# Proximal Policy Optimization with Graph Neural Networks for Optimal Power Flow

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Abstract—Optimal Power Flow (OPF) is a key research area within the power systems field that seeks the optimal operation point of electric power plants, and which needs to be solved every few minutes in real-world scenarios. However, due to the nonconvex nature of power generation systems, there is not yet a fast, robust solution for the full Alternating Current Optimal Power Flow (ACOPF). In the last decades, power grids have evolved into a typical dynamic, non-linear and large-scale control system known as the power system—, so searching for better and faster ACOPF solutions is becoming crucial. The appearance of Graph Neural Networks (GNN) has allowed the use of Machine Learning (ML) algorithms on graph data, such as power networks. On the other hand, Deep Reinforcement Learning (DRL) is known for its powerful capability to solve complex decision-making problems. Although solutions that use these two methods separately are beginning to appear in the literature, none has yet combined the advantages of both. We propose a novel architecture based on the Proximal Policy Optimization (PPO) algorithm with Graph Neural Networks to solve the Optimal Power Flow. The objective is to design an architecture that learns how to solve the optimization problem and, at the same time, is able to generalize to unseen scenarios. We compare our solution with the Direct Current Optimal Power Flow approximation (DCOPF) in terms of cost. We first trained our DRL agent on the IEEE 30 bus system and with it, we computed the OPF on that base network with topology changes.

Index Terms—Optimal Power Flow (OPF), Graph Neural Networks (GNN), Deep Reinforcement Learning (DRL), Proximal Policy Optimization (PPO)

#### I. INTRODUCTION

After several decades of development, power grids have evolved into a typical dynamic, non-linear and large-scale control system, known as the power system [1]. Nowadays, this power system is changing because of different causes. First of all, the high penetration of Renewable Energy Sources (RES), such as photovoltaic plants and wind farms, brings fluctuation and intermittence to power systems. This generation is unstable, being affected by various external factors like solar irradiation and wind velocity for solar and wind power, respectively [2]. At the same time, the integration of flexible sources (e.g., electric vehicles) introduces changes to distribution networks, such as relay protection, bidirectional power flow, and voltage regulation [1]. Finally, new concepts like Demand Response —which can be defined as the changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time— change the operation point in the

electrical grid [3]. All these changes make the optimization of production in power networks increasingly complex. In this context, Optimal Power Flow are set of techniques that attempt to find the best operating point by optimizing the power of generators in power grids [3].

The traditional way to solve the OPF is with numerical methods [2] and the most typically used is Interior Point Optimizer (IPOPT) [4]. But as networks become more complex it is more difficult for traditional methods to converge due to their non-linear and non-convex nature [2]. Nonlinear ACOPF problems are commonly approximated by linearized DCOPF solutions to obtain real power solutions where voltage angles and reactive power flows are removed by substitution (remove Alternating Current (AC) electric behaviour). However, this approximation is no longer valid when power grids are heavily loaded [5]. Moreover, the OPF problem is non-convex due to the sinusoidal nature of electrical generation [3]. Other techniques approximate the OPF solution by relaxing this non-convex constraint with methods like Second Order Cone Programming (SOCP) [3]. In day-to-day operations that require solving OPF within a minute every five minutes, TSO is forced to rely on linear approximations. Solutions produced by these approximations are inefficient and therefore waste power and overproduce hundreds of megatons of CO2-equivalent per year. Today, 50 years after the problem was formulated, we still do not have a fast, robust solution technique for the full Alternating Current Optimal Power Flow [6]. For large and complex power system networks with large numbers of variables and constraints, finding the optimal solution for realtime OPF on time requires a massive amount of computing power [7] and remains a challenge nowadays.

In power systems, like in many other fields, algorithms of ML have recently begun to be used. The latest proposals use Graph Neural Networks, a neural network which naturally allows graph data to be processed [8]. There is an increasing number of tasks in power systems that are starting to be solved with GNN such as time series prediction of loads and RES, fault diagnosis, scenario generation, operational control, etc [9]. The main advantage is that processing power grids as graphs GNN can be trained with some grid topologies and then be applied to different ones, generalizing results [8]. On the other hand, Deep Reinforcement Learning is known for its capability to solve complex decision-making problems in a computationally efficient, scalable and flexible manner —

which otherwise is numerically intractable [2]—, and it is considered one of the state-of-the-art frameworks in Artificial Intelligence (AI) for solving sequential decision making problems [10]. DRL based approach aims to learn gradually how to optimize power flow in Distribution Networks and dynamically find the optimal operating point. Some approaches use different DRL algorithms, but none of them combine it with GNN, so they cannot generalize and do not take advantage of the information of connections between buses and properties of the electrical lines connecting them. Given that, and also because combining DRL and GNN have shown to gain in generalizability and reduce computational complexity in other domains [10], we explore their implementation in this work.

**Contribution:** This paper's main contribution is the proposal of a novel architecture based on the Proximal Policy Optimization algorithm with Graph Neural Networks to solve the Optimal Power Flow. At the time of writing this paper and to the best of our knowledge, a similar architecture has not been used before to tackle this problem. The goal is to test our architecture design, proving it is capable of solving the optimization problem by learning the internal dynamics of the power network, as well as to analyze if it is also able to generalize to new scenarios that were not seen during the training pipeline. We compare our solution with the DCOPF in terms of cost after having trained our DRL agent on the IEEE 30 bus system. On that base network, with topology changes regarding the number of edges and loads, we obtain better cost results than the DCOPF, reducing the cost of generation up to 30%.

## II. RELATED WORK

Methods can be found in the literature using each of the approaches independently. Data-driven methods based on deep learning have been introduced to solve OPF in approaches like [5], [7], [9], [11] among others. However, these approaches require a large amount of historical data to train and need to recollect a large amount of data once something in the grid has changed. On the other hand, DRL based approach aims to learn gradually how to optimize power flow in Distribution Networks and dynamically find the optimal operating point. Approaches like [2], [12]-[14] use different DRL algorithms to solve the OPF, but none of them use GNN, so they lack the ability to generalize.

## III. PROBLEM STATEMENT

First, an agent is trained using DRL. During several episodes, the agent modifies the generation values of a power grid trying to maximize the reward, which represents the reduction of the generation cost in comparison with the previous timestep. Once this agent has been trained on a base case minimizing the cost and optimizing the search for feasible solutions, this agent can be used to compute OPF in a power grid with changes in the topology (like the fall of an electrical line due to maintenance or the disconnection of a load) obtaining better or similar results, in terms of the cost, than the DCOPF.

#### IV. BACKGROUND

In this section, we provide the necessary background for GNN, the DRL algorithm used and we expand the definition of OPF. Commonly, OPF minimizes the generation cost, so the objective is to minimize the cost of power generation while satisfying operating constraints and demands. Some of these constraints are restrictions of both maximum and minimum voltage in the nodes or that the net power in each bus is equal to the power consumed minus generated [6]. At the same time, the Power Flow (PF) or load flow refers to the generation, load, and transmission network equations. It is a quantitative study to determine the flow of electric power in a distribution network under given load conditions whose objective is to determine the steady-state operating values of an electrical distribution network [6].

## A. Graph Neural Networks

Graph Neural Networks are deep learning-based methods that operate on the graph domain. Due to its performance, GNN has recently become a widely applied graph analysis method [1]. GNN first introduced by [15]. The architecture can be seen as a generalization of convolutional neural networks for graph structures by unfolding a finite number of iterations. We use Message Passing Neural Networks (MPNN) introduced in [16], which is a type of GNN whose operation is based on an iterative message-passing algorithm that propagates information between elements in a graph G = (N, E). First, the hidden states of the nodes are initialized with graph's node-level features of the data, then, the message-passing process [16]: Message (equation 1), Aggregation (equation 1), and Update (equation 2). After a certain number of message passing steps a readout function r() takes as input the final node states  $h_v^K$  to produce the final output of the GNN model. Readout can predict different things at different levels depending on the problem.

$$M_v^k = a(\{m(h_v^k, h_k^i)\}_{i \in \beta(v)})$$

$$h_v^{k+1} = u(h_v^k, M_v^k)$$
(2)

$$h_v^{k+1} = u(h_v^k, M_k^v) (2)$$

## B. Deep Reinforcement Learning

The goal in Reinforcement Learning (RL) is learning a behaviour (policy). In RL, an agent learns a behaviour while interacting with an environment to achieve a goal [17]. It is based on the reward assumption: all goals can be formalized as the outcome of maximizing a cumulative reward. DRL is known for its powerful capability to solve complex decisionmaking problems, so it can be adopted here to capture the dynamic in the power flow reallocation process [2].

Within the DRL algorithms, we use Proximal Policy Optimization, formulated in 2017 ([17]) and becoming the default reinforcement learning algorithm at *OpenAI* [17] because of its ease of use and its good performance. As an actor-critic algorithm, the critic evaluates the current policy and the result is used in the policy training. The actor implements the policy and it is trained using Policy Gradient with estimations from the critic [17]. PPO strikes a balance between ease of implementation, sample complexity, and ease of tuning, trying to compute an update at each step that minimizes the cost function while ensuring that the deviation from the previous

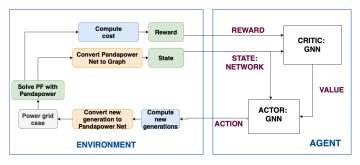


Fig. 1. PPO architecture implementation.

policy is relatively small [17]. PPO uses Trust Region and imposes policy ratio to stay within a small interval (policy ratio  $r_t$  is clipped), rt will only grow to as much as  $1+\varepsilon$  (equation 4) [17]. The total loss function for the PPO consists of  $L^{CLIP}$  (equation 4), the mean-square error loss of the value estimator (critic loss), and a term to encourage higher entropy (greater exploration) (equation 3). PPO uses Generalized Advantage Estimate (GAE) to calculate the advantage  $(\hat{A}_t)$ , equation 5. This advantage method is presented in [18].

$$L_{TOTAL} = L^{CLIP} + L^{VALUE} * k_1 - L^{ENTROPY} * k_2$$
(3)  

$$L^{CLIP}(\theta) = \hat{E}_t \left[ min(r_t(\theta)\hat{A}_t, clip(r_t(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A}_t) \right]$$
(4)  

$$A_0^{GAE} = \delta_0 + (\lambda \gamma) A_1^{GAE}$$
(5)

## V. PROPOSED METHOD

In this section, we explain our approach, schematically shown in Fig. 1. Both actor and critic of the DRL agent are represented as GNN and the state of the environment is the resulting graph of the power grid. In the DRL environment the agent takes an action at each time step, changing the power of the generator. After that, the power grid graph is updated with a PF. We treat our power grid as graph-structured data using the information on the power grid topology (electrical lines as edges and buses as nodes), the loads and the generations. For the electrical lines, as features, we use the resistance R and reactance X ( $e_{n,n}^{ACLine} = [R_{n,m}, X_{n,m}]$ ). For the buses, we use the voltage information (its magnitude V and phase angle  $\theta$ ) and exchange power in that bus between the loads and generators connected to it,  $X_n^{AC} = [V_n, \theta n, P_n, Q_n]$ .

The global architecture of the GNN is in Fig. 2. The message passing part and the readout part. At every message-passing step k, each node v receives the current hidden state of all the nodes in its neighbourhood and processes them individually by applying a message function m() (NN) together with its own internal state  $h_v^k$  and the features of the edge which connects them. Then, these messages are aggregated (concatenation of min, max and mean). Combining this message aggregation together with the node's hidden state and, after updating the combination with another NN, new hidden state representations are computed. After a certain number of message passing steps, a readout function r() takes as input the final node states  $h_v^K$  to produce the final output

of the GNN model. For the actor, whose output is the RL policy, the readout is a 3-layer MLP NN in which the input is each of the node representations. We pass through this readout the representation (independently) of all the nodes that have a generator, so we have N output values. Each of the output values represents the probability of choosing that generator to increase its power. We manage the readout in this way to make the architecture generalizable to any number of generators. These values are used to create a probability distribution. Then, a value is sampled (which is the ID of the generator from which the generation is increased in that horizon t). Critic uses a centralized readout that takes as inputs all node's hidden states (concatenates the sum, minimum and maximum), and whose output is the value function estimation. So, the input dimension is 3 \* node representation and only one output for the whole graph. Critic is also a 3-layer MLP.

Regarding the environment with which the agent interacts (Fig. 1), at each time instant t, the state is defined by the graph updated by the Power Flow. In each horizon step (t), the action that the agent performs is to increase the generation of one of the generator nodes. The agent will decide which one of the available generators increases the generation one portion. For each generator, the power range between its maximum and minimum power will be divided into N portions. When a generator has reached its maximum power, generation can not be increased, so the power grid (and therefore the state of the environment) remains the same. When the PF does not converge, it implies that with that demand and that generation, it is not possible to meet the constraints, we say that the solution is not feasible. When initializing one episode (initial state of the power grid), we want the generation to be as low as possible, so that the agent can raise it until it reaches the optimum. Besides, we have to take into account that if it is too low in the first time steps, the solution may not be feasible. Therefore, we decide to set the minimum generation by 20%. Reward in t is computed as the improvement in the solution's cost concerning t-1. The reward is positive in a time step when the agent's action decreases the generation cost. If the agent chooses a generator which is already at its maximum capacity, ends in a non-feasible solution or increases the cost, the reward is negative.

#### VI. PERFORMANCE EVALUATION

This section details the experimentation used to validate the proposed approach, the data used and discusses the obtained results.

**Overview:** We train the agent with a base case and later we evaluate the performance in modified cases. On the one hand, we modify the number of loads and their values, since, in real power grid operation the loads change continuously and, on the other hand, we remove some electrical lines simulating that they are not available due to any breakdown or maintenance. This way we show that the agent, once it is trained, can generalize to unseen cases. We compare the difference in cost concerning the OPF of our method to the industry standard method, the DCOPF. Our objective is to prove that our method

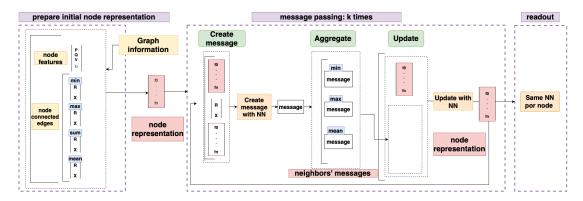


Fig. 2. GNN architecture

is capable of generating a solution with an equal or better result without the disadvantages of DCOPF.

## A. Experimental Setting

We train the agent with the IEEE 30 bus system as a case base. It is formed by thirty nodes, forty links, five generators and twenty loads. All generators are modelled as thermal generators. We use *Pandapower*, a Python-based BSD-licensed power system analysis tool [4]. The tool allows calculations such as OPF (with IPOPT optimizer) and PF, which we use to compare our cost and update our environment.

The objective of the training is to optimize the parameters so that the actor becomes a good estimator of the optimal global policy and the critic learns to approximate the state value function of any global state. Many hyperparameters can be modified and they are divided into different groups. Grid search has been performed on many of them and the final selected values of the most important ones are shown below.

- Related to learning loop: Minibatch (25), epochs (3) and optimizer (ADAM), with its parameters like learning rate lr (0.003).
- Related to the power grid: Generator portions (50).
- Related to RL: Episodes (500), horizon size T (125), reward  $cte_1$  (-1) and  $cte_2$  (-2).
- Actor and Critic GNN: Message iterations k (4), node representation size (16). The NN to create the messages is a 2-layer MLP and the updated one is 3-layer MLP.

PPO is an online algorithm and as any reinforcement learning algorithm does, it learns with experience. The training pipeline is as follows:

- An episode of length T is generated by following the current policy. While at the same time the critic's value function V evaluates each visited global state; this defines a trajectory  $\{s_t, a_t, r_t, p_t, V_t, s_{t+1}\}_{t=0}^{T-1}$ .
- This trajectory is used to update the model parameters
   -through several epochs of minibatch Stochastic Gradient
   Descent- by maximizing the global PPO objective.

The same process of generating episodes and updating the model is repeated for a fixed number of iterations to guarantee convergence. *MinMaxScaler* has been used for data preprocessing for node features, edge features and generation

output. More implementation details can be found in the public repository <sup>1</sup>.

#### B. Experimental Results

Once the training has been done and the best combination of hyperparameters, network design and reward modelling has been chosen, the best checkpoint of the model is selected to compute OPF in different networks. To validate our solution, we use the deviation of the cost concerning the minimum cost, the one obtained with the ACOPF. We compare it with the cost deviation obtained with DCOPF. We compute the ratio between these two deviations. We also use the convergence ratio as the proportion of solutions that do not respect the physical constraints concerning the number of solutions that are evaluated. Once the model is trained, only the actor part is used in the evaluation. During T steps of an episode, the actions sampled from the probability distribution obtained from the actor for each state of the network are executed. Finally, the mean cost of the best ten evaluations is measured, as well as the convergence of the problem. We evaluate 100 times for each test case. In Tables I - III, it is highlighted between the deviation in % of our solution concerning the OPF's one and the deviation obtained by the DCOPF, the lowest for each test.

First, all network loads are varied by multiplying their value by a random number between a value less than 1 and a value higher than 1 (Table I). Each row in the table is a test in which the name specifies the upper and lower percentages by which all loads have been varied. In all tests, performance with our method is better with ratios of up to 1.30.

 $\begin{tabular}{l} TABLE\ I\\ Results\ on\ case\ IEEE\ 30\ varying\ loads\ from\ base\ case. \end{tabular}$ 

	% DRL+OPF perf.	%DCOPF perf.	ratio
load_inf0.1_sup0.1	0,75	0,77	1,02
load_inf0.2_sup0.1	0,59	0,68	1,16
load_inf0.3_sup0.1	0,53	0,73	1,38
load_inf0.4_sup0.1	0,61	0,67	1,10

After varying the load value, we experiment with removing n loads from the grid. We randomly choose several loads,

<sup>&</sup>lt;sup>1</sup>https://github.com/anlopez94/opf\_gnn\_ppo

remove them from the network and evaluate the model (Table II). Each row in the table is a test in which the name specifies the number of loads that have been removed. Our cost deviation is lower or similar than the DCOPF even by eliminating almost 50% of the loads. Finally, in Table III we show the results of creating networks from the original one by removing one or more electrical lines (edges). Each row in the table is a test in which the name specifies the number of power lines removed.

 $\begin{tabular}{l} TABLE \ II \\ Results \ on \ case \ IEEE \ 30 \ removing \ loads \ from \ base \ case. \\ \end{tabular}$ 

	% DRL+OPF perf.	%DCOPF perf.	ratio
load_1	0,67	0,72	1,07
load_2	0,71	0,71	1,00
load_3	0,67	0,67	1,00
load_4	1,06	0,68	0,65
load_5	0,61	0,64	1,05
load_8	1,10	0,63	0,52

 $\label{thm:table III} \textbf{Results on case IEEE 30 removing edges from base case}.$ 

	% DRL+OPF perf.	%DCOPF perf.	ratio
edge_1	0,73	0,77	1,05
edge_2	0,41	1,16	2,83
edge_3	0,62	0,61	0,99
edge_4	0,65	0,88	1,36
edge_5	0,90	0,96	1,07
edge_8	0,59	0,89	1,51

In experiments removing electrical lines (Table III) as more power lines are removed (more than 8), sometimes, the agent does not find a good feasible solution. In the second test in Table I, because we increased loads too much, the tests did not converge. With the other changes in topology, 100% of tests converged, so we can conclude that our model is capable of generalizing to unseen topologies (based on the trained one).

#### VII. DISCUSSION

We successfully design a solution to solve the OPF, capable of generalizing, using DRL and GNN. The network topology has been changed and we have shown that the agent is capable of finding a good solution (performance very similar to the current industry standard DCOPF) and that this solution is feasible and meets the constraints. Due to the way how GNN has been designed, it can be trained on different cases and then used to compute on different ones. In this paper, we have validated that this architecture is capable of successfully addressing OPF, and the generalization ability of our solution, by considering modifications over the network scenario seen during training (different loads and reducing the number of edges). By joining these two technologies for the first time, we conclude that it is possible to combine them, obtaining the advantages of both. Our results suggest that the designed architecture is a promising start to solve the OPF. As a future work, it would be interesting to explore the inclusion of more features in the node representation such as the maximum and minimum allowed voltage.

#### VIII. ACKNOWLEDGMENT

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