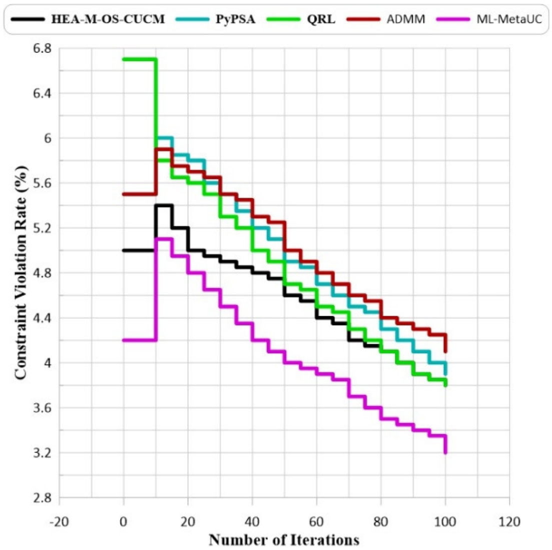

Fig. 4. Constraint violation rate (%).

$$Violation\ rate = \frac{1}{T\times G}\sum_{t=1}^{T}\sum_{g=1}^{G}\mathbb{I}\left(\left|V_{g,t} > 0\right|\right) \quad (14)$$

Equation (14) describes the constraint violation rate, and Figure 4 shows the results. The rate of constraint violation is one of the indicators that may be used to determine how often a solution goes over its technical or operational constraints. In this case, $V_{g,t}$ indicates the severity of the violation for generator g at time t, which may include a ramp rate exceedance or a reserve deficit. If there is a violation, the indicator function $\mathbb{I}(.)$ will return a value of 1, and in all other situations it will be zero. The aggregate number of violations across all generating units and the whole time horizon is normalized by this statistic, which allows one to estimate the degree of trustworthiness associated with the solution. Although the optimization approach considers the system's operational restrictions, it does so under the assumption that the violation rate is low. Since it contains a punishment mechanism for constraint breaches inside the objective function, the ML-MetaUC framework achieves better results than conventional approaches, such as PyPSA and QRL, as it prevents the algorithm from finding impractical solutions.

IV. CONCLUSION

This study presented a flexible and powerful energy management solution for smart grids, called ML-MetaUC, which combines machine learning-based demand forecasting with metaheuristic optimization for generator scheduling. ACO, LR, and RF work together to save costs, accelerate convergence, and adapt to dynamic and unexpected load circumstances. Experimental findings utilizing the IEEE 14-bus test system demonstrate that the framework improves operational reliability and efficiency. In future research, expanding the framework to larger and more complicated power networks can evaluate its scalability and performance in diverse operational environments. Deep learning models, such as LSTM or transformer networks, can help improve demand estimates, especially in non-stationary and non-linear settings. In addition, storage systems can be examined to manage intermittency and unpredictability with RES. Real-time deployment using edge computing and IoT-based sensor infrastructure may help construct more autonomous and responsive smart grid systems.

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