Machine Learning Assisted Approach for Security-Constrained Unit Commitment

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Abstract— Security-constrained unit commitment (SCUC) which is used in the power system day-ahead generation scheduling is a programming mixed-integer linear problem computationally intensive. A good warm-start solution or a reduced-SCUC model can bring significant time savings. In this work, a novel approach is proposed to effectively utilize machine learning (ML) to provide a good starting solution and/or reduce the problem size of SCUC. An ML model using logistic regression algorithm is proposed and trained using historical nodal demand profiles and the respective commitment schedules. The ML outputs are processed and analyzed to assist SCUC. The proposed approach is validated on several standard test systems namely, IEEE 24-bus system, IEEE 73-bus system, IEEE 118-bus system, synthetic South Carolina 500-bus system and Polish 2383-bus system. Simulation results demonstrate that the prediction from the proposed machine learning model can provide a good warm-start solution and/or reduce the number of variables and constraints in SCUC with minimal loss in solution quality while substantially reducing the computing time.

Index Terms— Constraint reduction, Logistic Regression, Machine learning, Mixed-integer linear programming, Security-constrained unit commitment, Warm-start solution.

I. INTRODUCTION

The day-ahead generation scheduling in power systems is modeled as a complex optimization problem: security-constrained unit commitment (SCUC). It involves many physical and reliability constraints that ensure feasible and secure solutions while minimizing total system operational costs. However, as a mixed-integer linear programing (MILP) model that determines the commitment schedule of generators, SCUC is computationally intensive. In practice, independent system operators (ISO) has limited time to solve the SCUC problem and post the solutions. Several literatures attempt to speed up the SCUC process by using techniques such as feasible region reduction, decomposition and/or heuristics [1]-[3]. A good warm-start solution also speeds up the process as seen in an example in [1]. However, identifying a good starting solution is hard.

Recently, machine learning (ML) methods have shown to be promising when used as a prediction or decision support mechanism in complex problems. Combining ML techniques with traditional algorithms can improve the overall performance. Not only that, ML algorithms are robust to handle missing or noisy data, which can be a benefit for the sparse nature of complex bulk power system data during the learning process. Therefore, ML as a tool to learn the starting solution can be considered [4]-[5]. However, [5] uses support vector method and k-nearest neighbor classification algorithm

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to learn warm-starting points for SCUC but are associated with drawbacks from infeasible problems.

This paper emphasizes that the commitment schedule data collected by ISOs can be utilized to train an ML model to improve grid operations and planning. The contributions of this work are presented as follows:

- A logistic regression-based ML model is proposed to use nodal demand profile as input to predict generation commitment schedule.
- Various procedures are proposed to utilize the ML outputs to provide warm-start points and/or reduced-SCUC (R-SCUC) models while maintaining solution quality.

II. METHODOLOGY

A. SCUC Formulation

The objective of the SCUC is to minimize the operational cost of generators, F(x,y) in (1), which includes the production, start-up and no-load costs. In (1), x denotes the continuous variables of the problem such as generator dispatch points, power flows and bus phase angles; and y denotes the commitment status and start-up binary variables. This is performed subject to generation, power flow constraints and reliability constraints in (2)-(3). The inequality constraints are modelled in (2) represent the minimum and maximum generation and transmission limits, the hourly generation ramp capability, and emergency 10-min reserve ramping capability while ensuring that reserves are held at the least to handle the failure of the largest generator. The equality constraints in (3) represent the nodal power balance and the power flow calculation. A detailed SCUC model can be obtained from our prior work [6].

Objective:

$$Min F(x, y) \tag{1}$$

s.t.:

$$G(x,y) \le b \tag{2}$$

$$H(x,y) = d (3)$$

Since this work focuses on the ML based approach and its benefits, a simplistic SCUC model with only relevant basecase constraints are formulated. However, in future, a complete *N*-1 SCUC model can be utilized.

B. Data Generation

To train ML models, a large amount of data is required. ISOs may possess historical data related to day-ahead operations, namely, commitment and demand schedules. These historical data would form a great starting point for practical real-world systems. For the test systems considered in this work, we have artificially created this dataset. By adding random noises in the standard nodal profile, several

demand curves, $d_{i,g,t}$, were generated and their corresponding commitment schedule, $u_{i,g,t}$, can be obtained by solving the SCUC model described in sub-section A.

Approximately, 1200-1500 samples denoted as M are created for each test system, which can be considered as an equivalent of 3-4 years of data. The number of samples can vary for each system since infeasible load profiles are negated from the initially curated data. The created M samples, once shuffled, are split into two datasets: 80% training samples M^{train} and 20% testing samples M^{tes} .

C. ML Model

The overall supervised ML approaches are described at a fundamental level in Fig. 1. The training and test samples are produced using data generation mentioned in sub-section B.

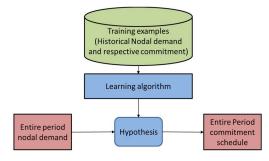


Fig. 1. Supervised ML approach.

The training model/algorithm considered in this work is the logistic regression (LR) model [7]. The LR model is a regression model which predicts the value of probability of an output being 1. This fits the scope of the overall objective since we are building an ML model to predict the commitment status of each generator in day-ahead operations (24 hours) which are the outputs or targets. The commitment status of 1 implies the generator is ON whereas 0 represents the generator is OFF. The input features are the respective normalized nodal demand values. The LR model is trained using M^{train} and tested using M^{test} .

The ML model accuracy can be verified using the post-processed outputs. Once the model is trained, the output probabilities, $P(u)_{i,g,t}^{ML}$, are post-processed to obtain the predicted commitment schedule $u_{i,g,t}^{ML}$: 1 if $P(u)_{i,g,t}^{ML} \geq P^{th}$, and 0 if $P(u)_{i,g,t}^{ML} < P^{th}$. P^{th} is the probability threshold and varies between $0.5 \leq P^{th} \leq 0.9$. The accuracy in terms of $u_{i,g,t}^{ML}$ is calculated for both $i \in M^{train}$ and $i \in M^{test}$ using the commitment schedules, $u_{i,g,t}$, data obtained earlier.

$$Accuracy = 1 - \frac{1}{m} \sum_{i=1}^{m} |u_{i,g,t} - u_{i,g,t}^{ML}|, \forall g \in G, t \in T$$
 (4)

D. Proposed Methods

In this paper, the LR method proposed in sub-section C is extended with four proposed post-processing procedures. Since the trained LR method predicts the probability of a generator being ON, those probabilities can further be processed to provide additional insights to reduce the complexity of the SCUC. The SCUC model represented in sub-section A is the benchmark model (*Base* method) that does not utilize any ML information. The following are the proposed four procedures, *P1* through *P4*, to utilize the ML

outputs to assist in solving SCUC for each power grid load profile of the testing samples:

- PI: uses the ML outputs $(u_{g,t}^{ML})$ to warm-start SCUC. That is, use $u_{g,t}^{ML}$ as the starting point for $u_{g,t}$ and then solve the SCUC.
- P2: fix $u_{g,t} = u_{g,t}^{ML}$ and solve the reduced SCUC (linear model in P2). Effectively runs an economic dispatch.
- P3: R-SCUC where fix $u_{g,t} = 1$ if $u_{g,t}^{ML} = 1$. The warm-start uses $u_{g,t} = 0$ if $u_{g,t}^{ML} = 0$.
- P4: R-SCUC where always ON/OFF generators are identified using $u_{g,t}^{ML}$. For each testing sample (grid profile), if a generator g is predicted to be always ON in 24-hour period then fix $u_{g,t} = 1$ for the entire 24-hour period for the corresponding generator. Similarly, if generator g is always OFF in 24-hour period, then fix $u_{g,t} = 0$ for all periods for the corresponding generator. For all other generators, use warm-start $u_{g,t} = u_{g,t}^{ML}$.

For each sample $i \in M^{test}$, the above procedures P1-P4 are implemented and the respective SCUC is solved to verify the quality of the ML solution. The overall flow of the proposed ML assisted SCUC process is represented in Algorithm 1.

Algorithm 1 ML assisted SCUC process

- 1: For $i \in M$
- 2: randomize nodal demand
- 3: Solve SCUC
- 4: Store $d_{i,q,t}$, $u_{i,q,t}$, objective value and computing time
- 5: End
- 6: **Shuffle** *M* samples
- 7: **Split** M as 80% for M^{train} and 20% for M^{test}
- 8: Train LR using M^{train} for different hyperparameters
- 9: Calculate training accuracy and test accuracy
- 10: Tuning: identify hyperparameters with best accuracy
- 11: Save ML predicted output probabilities
- 12: For $i \in M^{test}$
- 13: Perform P1-P4 and verify SCUC for $d_{i,q,t}$
- 14: record objective value and computing time
- 15: End

III. RESULTS AND ANALYSIS

The SCUC mathematical model is implemented in AMPL. The data creation and verification steps are thus conducted using AMPL and solved using Gurobi solver with MIPGAP = 0.01. The ML step is implemented in Python 3.6. The proposed methods were validated with the following standard test systems summarized in Table I. Simulation results are presented in the following sub-sections.

TABLE I. SUMMARY OF TEST SYSTEMS

System	Gen cap (MW)	# gen	# branch
IEEE 24-bus	3,393	33	38
IEEE 73-bus	10,215	99	117
IEEE 118-bus	5,859	54	186
South Carolina 500-bus	12,189	90	597
Polish 2383-bus	30,053	327	2,895

A. ML Training

Each system is trained using the LR-based ML method separately by utilizing the respective generated data, M^{train} . During training, the samples are considered as a single full batch. For each system, the hyperparameter learning rate (δ) is

varied from 0.001-0.05. For each δ , the LR algorithm is trained for 1000 iterations and the accuracy was then calculated using (4). Table II summarizes the M, M^{train} , M^{test} , δ and accuracy for each system. The LR algorithm provides high accuracy >93% for both the training and test samples for all test systems considered in this work.

TABLE II. TRAINING SUMMARY

# Bus	Samples			Learning	Accuracy (%)	
# Dus	Total	Train	Test	rate	Train	Test
24	1,446	1,157	289	0.01	98.97	98.96
73	1,391	1,113	278	0.003	96.89	96.88
118	1500	1200	300	0.01	93.61	93.53
500	1499	1200	299	0.05	98.56	98.51
2383	1200	960	240	0.05	95.94	95.86

B. Verification of the Proposed Method

Once each system was trained, a verification process was conducted for *P1-P4*. This was benchmarked against the *Base* method which does not use any ML solution. Therefore, the solution quality from the traditional *Base* method is considered as 100% since it is purely an MILP optimization.

Fig. 2 and Fig. 3 presents the *Base*-normalized objective value and computing time in percent when averaged over all test samples for each test system, respectively. From Fig. 2, PI provides slightly better solutions by using the ML solution as a warm-start solution which results in a tighter gap. P4 also provides comparable solution quality to the *Base* method. However, P2 and P3 lead to increased costs since the ML solution may result in scheduling sub-optimal generators. A key observation here is that not all samples of P2 are feasible even though the accuracy is >93%. This is because P2 fixes the status for all generators and only an optimal economic dispatch is then implemented. Yet, P2 results only in marginal loss of solution quality in IEEE 24-bus system (0.76%) and Polish system (2.02%). However, the solution quality can be improved by P1, P3 and P4 without infeasible problems.

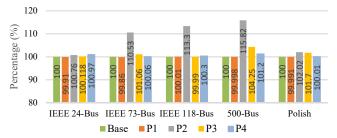


Fig. 2. Normalized objective value in percent averaged over test samples.

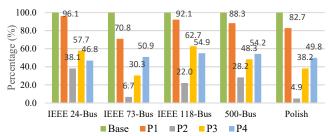


Fig. 3. Normalized computing-time in percent averaged over test samples.

From Fig. 3, though P2 results in lower solution quality, it provides the most computational time savings ~95% in the Polish system since this eliminates all the binary variables in the problem. P1 also results in significant time savings in

several samples (as much as 50% reduction in time was observed) in M^{test} ; but few samples result in longer computational time since the ML solution cannot be 100% accurate which increases the average time. P3 and P4 are R-SCUC models which reduce the number of variables and constraints and therefore result in considerable time-savings.

C. Problem Size Reduction

Since *P2-P4* uses ML solutions to fix the status of generators, this results in R-SCUC models. In particular, *P2* eliminates all binary variables in the problem whereas *P3-P4* results in decreased variables and constraints as seen in Table III. It is expected that *P1* has the same problem size as the *Base* method since the ML solution is only used as a warmstart solution. By utilizing the ML solution, *P2-P4* effectively reduces linear variables, binary variables, constraints and nonzeroes in the SCUC problem. As a result, it leads to smaller problem which results in time-savings.

TABLE III. AVERAGE PROBLEM SIZE FOR POLISH SYSTEM

Procedure	Linear Var	Binary Var	Constraints	Non-zeroes
Base	142,296	15,696	197,112	3,176,376
P1	142,296	15,696	197,112	3,176,376
P2	125,330	0	136,168	2,027,850
P3	128,856	3,700	153,296	2,924,834
P4	142,296	10,464	184,104	3,135,024

IV. CONCLUSIONS

This paper proposes an ML assisted SCUC algorithm to decrease the computational burden of the MILP problem. Several post-processing techniques, *P1-P4* to effectively utilize the ML predicted outputs, have been examined. *P1* does not change the problem size but benefit from computational time-savings due to good starting point for SCUC while bettering the solution quality. *P2-P4* result in problem size reduction and warm-start capability which result in significant time-savings across multiple test systems.

P2 provides 95% computational time savings for large systems but is affected by solution quality or infeasible problems. P3-P4 result in time savings of 52.56% and 48.68%, respectively, on average across all the test systems while also resulting in high-quality solutions.

V. References

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