Deep Neural Network-Based Method for Economic Dispatch in Microgrid

Ziyu He
Department of Electrical Engineering
Columbia University
New York, New York 10027
Email: zh2255@columbia.edu

Wenyuan Tang
Department of Electrical Engineering and Computer Sciences
University of California, Berkeley
Berkeley, California 94720
Email: tangwenyuan@berkeley.edu

***Abstract*—This paper experiments a deep neural network-based method to solve microgrid economic dispatch (ED) problems considering renewable generations. We test our method on three formulations of ED with three renewable penetration levels. Numerical tests show that our method is applicable when the penetration level is relatively high and the time efficiency of our method outweigh standard algorithms.**

I. Introduction

The unit commitment (UC) and economic dispatch (ED) problems in power systems are typically formulated as stochastic optimization problems with uncertainties introduced by load forecasting error, renewable generation (solar, wind, etc.), mobility of EV, market price, etc. There are various ways to model the uncertainties in UC/ED problems: direct deterministic formulations with point estimation of uncertainties [1]; robust formulations with different constructions of uncertainty sets [2] [3]; stochastic programming problems with probabilistic modeling of uncertainties [4]–[6].

Different from those conventional optimization formulations, a number of previous papers applied neural networks-based methods to solve UC/ED problems. These neural network-based methods can be further categorized into two different approaches. The first approach maps the original optimization problem to a Hopefield neural network hence unifies problem solving and neural network training [7]–[11]. Instead of treating the neural network itself as an "algorithm", the second approach aims to apply neural network to approximate an algorithm for solving optimization problem. In this paper, we adopt the idea in the second approach.

The general structure of the second approach is: sample observations of system uncertainties from a pre-defined data generating mechanism, solve a set of optimization problems determined by these observations, train a neural network based on a training data set constructed by these solutions. With sufficient data and proper training algorithm, the neural network will eventually learn the non-linear mapping between the realizations of problem uncertainties and the solutions.

In [12], an artificial neural network (ANN) is implemented to predict the pre-scheduling of an UC problem with a modified dynamic programming to post-process the undetermined commitment states. The input and output of the ANN is designated as predicted load and unit scheduling. [13] applies the same method but considers a genetic algorithm to initialize the ANN. The method in [14] is similar to [12] [13] but it applies an expert system to handle the uncertain states in output. [15] presents a hybrid method (ANN with heuristic post-processing) to solve ED problem. With a similar schema, [16] uses an ANN to predict the solution of a combined ED and emission dispatch problem. Fuzzy neural network is also considered in the previous work. [17]–[19] design hybrid models with a fuzzy neural network which takes fuzzified load profile as input and commitment schedule as output, with an adaptive expert system to deal with infeasible outputs.

The aforementioned work only considers load as the source of uncertainty, which is not a reasonable assumption in the context of modern power systems (e.g. microgrids). Therefore, it would be interesting to experiment the neural network-based method in an extended problem setting which incorporates renewable generations (solar power, wind power) as additional uncertainties. More importantly, most of the previous works only applied very simple neural networks on deterministic problems. With more sources of system uncertainties, we can potentially generate a larger training dataset which will enable advanced deep learning techniques and we can also test deep neural network (DNN) on other problem formulations.

This paper proposes a deep neural network-based method for generation scheduling in microgrid with distributed renewable penetration (PV, wind power), storage units and elastic loads. In this paper, we focus on ED problems. We first solve large numbers of microgrid ED problems and each problem corresponds to a specific combination of realizations of loads, renewable generations and market price. Then a DNN can be trained based on a training dataset constructed by these solutions. Followed by a proper post-processing procedure to check and rectify the output's infeasibility, our neural network-based method can be implemented to produce a nearly-optimal solution for ED problem in a time efficient manner. Our method is tested on three cases with different levels of uncertainty modelings: point estimation (i.e. deterministic formulation), uncertainty sets (i.e. robust formulation), probabilistic modeling (i.e. stochastic programming), and for each case we also consider three different levels of renewable penetration (50%, 80%, 200%).

The remainder of this paper is organized as follows. Section

II provides three formulations of microgrid ED problem. We discuss the implementation of deep neural network as well as the test result in Section III and IV. In Section V, we present the conclusion.

II. Optimization Problem Formulations

This section details the formulations of microgrid ED problem. Specifically, we construct three formulations with different scale of uncertainty modeling: deterministic formulation, robust formulation and stochastic programming.

We consider a microgrid with conventional generators, distributed solar power and wind power, non-dispatchable loads and dispatchable loads, and storage units. The optimization problems aim to solve the scheduling decisions of all the microgrid components in a time horizon with fixed number of slots, except for non-dispatchable load which is treated as deterministic with predicted value. Load loss, transmission loss and power flow constraints are not considered.

A. Deterministic Formulation

Here we formulate a non-linear mixed integer problem and assume that the renewable generations can be scheduled as well. The uncertainties of the "actual" renewable generations are modeled by their point estimations.

$$
\begin{aligned}
\min_{\mathcal{D}} \quad & \sum_{t=1}^{T}\Big(\sum_{i=1}^{N_G} F_{Gi}(P_{Git}) - \sum_{i=1}^{N_{L2}} F_{Ej}(P_{Ejt})\Big) \\
\text{s.t.} \quad & \mathcal{D} = \{\mathbf{P_G}, \mathbf{P_B^+}, \mathbf{P_B^-}, \mathbf{S^+}, \mathbf{S^-}, \mathbf{P_W}, \mathbf{P_S}, \mathbf{P_E}\} \\
& \sum_{i=1}^{N_G} P_{Git} + \sum_{i=1}^{N_W} P_{Wit} + \sum_{i=1}^{N_S} P_{Sit} \\
& = \sum_{i=1}^{N_{L1}} P_{Lit} + \sum_{i=1}^{N_{L2}} P_{Eit} + \sum_{i=1}^{N_B} P_{Bit}^{Grid}, \ \forall t \qquad (1) \\
& \underline{P}_{Gi} \le P_{Git} \le \overline{P}_{Gi}, \ \forall i, \forall t \qquad (2) \\
& -\underline{R}_i \le P_{Git} - P_{Gi(t-1)} \le \overline{R}_i, \ \forall i, \forall t \qquad (3) \\
& \sum_{i=1}^{N_G} (\overline{P}_{Gi} - P_{Git}) \ge P_t^{SR}, \ \forall t \qquad (4) \\
& 0 \le S_{it}^+ + S_{it}^- \le 1, \ \forall i, \forall t \\
& S_{it}^+, S_{it}^- \in \{0,1\}, \ \forall i, \forall t \qquad (5) \\
& S_{it}^+ \underline{P}_{Bi}^+ \le P_{Bit}^+ \le S_{it}^+ \overline{P}_{Bi}^+, \ \forall i, \forall t \\
& S_{it}^- \underline{P}_{Bi}^- \le P_{Bit}^- \le S_{it}^- \overline{P}_{Bi}^-, \ \forall i, \forall t \qquad (6) \\
& P_{Bit} = \eta_i P_{Bit}^+ - \frac{P_{Bit}^-}{\eta_i}, \ \forall i, \forall t \\
& P_{Bit}^{Grid} = P_{Bit}^+ - P_{Bit}^-, \ \forall i, \forall t \qquad (7) \\
& \underline{E}_i \le E_{i0} + \sum_{\tau=1}^{t} P_{Bi\tau}\Delta t \le \overline{E}_i, \ \forall i, \forall t \qquad (8) \\
& \underline{P}_{Ei} \le P_{Eit} \le \overline{P}_{Ei}, \ \forall i, \forall t \qquad (9) \\
& \underline{P}_{Wi} \le P_{Wit} \le \overline{P}_{Wi}, \ \forall i, \forall t \qquad (10) \\
& \underline{P}_{Si} \le P_{Sit} \le \overline{P}_{Si}, \ \forall i, \forall t \qquad (11) \\
& P_{Wit} \le \hat{W}_{it}, \ \forall i, \forall t \qquad (12) \\
& P_{Sit} \le \hat{V}_{it}, \ \forall i, \forall t \qquad (13)
\end{aligned}
$$

$F_{Gi}(P_{Gi}) = a_{Gi} + b_{Gi}P_{Gi} + c_{Gi}P_{Gi}^2$ is the cost function of generator and $F_{Ei}(P_{Ei}) = d_{Ei}P_{Ei} + e_{Ei}P_{Ei}^2$ is the utility function of elastic load (to simplify our problem we assume that it is concave). $\mathbf{P_G}, \mathbf{P_W}, \mathbf{P_S}, \mathbf{P_B^+}, \mathbf{P_B^-}, \mathbf{S^+}, \mathbf{S^-}, \mathbf{P_E}$ are the decision variables. $\mathbf{P_G}, \mathbf{P_W}, \mathbf{P_S}$ denote generations of generators, wind power and solar power. $\mathbf{P_E}, \mathbf{P_L}$ are consumptions of dispatchable and non-dispatchable loads. $\mathbf{P_B^+}, \mathbf{P_B^-}$ denote charging and discharging power of storage devices (defined from the grid side). $\mathbf{S^+}, \mathbf{S^-}$ are the binary indicators of charging and discharging decisions. $\hat{\mathbf{W}}, \hat{\mathbf{V}}$ are predicted wind and solar power. $N_G, N_W, N_S, N_{L1}, N_{L2}, N_B$ are the number of generators, wind units, solar units, non-dispatchable loads, dispatchable loads, and storage devices.

(1) is the power balance constraint. (2)-(4) are upper and lower bound of generators' generation, ramp up and ramp down limits and spinning reserve constraints. (5)-(8) are constraints w.r.t. storage units. (5) indicates that a storage device can not be charged and discharged in the same time slot. (6) shows the upper and lower bound of charging and discharging power. (7) defines the net charging power on the side of storage units and grid. (8) is storage units' energy constraint in each time slot. (9)-(13) present the upper and lower bound of elastic load consumption, wind power and solar power generations.

B. Robust Formulation

For the robust formulation, we extend the model assumptions to allowing transactions between microgrid and utility. The uncertainties in renewable generations are modeled by uncertainty sets constructed by corresponding interval estimations. Here we adopt a worst case transaction modeling similar to [2] and we aggregate all the renewable generation units to a single unit $\mathbf{P_R}$ for simplicity.

$$
\begin{aligned}
\min_{\mathcal{D}} \quad & \sum_{t=1}^{T}\Big(\sum_{i=1}^{N_G} F_{Gi}(P_{Git}) - \sum_{i=1}^{N_{L2}} F_{Ej}(P_{Ejt})\Big) \\
& + \max_{\mathbf{R}\in\mathcal{R}} \Big\{ \sum_{t=1}^{T} F_T(P_{Rt}, P_{Bt}^{Grid}, c_{bt}, c_{st}) \Big\} \\
\text{s.t.} \quad & \mathcal{D} = \{\mathbf{P_G}, \mathbf{P_B^+}, \mathbf{P_B^-}, \mathbf{S^+}, \mathbf{S^-}, \mathbf{P_R}, \mathbf{P_E}\} \\
& \mathbf{R} = \{R_t | 1 \le t \le T\} \\
& \mathcal{R} = \{\mathbf{R} | \underline{R}_t \le R_t \le \overline{R}_t, \ \forall t\} \\
& (1) - (9) \\
& \underline{P}_R \le P_{Rt} \le \overline{P}_R \qquad (14)
\end{aligned}
$$

$F_T(\cdot)$ is the transaction function defined as:

$$
\begin{aligned}
F_T(P_{Rt}, P_{Bt}^{Grid}, c_{bt}, c_{st}) = c_{bt}\Big[P_{Rt} - R_t - \sum_{j=1}^{N_B} P_{Bjt}^{Grid}\Big]^+ \\
- c_{st}\Big[P_{Rt} - R_t - \sum_{j=1}^{N_B} P_{Bjt}^{Grid}\Big]^- \qquad (15)
\end{aligned}
$$

c_{bt}, c_{st} are the market buy price and sell price which are assumed to be deterministic with predicted values. Functions $[\cdot]^+$ and $[\cdot]^-$ are defined as $[x]^+ = \max\{x, 0\}$, $[x]^- = \max\{-x, 0\}$. Using the properties of $[\cdot]^+$ and $[\cdot]^-$, (15) can be transformed as the following:

$$F_T(P_{Rt}, P_{Bt}^{Grid}, c_{bt}, c_{st}) = \frac{c_{bt} - c_{st}}{2}\Big|P_{Rt} - R_t - \sum_{j=1}^{N_B} P_{Bjt}^{Grid}\Big| + \frac{c_{bt} + c_{st}}{2}\Big(P_{Rt} - R_t - \sum_{j=1}^{N_B} P_{Bjt}^{Grid}\Big) \tag{16}$$

where is convex assuming that $c_{bt} \geq c_{st},\ \forall t$.

C. Stochastic Programming

Assume that renewable generation of a specific day can be modeled by a probability measure $P(R)$. We construct a two-stage stochastic programming problem which decides day-ahead scheduling in the first stage and determines the real time alternations of generators and elastic loads in the second stage. Note that the second stage objective is a transaction term. First stage:

$$\begin{aligned}
\min_{\mathcal{D}_1}\quad & \sum_{t=1}^{T}\sum_{i=1}^{N_G} F_{Gi}(P_{Git}) - \sum_{t=1}^{T}\sum_{i=1}^{N_{L2}} F_{Ej}(P_{Ejt}) \\
& + E_{P(\mathbf{R})}\big[F_2(\mathbf{P_G}, \mathbf{P_E}, \mathbf{P_B^{Grid}}, \mathbf{R})\big] \\
\text{s.t.}\quad & \mathcal{D}_1 = \{\mathbf{P_G}, \mathbf{P_B^+}, \mathbf{P_B^-}, \mathbf{S^+}, \mathbf{S^-}, \mathbf{P_E}\} \\
& (2) - (9)
\end{aligned}$$

Second stage:

$$\min_{\mathcal{D}_2}\quad F_2(\mathbf{P_G}, \mathbf{P_E}, \mathbf{P_B^{Grid}}, \mathbf{R}) \equiv \sum_{t=1}^{T}\bigg(c_{bt}\Big[\delta_t\Big]^+ - c_{st}\Big[\delta_t\Big]^-\bigg)$$

$$\begin{aligned}
\text{s.t.}\quad & \mathcal{D}_2 = \{\Delta P_{Git}, \Delta P_{Eit}\} \\
& \delta_t = \sum_{j=1}^{N_{L_2}}(P_{Ejt} + \Delta P_{Ejt}) + \sum_{j=1}^{N_{L1}} P_{Ljt} + \sum_{j=1}^{N_B} P_{Bjt}^{Grid} \\
& - \sum_{i=1}^{N_G}(P_{Git} + \Delta P_{Git}) - R_t,\ \forall t \qquad (17) \\
& \underline{P}_{Ej} \leq P_{Ejt} + \Delta P_{Ejt} \leq \overline{P}_{Ej},\ \forall j, \forall t \qquad (18) \\
& \underline{P}_{Gi} \leq P_{Git} + \Delta P_{Git} \leq \overline{P}_{Gi},\ \forall i, \forall t \qquad (19) \\
& -\underline{R}_i \leq P_{Git} + \Delta P_{Git} - P_{Gi(t-1)} - \Delta P_{Gi(t-1)} \\
& \leq \overline{R}_i,\ \forall i, \forall t \qquad (20) \\
& \sum_{i=1}^{N_G}(\overline{P}_{Gi} - P_{Git} - \Delta P_{Git}) \geq P_t^{SR},\ \forall t \qquad (21)
\end{aligned}$$

Based on the scenario of renewable generation $\mathbf{R}^{(s)}$ generated from a pre-defined data generating mechanism, we can apply scenario aggregation and obtain the deterministic equivalent of the original problem.

$$\begin{aligned}
\min_{\mathcal{D}}\quad & \sum_{t=1}^{T}\sum_{i=1}^{N_G} F_{Gi}(P_{Git}) - \sum_{t=1}^{T}\sum_{i=1}^{N_{L2}} F_{Ej}(P_{Ejt}) \\
& + \sum_{s}\frac{1}{S}\sum_{t=1}^{T}\Big(\frac{c_{bt} - c_{st}}{2}\big|\delta_t^{(s)}\big| - \frac{c_{bt} + c_{st}}{2}\big(\delta_t^{(s)}\big)\Big) \\
\text{s.t.}\quad & \mathcal{D} = \{\mathbf{P_G}, \mathbf{P_B^+}, \mathbf{P_B^-}, \mathbf{S^+}, \mathbf{S^-}, \mathbf{P_E}, \mathbf{\Delta P_G}, \mathbf{\Delta P_E}\} \\
& \delta_t^{(s)} = \sum_{j=1}^{N_{L_2}}(P_{Ejt} + \Delta P_{Ejt}^{(s)}) + \sum_{j=1}^{N_{L1}} P_{Ljt} + \sum_{j=1}^{N_B} P_{Bjt}^{Grid} \\
& - \sum_{i=1}^{N_G}(P_{Git} + \Delta P_{Git}^{(s)}) - R_t^{(s)},\ \forall t, \forall s \qquad (22) \\
& (2) - (9), (18) - (21) \\
& \text{with } \{\Delta P_{Git}, \Delta P_{Ejt}\} \text{ as } \{\Delta P_{Git}^{(s)}, \Delta P_{Ejt}^{(s)}\},\ \forall s
\end{aligned}$$

III. Implementation of Neural Network

Our method consists of three major modules: training data generation, deep neural network, post-processing. This section demonstrates the details of these modules and some specifications of implementation in practice.

A. Training Data

As mentioned earlier, the schema of our training data has realizations of uncertainties of a specific day as input features and solutions of the optimization problem defined by this set of realizations as response. To enable the application of deep neural network, we need a significant number of realizations of daily uncertainties which can not be satisfied by available open source datasets, hence we need to generate the realizations based on given datasets. Here, we apply Monte Carlo simulation and generate 50000 days amount of wind power data (based on "Eastern Wind Integration Data Set" [20]), solar power data (based on "Solar Integration Data Sets" [20]), load data (base on hourly load profile data [21]), and market price data (based on actual energy price [22]).

It is worth noting that these simulated datasets are the "actual" realizations of uncertainties which are not accessible for day ahead scheduling. In practice, we apply day ahead forecast of the uncertainties which means we need to predict load profile, wind power, solar power and market price for 50000 days. For the simplicity of implementation and to make our predicting method applicable to the three optimization formulations, we assume that all the uncertainties of each day are generated from several day-specific probability measures estimated based on data of previous days in a non-parametric manner. Specifically, we apply kernel density estimation [23].

With the forecast of model uncertainties (point estimation for the deterministic case, interval estimation for the robust formulation case, probability density function for scenario generation in stochastic programming), we can solve 50000 optimization problems with available solver (Gurobi) and further construct our training data set as specified earlier.

B. Deep Neural Network

To make our method more generic, we simply applied the classic feedforward multilayer perceptron neural network trained with state-of-art back-propagation (ℓ_2 norm loss). The neural network we applied has 6 hidden layers with

256 neurons in each hidden layer. The training procedure is standard hence omitted here. The dimensions of input and output, learning rate, neuron dropout probability, number of training epochs, training batch size and non-linear activation functions are case specific.

C. A Heuristic Post-processing Method

The post processing of neural network's output is important since theoretically it is possible that the output given by DNN will be infeasible w.r.t. the original optimization problem. Fortunately, violation of most constraints can be fixed by simply setting the value to its lower/upper bound (since violation of coupled constraints does not occur in tests). However, the power balance constraint can be difficult to satisfy. Here we compute the difference between supply and demand of each time slot (in a day) and if the power balance constraint is violated we solve a small-scaled optimization problem to alter the power of generator and consumption of elastic load.

$$
\begin{aligned}
\min_{\mathcal{D}} \quad & \sum_{i=1}^{N_G} \Big(F_{Gi}\big(P_{Git} + q_G(\Delta P_{Git})\big) - F_{Gi}(P_{Git}) \Big) \\
& + \sum_{i=1}^{N_{L2}} \Big(F_{Ej}(P_{Ejt}) - F_{Ej}\big(P_{Ejt} + q_E(\Delta P_{Ejt})\big) \Big) \\
\text{s.t.} \quad & \mathcal{D} = \{\Delta P_{Git}, \Delta P_{Ejt}\}_{\forall i,j} \\
& |\Delta_t| = \sum_{i=1}^{N_G} \Delta P_{Git} + \sum_{j=1}^{N_{L2}} \Delta P_{Ejt} \qquad (23) \\
& \underline{P}_{Ej} \le P_{Ejt} + q_E(\Delta P_{Ejt}) \le \overline{P}_{Ej}, \ \forall j \qquad (24) \\
& \underline{P}_{Gi} \le P_{Git} + q_G(\Delta P_{Git}) \le \overline{P}_{Gi}, \ \forall i \qquad (25) \\
& -\underline{R}_i \le P_{Git} + q_G(\Delta P_{Git}) - P_{Gi(t-1)} \le \overline{R}_i, \forall i \qquad (26) \\
& \sum_{i=1}^{N_G} \big(\overline{P}_{Gi} - P_{Git} - q_G(\Delta P_{Git}) \big) \ge P_t^{SR} \qquad (27) \\
& \Delta P_{Git} \ge 0, \ \forall i \quad \Delta P_{Ejt} \ge 0, \ \forall j \qquad (28)
\end{aligned}
$$

If shortage ($supply < demand$) in time slot t:

$$
q_G(\Delta P_{Git}) = \Delta P_{Git} \quad q_E(\Delta P_{Eit}) = -\Delta P_{Eit} \qquad (29)
$$

If surplus ($supply > demand$) in time slot t:

$$
q_G(\Delta P_{Git}) = -\Delta P_{Git} \quad q_E(\Delta P_{Eit}) = \Delta P_{Eit} \qquad (30)
$$

IV. Test Result and Discussion

Our method is tested on three problem formulations with different penetration levels ρ respectively (approximately $200\%, 80\%, 50\%$). Here the penetration level is defined as the ratio of mean renewable generation to mean non-dispatchable load. Objective value is selected as the criteria of comparing predicted results and original solutions. we consider the rate of error falls in the following intervals: $< 0\%$, $[0\%, 1\%]$, $[1\%, 2\%]$, $[2\%, 5\%]$, $[5\%, 10\%]$, $[10\%, 15\%]$, $> 15\%$. The histograms of test results of three formulation cases are shown in Fig. 1-3 respectively (the size of test dataset for the three formulations are 5000, 2500, 2500).

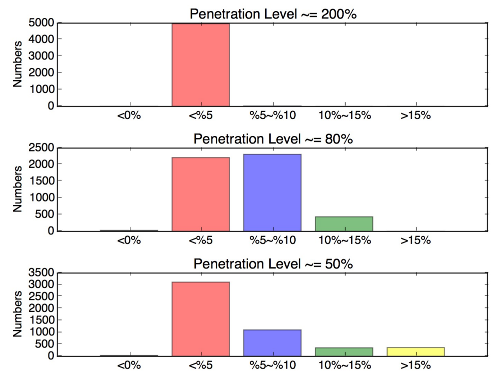

Fig. 1. Deterministic case: test results on three penetration levels

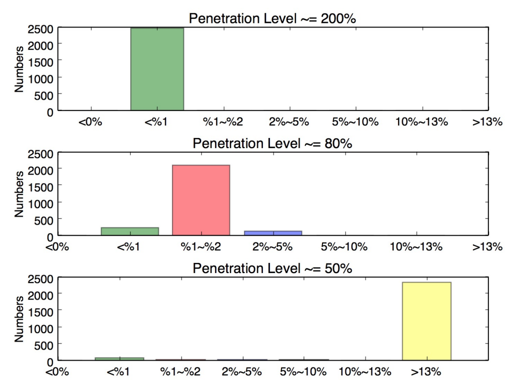

Fig. 2. Robust case: test results on three penetration levels

According to the test result, we can see that for all the problem formulations, when the penetration level is high $(200\%, 80\%)$, our method tend to produce better prediction w.r.t. objective value and the performance decreases along with penetration level. This is reasonable in a sense that when the penetration level is close to or higher than 100%, it is very likely that renewable generation will be suffice for demand hence we do not even need too much conventional generation. In other words, for the 200% and 80% penetration level cases, the scheduling for generators are very close to their lower bounds which means there is an explicit pattern in the training data for our DNN to learn. As the penetration level decreases, the pattern among data becomes more difficult for our DNN to learn and the prediction will be unstable. Take the 50% case for robust formulation as an example. Here we rescale the market price to induce more flexibilities in the training data, and the performance is vey unsatisfactory.

TABLE I
Time Efficiency Comparison

Cases	DNN	Deterministic	Robust	Stochastic
Time (sec)	3.57×10^{-5}	0.14	2921.96	304.06

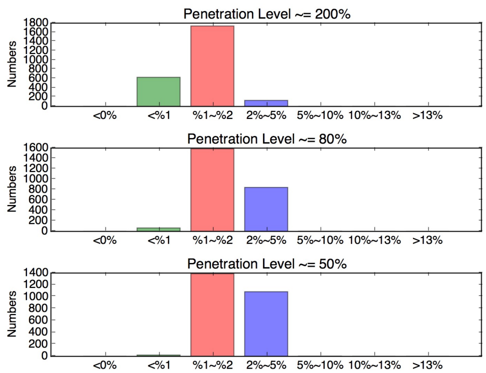

Fig. 3. Stochastic case: test results on three penetration levels

The optimization problems in this paper are multi-step mixed integer nonlinear programming problems which are NP-hard in nature. The time complexity of solving such problems is determined by the problem size, relaxation gap and model symmetries hence difficult to measure. However it is worth noting that time complexity of neural network forward propagation computation is typically $\mathcal{O}(N)$ (N is the number of hidden layers) which is irrelevant to the problem scale. Thus, despite the performance, our method will be much more efficient than standard algorithms when the scale of problem is large in practice. This is also shown in an empirical example of time efficiency comparison among our method and solving three formulations of problems with Gurobi (see Table I). Here the penetration level is set as 50% and the stochastic formulation considers 1000 scenarios. Our method is significantly faster than directly solving an optimization problem, especially for the robust and stochastic programming cases.

V. Conclusion and Future Directions

In this paper, we present a DNN-based method to approximate algorithms for microgrid ED problems considering renewable penetrations. We test our method on three problem formulations with three penetration levels. We find that when the penetration level is higher, our method can better recover the original solutions in a time efficient manner. In the future, it would be interesting to test if neural networks with more complicated structures will gain a better performance.

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