Topology-Aware Neural Networks: Leveraging Graph Structures for Efficient Learning

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Abstract- Solving the optimal power flow (OPF) problem is a fundamental task to ensure the system efficiency and reliability in real-time electricity grid operations. We develop a new topology-informed graph neural network (GNN) approach for predicting the optimal solutions of real-time ac-OPF problem. To incorporate grid topology to the NN model, the proposed GNN-for-OPF framework innovatively exploits the locality property of locational marginal prices and voltage magnitude. Furthermore, we develop a physics-aware (ac-)flow feasibility regularization approach for general OPF learning. The advantages of our proposed designs include reduced model complexity, improved generalizability and feasibility guarantees. By providing the analytical understanding on the graph subspace stability under grid topology contingency, we show the proposed GNN can quickly adapt to varying grid topology by an efficient re-training strategy. Numerical tests on various test systems of different sizes have validated the prediction accuracy, improved flow feasibility, and topology adaptivity capability of our proposed GNN-based learning framework.

Keywords – optimal power flow, system efficiency and reliability, real-time electricity grid operations, graph neural network, real-time ac-OPF problem.

INTRODUCTION

The optimal power flow (OPF) problem is one of the most fundamental tasks in market operations and power system management. It is instrumental for ensuring high efficiency and security of real-time operations, particularly under increasingly intermittent and variable energy resources such as renewables and flexible demands[1]. While there is a growing interest on a machine learning (ML) paradigm for OPF, most OPF learning problems have seldom embraced the physical models of the power grids nor systematically addressed the critical OPF constraints.

The accurate ac-OPF problem is known to incur high computation complexity due to its non-linear, non-convex formulation[2]. With active research on developing direct ac-OPF solvers, growing interest has emerged recently on ML for OPF by obtaining neural network (NN) based prediction models using extensive off-line training; to name a few[3], for ac-OPF and for dc-OPF. Nonetheless, almost all existing work relies on the fully connected NNs (FCNNs) that are agnostic to the power grid topology[4]. As a result, these FCNNs need to be completely re-trained whenever the grid topology and other operation conditions change in daily operations. This lack of topology adaptivity severely affects their adoption by grid operators due to the computation concern. In addition, the feasibility issue of those OPF learning solutions is very important, especially for the network-wide line limit constraints[5]. For example, a feasible domain technique w developed in, while KKT conditions for ac/dc-OPF were used for training regularization. While the first approach could affect the OPF solution optimality, the second one tends to add a large number of regularization terms, all of which require the design of weight coefficients (hyper-parameters)[6]. Therefore, it is of great importance to develop a physics-informed OPF learning framework that can adapt to fast-varying grid topology while simplifying the process of ensuring OPF feasibility[7]. The goal of this paper is to leverage the graph neural networks (GNNs) by incorporating the grid topology into a physics-informed OPF learning framework that extends our earlier work. When the nodal features exhibit a graph-based locality property or topology dependence, the GNN architecture is known to efficiently incorporate the underlying graph embedding; see e.g.,[8] . As a special case of NNs, GNNs work for graph learning by aggregating, or filtering the features from neighboring nodes only, thus significantly reducing number of parameters [16]. GNNs have been recently used for power system learning tasks such as fault localization in distribution networks. While recent work has proposed to use GNNs for OPF learning, the GNN output labels therein are the nodal power injections which are not topology dependent, critically affecting the prediction performance[9]. We put forth an innovative idea of predicting ac-OPF outputs that are topology-dependent, namely the locational marginal prices (LMPs) and voltage magnitudes. Both are recognized to strongly exhibit locality property, due to the power flow (PF) coupling and OPF duality analysis. Therefore, our proposed GNN model can effectively utilize the sparse graph embedding underlying these OPF outputs to greatly simplify the model complexity compared with FCNNs, and thus attain better generalizability during fast-varying operations[10]. The GNN model can be also used for other OPF learning tasks such as line congestion classification.

AC-FEASIBILITY REGULARIZATION

Regularization can greatly enhance the performance of NN models by mitigating data over-fitting and improving the training speed. Similarly for OPF learning, regularization has been introduced to e.g., improve the constraint satisfaction, or approach the first-order optimality. Nonetheless, the flow constraint in (1e) is by and large the most critical feasibility condition of ac-OPF, motivating us to develop a new ac-feasibility regularization (FR) approach[11]. The key of this FR approach lies in generating the line apparent power sij from the GNN outputs, as the ac power flow admits that

$$s_{ij} = |v_i||I_{ij}| = \left| |v_i|e^{j\theta_i} - |v_j|e^{j\theta_j} \right| |v_i||Y_{ij}|$$

where Yij is the admittance for line (i, j) from the Y-bus matrix, while {θi} are the bus voltage phase angles[12]. Using the LMP vector, the latter can be obtained by solving the nodal injection ˆp based on the optimality conditions. This way, our GNN models can generate both ˆp and ˆθ from ˆπ as latent Variables. The implicit KKT optimality condition allows to determine the injection p from the LMP, as for each node i[13].

$$\hat{p}_i = \underset{\underline{p}_i \leq p_i \leq \bar{p}_i}{\arg\min} \quad c_i(p_i) - \hat{\pi}_i p_i \ ,$$

which is basically the economic interpretation for OPF. For simplicity, consider a quadratic injection cost as ci(pi) = aip2 i +bipi with ai > 0, and thus the unique optimum becomes[14]

$$\hat{p}_i = \begin{cases} \underline{p}_i, & \text{if } \frac{\hat{\pi}_i - b_i}{2a_i} \leq \underline{p}_i, \\ \bar{p}_i, & \text{if } \frac{\hat{\pi}_i - b_i}{2a_i} \geq \bar{p}_i, \\ \frac{\hat{\pi}_i - b_i}{2a_i}, & \text{otherwise.} \end{cases}$$

GRID TOPOLOGY ADAPTIVITY OF GNN

Going beyond scalability and feasibility, it is truly important to enhance the applicability of the proposed GNN-for-OPF learning framework by considering grid topology adaptivity[15]. Almost all existing OPF learning solutions are limited to a fixed topology, and cannot be directly transferred in case of contingency. Nonetheless, the status of lines or transformers is known to change due to contingency or scheduled switching[17]. While this may not be an issue for direct OPF solvers, any variation of topology, or generally operating conditions, require to re-train the NNs after generating new samples. Both sample generation and training lead to concerns over the computation efficiency and real-time adaptivity[18]. To this end, we advocate the proposed GNN models can gracefully address these concerns by analyzing the topology adaptivity performance. Motivated by OPF security against line outages, we are particularly interested in this type of contingency, while the resultant analysis may be similarly extended to component failures such as generators or loads[19]. AS2 (Topology contingency). We consider the contingency of line k outage with no multiple concurrent failures, and the post-contingency network stays connected[20]. The single-line outage is assumed for simplicity of the analysis, and consider multiple-line outages in practical systems. For topology adaptivity, the key idea is to analyze the perturbation of OPF outputs under (AS2)[21]. Recall that the OPF outputs are generated by the eigen-space of the reduced B-bus B or its inverse, as consider the perturbation on these two matrices due to (AS2)[22].

NUMERICAL RESULTS

This presents numerical test results for the proposed GNN-based OPF learning framework on several benchmark systems of different sizes 1[23]. We generate data samples using the MATPOWER ac/dc-OPF solvers, on the ieee118-bus, pegase1354-bus, and wp2383-bus systems from the IEEE PES PGLib-OPF library. For all test cases, the nodal active and reactive power demands and generator cost coefficients have been randomly perturbed from the respective nominal values[24]. Specifically, the load perturbation ranges from 10-30% with higher perturbation level for smaller systems, where the optimal OPF solutions are obtained by MATPOWER. Specifically, the ac-OPF samples are generated by MATPOWER’s built-in primal-dual interior point solver (MIPS), while the dc-OPF ones by invoking the Gurobi convex[34] solver[25]. In addition, all the samples generated are split into the training/test datasets with a

80%/20% division[33]. All learning algorithms have been implemented with the PyTorch library in Python[26]. To train the GNN models, we initialize the graph filters {Wt} by the normalized B-bus matrix, and maintain the sparse structure by using a mask matrix. The FCNNs are also trained on the same datasets to compare with the GNN performance[27]. For both models, we used a total of six layers where the number of features per node is respectively {6, 5, 10, 10, 5, 5} for each laye[32]r, along with a final linear output layer. As for the dc-OPF training, the number of features per node is given by {4, 5, 10, 10, 5, 5}[28]. All NN models are trained by the standard ADAM algorithm with the same convergence criteria, using NVIDIA Quadro RTX 5000 for computation acceleration. Prediction and Feasibility Performance: We compare the proposed GNN models with the FCNN ones, both having multiple hidden layers[29]. Both types of NN models with and without the proposed FR term, have been considered for the ac-OPF comparisons on the 118-bus and 1354-bus systems, as well as for dc-OPF on the 118-bus and 2383-bus systems. For each system, we have generated 10, 000 samples, similar to other OPF-learning work[30]. We compare the test performance in predicting both π∗ and |v∗| (in dc-OPF only π∗) measured by the normalized mean squared error (MSE) with its standard deviation (STD). The attained flow feasibility rate is also included as a performance metric. To compare the model complexity, we list the number of parameters in each of the NN models. he test results for dc-OPF cases are presented in Fig. 1, while those for the ac-OPF in Fig. 2[31].

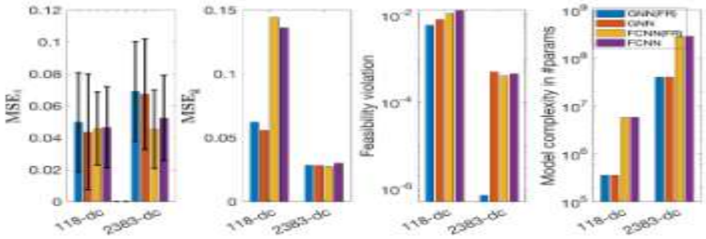

Figure 1- Comparisons of the proposed GNN with FCNN on two dc-OPF test cases (from left to right)[23]

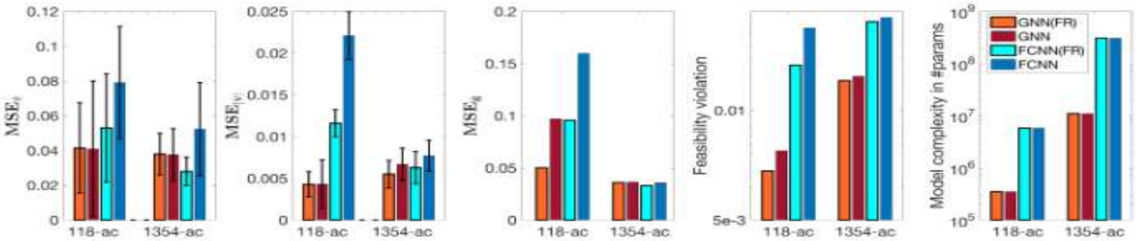

Figure 2- Comparisons of the proposed GNN with FCNN on two ac-OPF test cases (from left to right)[24]

CONCLUSION

This paper develops a new topology-informed GNN approach for predicting the optimal solutions of real-time ac-OPF problem. We put forth the GNN-based prediction of LMPs and voltage magnitudes, two important OPF outputs, that can capitalize on their topology dependency. The resultant GNN enjoys simplified model structure with significantly reduced number of parameters thanks to a sparse grid topology, and thus achieve good generalization performance. To further enhance the feasibility guarantees of OPF learning, we design an (ac-)feasibility regularization (FR) approach that can effectively reduce the line (apparent) power violation. Going beyond a fixed topology, we investigate the topology adaptivity of GNN models under line contingency, by providing the stability analysis of the graph subspace. Numerical results on various test systems have validated the performance of the proposed GNN models with the FR approach in terms of attaining high prediction accuracy and increasing flow feasibility at significantly fewer parameters. The GNN topology adaptivity is also confirmed with high computation efficiency in transferring to a new grid topology.

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