A Fast Learning-Based Unit Commitment Strategy with AC Optimal Power Flow for Large Grids with Direct Inclusion of Weather

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***Abstract*—This paper proposes a strategy to solve a fast, learning-based and computationally feasible unit commitment (UC) with ac optimal power flow (OPF) and direct inclusion of weather measurements for large grids. Through the proposed approach, we determine the on/off status of generating units and their dispatch. One of the main challenges is that UC with ac OPF is computationally intractable for large grids over long periods. The other challenge is that the status of all units are related and not independent. We leverage multi-label machine learning classifiers to predict the status of each generator. The proposed strategy considers load and weather changes at different times of the year and the availability of the resources in addition to weather changes. The results show the UC is predicted with high classification performance metrics and feasible ac OPF results are achieved. The code for this work is publicly available [1].**

***Index Terms*—Multi-label classification, Unit Commitment, Optimal Power Flow, Machine Learning**

I. Introduction

Large optimization problems need to be regularly solved for operation/planning and the analysis of power systems and electricity markets. Unit commitment (UC) is the process of determining which generating units to dispatch and when to dispatch these units. UC must also meet electricity demand at the lowest cost while satisfying operational constraints such as the available capacities, consideration of transmission constraints, and minimum on/off time constraints. Conventional UC is proposed and widely used in the literature for dc optimal power flow (OPF) by including binary variables for the on/off status of generating units [1] and is considered a mixed-integer linear programming (MILP). Wood et al. [2] provides an overview of basic principles of power system economics, reliability, and dispatch, as well as the technical details of UC and formulation of a conventional UC with binary variables. This approach creates challenges such as increased computation costs for large cases due to the non-linear growth of the optimization problem with the size of variables [3].

In order to have a more detailed model and consider reactive power limitations, it is necessary to solve ac OPF, which is non-linear and non-convex and makes the problem even further computationally expensive. Castillo et al. [4] propose an approach based on the outer approximation method that co-optimizes real and reactive power scheduling and dispatch. Authors of [5] employ a Benders decomposition approach to determine if a secure ac power flow (PF) solution can be achieved; in case of network violations, corresponding Benders cuts are generated and integrated into the master problem iteratively until ac violations are resolved. Reference [6] proposes a decomposition method using conic approximations of the ac equations. Reference [7] utilizes a data-driven linear ac PF approach that approximates the UC.

Since the size of industry grids are usually in the scale of thousands of buses and the problem includes nonlinear voltage/reactive power control settings, including binary variables to the ac OPF optimization problem will make the required problem NP-Hard [8], [9] and much more computationally expensive. Therefore, performing UC on industry-size grids in a timely manner using existing methods is not computationally feasible. It will be impossible to solve such problems with conventional approaches if the grid being tested is too large and the studied time horizon is long, as the calculations would not be solvable in the required time. Therefore, models must be modified to make the cases solvable in the required time.

Also, the ongoing and continuous increase in the penetration of renewable energy resources (RES) makes the UC more computationally expensive. Reference [10] reviews recent approaches to UC in the context of intermittent renewable energy resources. The review highlights the need for further research in the area of UC with intermittent RES, particularly in developing more accurate and efficient models that can handle the growing complexity of power systems with high levels of RES penetration.

Reference [11] disuses the challenges related to the computational complexity of UC in large electric grids, suggesting a problem reformulation to improve accuracy and efficiency,

[1]https://github.com/Advanced-Vision-and-Learning-Lab/UC_ML

with a focus on addressing ac UC instead of dc UC, while emphasizing the potential benefits of ML. Reference [12] reviews applications of ML techniques for optimizing PF and economic dispatch. Reference [13] suggests ML models such as random forest to achieve a fast solution for the UC. Deep learning-based approaches have also been applied to the area of ac OPF. Reference [14] investigated augmenting training data for more representative samples to improve the generalization of the model to new data. Graph neural networks were also used to reduce the number of constraints [15]. A training strategy using concepts of reinforcement learning [16] helped with adding additional versatility to the deep neural network. However, none of these references are solving ac OPF with UC.

This paper proposes a novel strategy to solve a fast, learning-based and computationally feasible UC with ac OPF with direct inclusion of weather measurements for large grids to determine the on/off status of generating units and their dispatch. The main benefit of this strategy is when UC is needed for power system analysis of large grids over long periods with ac OPF that is computationally intractable. The main challenge for a leaning strategy is that the status of all units are related and not independent. The proposed strategy considers load and weather changes at different times of the year and the availability of the resources changes with the weather. The proposed learning strategy is a multi-label classification to determine the on/off status of the generators and also consider potential relationships among the generators.

II. Preparing Training Data with Directly Including Weather measurements

The problem for the training data is to determine the on/off status of units with the goal of minimizing the operation cost subject to the related constraints that need to be satisfied, which is minimum on/off times. The output power and commitment of RES such as wind turbines and solar power plants and their commitment are directly related to the weather measurements. We proposed a strategy in our previous work [17] for direct inclusion of weather measurements such as wind speed, wind direction, temperatures, and cloud coverage, in the OPF. The renewable generators are mapped to the closest weather stations and their power models determine the power output and commitment based on the availability of their resources. Since renewable generators have usually negative cost offer curves and use free resources, it is beneficial for the environment and economy to generate power with their available capacity so we assume that the outputs of renewable resources are their available capacities at time point and they are commited if they can generate power.

Also, because of the significant cost associated with the startup and shutdown, and creation of nuclear power plants, these units are assumed to remain continuously connected to the electrical grid, throughout their operational lifespan and are only disconnected for maintenance in predetermined schedules, ensuring their reliability and safety. Therefore, the commitment of nuclear units is predetermined.

The main inputs for the training data creation include the load at each time point, the fuel type of generators, cost curves of generators, weather-related available capacities of generators at each time, and electric grid data. The proposed UC is mainly based on the energy prices, time-aware generation capacity and load in a way that the cheapest units become on until enough generation capacity is available to satisfy the load and losses in each time step and each area considering a percentage of load for reserves. To make the UC more computationally feasible, we ignore the minimum on/off constraints initially and sort the generators based on their cost offer values at each point. The algorithm starts by turning on the cheapest generation until the demand, reserve, and loss requirements are met. After the initial commitment is determined, we add a counter and update the on/off status of units if minimum on/off constraints are not satisfied.

III. Proposed Multi-Label Learning Strategy

The processed data from Section II will be used as an input to the ML models in order to predict the on/off status of the generators based on the weather, demand and cost offer curves of generators. The input to the ML model will be "features" or information about the electric grid at given time points such as the load, weather-informed capacity of generators, the generator constraints such as minimum on/off time limits and their cost offer curves to satisfy demand. Therefore, the total number of features depends on the grid size (and the number of corresponding generators and load entities) and the number of samples depends on the number of time steps and the study horizon. The output of the model will be the on/off status of the generators with the given input features.

Formally, given samples or time points for the generator with d number of features (*e.g.*, weather-informed generation capacities, hourly demand) $\mathcal{X} \in \mathcal{R}^d$ and outputs representing the on/off status of m generators, $\mathcal{Y} \in \mathcal{R}^m$, the goal of the multi-output is to find a function, f, that maps the model's input and output, $f : \mathcal{X} \to \mathcal{Y}$. The function ($f$) is learned using the training data and used to predict new, unseen data. There are five relevant features used per generator: generation capacity, generator type, minimum on/off time, generator cost, and overall load at each hour. The number of input features, d, can be calculated by multiplying the number of generators (g) by five and adding features for the load, resulting in the total number of features increasing as the grid size (and the number of corresponding generators) increases. The labels or UC results are determined based on these features.

The problem grows exponentially as the number of outputs increase (*i.e.*, to predict the on/off status of the generators, the number of solutions would be 2^m where m is the number of generators) since the status of these generators is not independent of each other. Therefore, algorithms that can work in a multi-label setting and scenario reductions based on probabilities are needed. The training process for this model is a supervised multi-label classification problem [18] that involves multiple outputs as possible arrays of on/off values for each generator (sample) as opposed to a single output for binary or multi-class classification. Final status of units are determined based on the highest probabilities of them being on or off in the possible arrays. This work investigated three models that can be adapted to the multi-label setting: K-Nearest Neighbors (KNN), random forest, and multilayer perceptron (MLP). After UC is determined, the ac OPF is solved based on the input status of units.

IV. Case Study

Due to restrictions on accessing critical energy infrastructure information, the actual data on power grids are not available for research. Therefore, synthetic grids [19], which are created based on generation data from the U.S. Energy Information Association [20] are used. More information on the creation of these grids are available in [21]–[23] and these realistic synthetic grids are validated based on the actual grids in [24] and [25]. The electric grid used in this study is a synthetic network geographically sited in Texas, U.S., and covers the geographic footprint of ERCOT with 6717 buses. This grid's detailed data is available at [19].

To construct yearly hourly time series data representing the load at individual bus levels, the authors employ a procedure described in previous works [26], [27]. This method involves utilizing the geographic coordinates of each bus to establish a distinct electricity consumption pattern for it. Subsequently, publicly accessible time series data pertaining to building and facility-level loads are incrementally aggregated to form a unified load representation at the bus level. The research employs the proportion of residential, commercial, and industrial loads at each node in the network, in combination with location-specific standard load patterns for buildings and facilities. These elements are utilized to formulate time series data for loads at the node level. After generating the load data at the bus level, the total load within each geographical area is computed and subjected to validation, as described in references [26], [27]. The validation process relies on publicly accessible hourly load data for various ERCOT areas, as accessible from [28].

V. Results

Common metrics to measure ML performance include precision, recall, F1 score, and average precision. These metrics are adapted for the multi-label setting through two averaging strategies such as macro (treats labels independently) and micro (equal weight to each data point) [18]. These metrics range from zero (worse) to one (best). We present results of the UC scenario, in Table II. The initial data was divided into 70% for training and 30% for testing. Five-fold cross validation was performed using the training data to find the optimal hyperparameter settings for three ML algorithms: KNN, random forest, and MLP.

As noted in Table II, all of the models perform well across the different metrics. Precision was the highest performing metrics for all three models overall (except for the micro average recall for the MLP model). This metrics captures that the models were successful at achieving a low number of false positives (*i.e.*, predicting a generator was on, but the generator was actually off). Major differences occur between the model when observing the recall metric. Recall captures if the model was affected by false negatives (*i.e.*, predicting a generator was off, but the generator was actually on). The MLP was the most effective at reducing the false negative rate showing that this model captured more the relationships between the generator information (or features) and the corresponding generator status. F1 score measures the harmonic mean of precision and recall. Since the MLP model achieved a higher recall, the corresponding F1 scores are higher for this model in comparison to the KNN and RF models.

To provide more insight in the models' performance, we also investigate how the performance of the model is based on fuel type. In Table I, the classification metrics for the MLP model are shown. The model performs well on the renewable generators (wind turbines and solar cells) since with the direct inclusion of weather, the commitment of these units directly depends on the weather measurements so with reasonable weather forecasts there are no misclassifications (metrics scores are 1 in case of using historical weather data). Also, nuclear generators are usually on service and only get offline for maintenance with scheduled times so their status can be predicted easily. The "other" fuel type mentioned in the Table I refers to a variety of fuel types such as wood, biomass and geothermal so have a wide range of fuel prices but since it is mostly using cheap fuels, the performance measures of this type is also high. Despite this success, the model does struggle with some of the more expensive fuel types such as coal, which have more UC changes. Our results show that using ML to predict the status of the generators is feasible. Figure 1 shows a visualization of Table I through the precision-recall curves. Ideally, the curve should have high precision and recall which is indicated if the curves starts at a precision of 1 and maintains a precision of 1 as the recall changes. We can observe here that the MLP model performed well across the different fuel types as captured in Table I and the precision-recall curves shown in Figure 1. The generator type with the worst performance was coal across the three models.

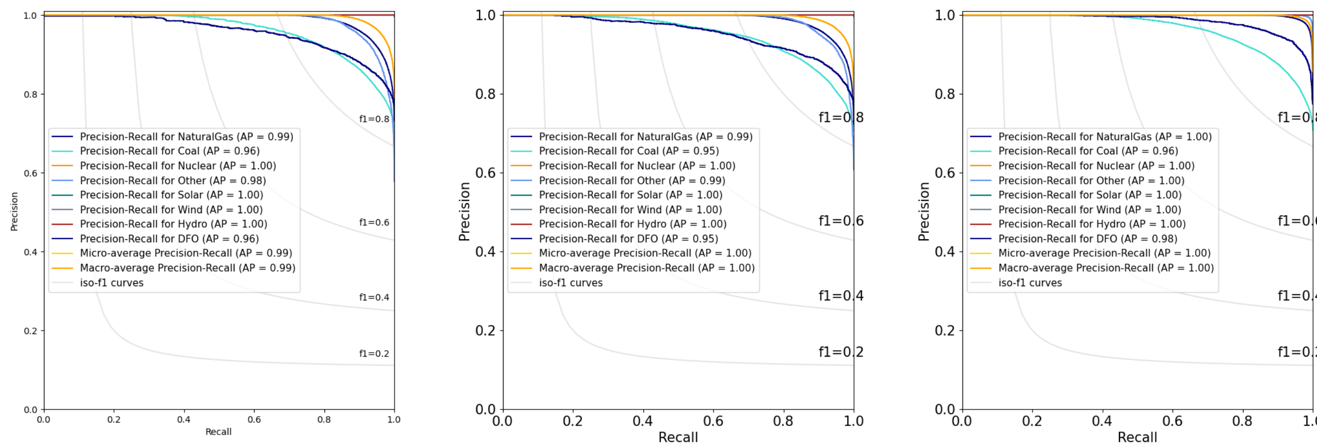
VI. Conclusion

This paper presents a novel approach to address the challenges of solving a UC with ac OPF in large power grids over longer time horizons by incorporating weather conditions that impact resource availability and demand. The proposed strategy offers a fast, learning-based, and computationally efficient solution that optimizes the on/off status and dispatch of generating units considering economic factors. Based on the interdependence of unit status, we proposed a multi-label machine learning approach to consider possible commitment arrays.

The annual UC results are used for training the supervised multi-label ML algorithms to solve UC more efficiently. The ML performance metrics include precision, recall, F1 score, and average precision show the efficiency of the proposed multi-label approach using KNN, RF, and MLP. After UC is

TABLE I:
CLASSIFICATION PERFORMANCE OF MLP ON TEXAS SYNTHETIC GRID BASED ON FUEL TYPE

Fuel Type	Precision (Macro)	Precision (Micro)	Recall (Macro)	Recall (Micro)	F1 Score (Macro)	F1 Score (Micro)
Coal	0.825	0.885	0.800	0.886	0.806	0.886
Distillate Fuel Oil	0.920	0.922	0.951	0.953	0.935	0.937
Hydro	1.000	1.000	1.000	1.000	1.000	1.000
Natural Gas	0.960	0.977	0.960	0.981	0.960	0.979
Nuclear	1.000	1.000	1.000	1.000	1.000	1.000
Other	0.972	0.992	0.972	0.992	0.972	0.992
Solar	1.000	1.000	1.000	1.000	1.000	1.000
Wind	1.000	1.000	1.000	1.000	1.000	1.000



(a) KNN (b) RF (c) MLP

Fig. 1: Precision-Recall curves for KNN, RF, and MLP on the Texas synthetic grid based on fuel type are shown in Figures 1a - 1c respectively. The average precision (AP) score is shown for each curve. AP is between 0 (worst) and 1 (best). The isocurves (gray lines) show the corresponding F1 scores computed from the precision and recall values.

TABLE II: PRECISION, RECALL, AND F1 SCORE ON TEXAS SYNTHETIC GRID FOR EACH MODEL. THE MACRO- AND MICRO-AVERAGES ARE REPORTED RESPECTIVELY FOR EACH METRIC AND SEPARATED WITH A SLASH.

Model	Precision	Recall	F1 Score
KNN	0.930/0.959	0.849/0.956	0.857/0.957
RF	0.918/0.960	0.852/0.957	0.855/0.958
MLP	0.968/0.983	0.967/0.985	0.967/0.984

determined, ac OPF is solved and the outputs were verified to be feasible results. Future work on the machine learning aspects of the work includes developing novel training strategies to improve the generalization of the methods to account for changes in the grid. Additionally, new multi-label algorithms can be developed to incorporate additional constraints such as load requirements and cost curves of the ac OPF. The findings underscore the potential benefits of coupling machine learning techniques with power system optimization, paving the way for faster, more environmentally conscious and economically viable power grid operation.

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