Constraint-Guided Machine Learning for Solving Optimal Power Flow Problem

by

Amir Lotfi

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of contributions

Amir Lotfi was the sole author for all Chapters which were written under the supervision of Dr. Mehrdad Pirnia. The outcomes of this thesis is published in:

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Abstract

Due to the nonlinear and non-convex attributes of the optimization problems in power systems such as Optimal Power Flow (OPF), traditional iterative optimization algorithms require significant amount of time to converge for large electric networks. Therefore, power system operators seek other methods such as DC Optimal Power Flow (DCOPF) to obtain faster results, to obtain the state of the system. However, DCOPF provides approximated results, neglecting important features of the system such as voltage and reactive power. Fortunately, recent developments in machine learning have led to new approaches for solving such problems faster, more flexible, and more accurate. In this research, a Deep Neural Network-based Optimal Power Flow (DNN-OPF) algorithm is implemented on small to large case studies to show the accuracy and efficiency of the ML-based algorithms.

Since the ML methods such as NN are considered black-box approaches, the system operators are not satisfied with solving power system models using them, as such methods do not explain the reasoning behind the generated solutions. Moreover, there is no guarantee that the obtained solutions would be converging and close to optimality. To overcome such issues this research provides a novel approach to first classify the converging and non-converging ACOPF problems, and then suggests a constraint-guided method, based on normalizing outputs and using particular activation functions to satisfy the technical limits of the generators such as maximum and minimum generation. Furthermore, a post-processing approach is incorporated to check for the convergence of the power flow equations which are in form of equality constraints.

The suggested method is applied on IEEE24-bus, IEEE 300 bus, and PEGASE 1354 bus systems and the results show significant improvement on execution time, comparing to traditional gradient-based methods, such as Newton-Raphson and Gauss–Seidel methods. Also, the approach has been benchmarked against DCOPF model and it is shown that the proposed DNN-OPF not only provides faster speed, but also ensures higher accuracy on the final results. Furthermore, since is a need to run ACOPF problem using different scenarios, to account for continuous changes in the demand, the suggested DNN-OPF is solved for various scenarios from 1 to 10,000 to appreciate the improved execution time obtained from the ML-based approaches. Our results show that DNN can improve execution time a factor of 400 to 800 for large to small networks.

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List of Acronyms

ACOPF AC Optimal Power Flow

AI Artificial Intelligence

ANN Artificial Neural Network

BPNN Back-Propagation Neural Network

CNN Convolutional Neural Network

DCOPF DC Optimal Power Flow

DNN Deep Neural Network

FCNN Fully Connected Neural Network

FFNN Feed Forward Neural Network

GNN Graph Neural Network

ISO Independent System Operators

ML Machine Learning

NN Neural Network

OPF Optimal Power Flow

RL Reinforcement Learning

RNN Recurrent Neural Network

Chapter 1

Introduction

1.1 Motivation

The cost of generation, delivering, and operations of power systems is significant in energy markets around the world and therefore finding efficient solution methodologies to obtain economical decision for the operations of power systems, could save a lot for such systems. For example, the total generated electrical energy in Canada in 2020 was 630 billion kWh. Assuming the electrical energy price to be 18 cents per kWh in Canada, the total electricity generation cost in Canada would be 113 billion dollars per year. Hence, if the power system operators could increase the accuracy of the decision making models by only 5%, the annual cost saving would be 6 billion dollars in Canada. This example is an indication of the importance of proper modelling of the systems, as small improvements could lead to significant social benefits [1].

Optimal Power Flow (OPF) is one of the most important problems in power systems operations, which its efficient solving could benefit Independent System Operators (ISO) and their customers. As they should run OPF problem to find generation setpoints, considering variations in demand in a very short time to come up with reliable decisions for the operation of the system. A special type of OPF, AC Optimal Power Flow (ACOPF), was formulated in 1962 [2], as a nonlinear and non-convex optimization problem, which is considered a hard optimization problem due to the characteristics of the model and inherent computational complexities, as it includes continuous and binary variables contributing to its non-convexity. The binary variables are driven from the shut down or start up of generators, transmission lines, switches, and other electrical devices in the network in order to quickly respond to specific event within the network. Also the non-linear and non-convex characteristics of power flow equations contribute to the complexity associated with solving this problem. Moreover, ACOPF should be run with different scenarios in real time to consider the uncertainties associated with the operations of the power system fir the ISOs to be prepared for variations in the systems [3]. More importantly, the increasing penetration of renewable energy sources, has made it challenging for system operators to maintain balance between system efficiency and reliability and therefore, OPF problems should be executed in a short time to provide the system operators with insights on the status of the power system networks.

Since ACOPF is required to be solved in small to large time resolutions, as shown in table 1.1, its execution time is very important and depending on the added constraints and complexities it can be from 8 hours to 30 seconds [3]. The execution time of the system increases as the size of the network grows, for example, in large networks, such as Ontario power system, the execution time may exceed the requirement, and therefore the system operators rely on approximation methods for faster solution time.

Table 1.1: Characteristic comparison of different problems in power system.

ACOPF resolution	Weekly	Daily	Hourly	Every five minutes	Post-contingency
Run-time	8 hours	2 hours	15 minutes	1 minute	30 seconds

Traditional iteration-based solvers, on the other hand lack the desired speed for solving OPF problems. For the operation of contemporary power systems to be efficient, cost-effective, and dependable, it is thus essential to create accurate and fast OPF solutions. Therefore, improving the execution time of the ACOPF problems, while maintaining the accuracy of results play a significant role in future power systems with large networks and added uncertainties requiring faster solution times [4].

Recently, learning-based methods are utilized to overcome deficiencies raised by tradition methods used to solve OPF problem. Such methods take advantage of the universal approximation theorem derived from the solution of Neural Network (NN) to learn the mapping between input and model outputs, which in the context of power system, incorporate electricity demand as the input layer, fed into the trained Deep Neural Network (DNN) to predict solutions immediately [4]. The accuracy of such learning is highly dependent on quality of the data and the architecture of DNN. Thus, this research explores the possibility of employing DNN to solve OPF problems.

The remainder of this chapter provides a review of literature using learning-based method to solve OPF problems and highlights the contributions of this research. The rest of the thesis is organized as follows: In chapter 2, the application sof Machine Learning (ML) for OPF problems in power system are introduces, including an explanation of end to end learning for optimization problems, DNNs, and OPF problem by thoroughly elaborating on the definition of ACOPF and DCOPF. In chapter 3, a detailed explanation of the proposed methodology method for solving OPF problem as well as the three case studies, namely, IEEE 24, 300, and 1354 bus system which are examined to evaluate the performance of the proposed DNN method is provided. Finally, chapter 4 will provide conclusions and future directions for this research.

1.2 Literature review

In this section, an overview of the current state of the literature, focusing on solving general optimization problems and specially OPF, using ML is provided.

In [5] the features and problems of smart dispatch systems of the next generation of power systems are discussed and a framework for smart dispatch of electricity is presented. The evolution of ML techniques in power systems, including intelligent generation control, OPF, security assessment, and intelligent dispatch is also provided. Lastly, the dispatching robot technology framework based on parallel learning is shown.

ML algorithms can be utilized to learn the non-linear dependencies in optimization problems to provide optimal or near optimal solutions in a short time [6]. Such methods can be used to solve ACOPF problem generating credible results [7, 8]. Therefore, applying ML-based algorithms to solve ACOPF problems have gained popularity among power system researchers in recent years.

1.2.1 Learning DCOPF solutions

A number of researches obtain the data using DCOPF runs [9]. The authors in [9] suggest using classification algorithms to train the best mapping between the uncertainty realisation and the active set of constraints of DCOPF, hence increasing the computing effectiveness of the real-time forecasting. The authors deploy NN classifiers for this purpose and show the superior performance of the proposed approach on a variety of systems from the IEEE PES PGLib-OPF benchmark library.

In [10], the authors present a method that supplements the ML-based approach to solving OPF by using solutions from a previously established linearized OPF model. They convert the solutions of linear OPF to nonlinear control variables using supervised learning. In contrast to the typical ML-based approaches for solving OPF problem, which approximate the entire distribution feeder model using function approximation, their approach approximates radial networks with two nodes. The suggested method is verified using the IEEE 123 bus test system for OPF solutions derived from nonlinear OPF models.

1.2.2 Ensuring feasibility and near-optimility

In order to apply learning for solving OPF, the authors in [11] present a methodology for obtaining proven worst-case guarantees for NN performance. The provided NN approach can drastically improve OPF solution computation times. This research formulates mixed-integer linear programs in order to achieve worst-case guarantees for NN predictions for maximum constraint violations, maximum distances between computed and optimum decision variables, and maximum sub-optimality. This article illustrates the methodology on a variety of PGLib-OPF networks with as much as 300 buses.

In [12], a novel method is suggested to model the security and stability of constraints in ACOPF problem using NNs representing the security boundaries of the system using Back-Propagation Neural Network (BPNN) constraints. The paper first generates security boundaries, and then, BPNN are trained and evaluated to check the representation of the boundaries. After that, a security bounded constraint OPF model is introduced for optimal dispatch for the electrical energy market considering its competitive nature.

In [4], the authors introduce DeepOPF solution methodology which is a DNN-based method for solving ACOPF in a fraction of time required by standard iterative solvers. A fundamental challenge in applying ML approaches to ACOPF is ensuring that the derived solutions adhere to physical and operational limits, enforced by regarding equality and inequality constraints. DeepOPF first trains a DNN model to forecast a set of independent operational variables, and then directly computes the remaining variables by solving the power flow equations. In addition to preserving the power flow balance equality criteria, this method minimizes the number of variables that must be predicted by DNN, hence reducing the number of neurons and training data required. Additionally, DeepOPF then uses a penalty method with a zero-order gradient prediction function throughout the training procedure to ensure the inequality criteria are met.

Moreover, the authors in [13] provide a method for solving OPF issues that may significantly decrease the execution time of two-step hybrid systems consisting of a NN followed by an OPF past processing step guaranteeing optimum answers. Utilizing a NN that predicts the binding state of the system's constraints, an initial reduced OPF issue is generated by eliminating the projected non-binding constraints. This simplified model is then developed iteratively until an optimum solution to the whole OPF problem is guaranteed. The classifier is trained with a meta-loss objective, which is defined as the entire computing cost of answering the reduced OPF problems created throughout the iterative approach. Using a broad variety of DC Optimal Power Flow (DCOPF) and ACOPF problems, this study reveals that achieving this "meta-loss" goal results in a classifier that beats standard loss functions used to train NN classifiers by a large margin.

1.2.3 Heuristic methods to obtain optimal solutions

In [14], authors examine a data-driven algorithm design technique for large combinatorial optimization problems that may use current state-of-the-art solvers for general purpose applications. The objective is to develop innovative methods that can consistently outperform current solutions in faster time. The strategy is based on the large neighbourhood search (LNS) paradigm, which repeatedly selects a subset of variables to optimize while leaving the rest unchanged. LNS is appealing because it can readily employ any existing solution as a subroutine, inheriting the advantages of properly designed heuristic or exhaustive algorithms and their software implementations. This research demonstrates that a competent neighbourhood selector may be learned using imitation and Reinforcement Learning (RL) approaches. Through thorough empirical validation in bounded-time optimization, this research shows that the LNS framework outperforms state-of-the-art commercial solvers such as Gurobi by a large margin.

1.2.4 Training based on historical OPF data

The authors in [15] develop an online technique that employs ML to get viable solutions to ACOPF problems with low optimality gaps on very short time frames (e.g., milliseconds) and without the need to solve an ACOPF. As the number of renewable power production, controlled loads, and other inverter-interfaced devices on the power grid increases, faster system dynamics and more rapid variations in the power supply are expected to occur. This study uses historical data to develop a mapping between system loading and ideal generation values, allowing the user to identify near-optimal and viable ACOPF solutions on very short timelines without addressing the optimization issue.

The author in [16] leverages large amount of historical data created by network operators for solving ACOPF throughout the years of operation and utilize this data for training to solve future ACOPF problems. This research establishes a Random Forest to predict ACOPF solutions. The article uses a multi-target technique to discover approximate voltage and generation solutions to ACOPF problem, while utilizing just network loads, without knowledge of additional network characteristics or system architecture, in order to retain correlations and linkages between predicted variables. The author investigates the advantages of using the learnt solution as an smart warm start point for solving the ACOPF, and tests the suggested framework on several IEEE test networks. The results of the learning-based ACOPF solutions depend of the solver and network, but shows potential for rapidly obtaining approximate ACOPF issue solutions.

In [17], the authors present a data-driven algorithm that uses historical data, sophisticated optimization techniques, and ML approaches to develop local controls that simulate optimum behaviour without using communication in distribution systems to reduce the need for such requirement. The performance of the enhanced local control is proven on a three-phase, unbalanced, low-voltage distribution network. The findings demonstrate that the data-driven strategy outperforms conventional industry-standard local control and effectively mimics optimal-power-flow-based control.

1.2.5 DNN for the solution of OPF

Training a sensitivity-informed DNN (SI-DNN) to match not only the OPF optimizers but also their partial derivatives with regard to the OPF parameters such as load is the focus of [18]. It has been shown that the necessary Jacobian matrices do, in fact, exist under relaxed circumstances, and that they can be easily calculated from the associated primal/dual solutions. The suggested SI-DNN is compatible with a wide variety of OPF models, such as a non-convex quadratically constrained problem (QCQP) models and can be solved using techniques such as semi-definite program (SDP) relaxation. In addition, the SI-DNN may be incorporated without any problems into existing "learning-to-OPF" methods. The advanced generalisation and constraint satisfaction capabilities of the OPF solutions predicted by a SI-DNN over a conventionally trained DNN have been validated by numerical tests conducted on three benchmark power systems.

The authors in [19] provide a unique ML method for predicting ACOPF solutions using training models which are rapid and flexible. The suggested technique is a two-stage procedure that employs a spatial decomposition of the power network consisting of a collection of areas. The first step learns to forecast the flows and voltages on the buses and lines connecting the regions, while the second stage trains the ML models for each area simultaneously. The forecasts are then used to seed a power flow to reduce physical constraint breaches, leaving only small operational constraint violations. Experimental findings on the French transmission system (up to 6,700 buses) and big test cases from the pglib library (up to 9,00 buses) illustrate the viability of the proposed method. Within a brief training period, the method predicts ACOPF solutions with very high accuracy, resulting in considerable advancements above the current state of the art. Thus, the suggested method enables rapid training of ML models to adapt to changing operational circumstances.

The researchers in [20] investigate a deep learning strategy for producing extremely effective and precise estimates of the solution of ACOPF problem. Specifically, the research proposes a combination of DNN with Lagrangian duality in order to incorporate physical and operational limitations. The resultant OPF-DNN model is assessed using real-world case studies from the French transmission network, which has up to 3,400 buses and 4,500 lines. The computational findings demonstrate that OPF-DNN generates plausible ACOPF approximations with their objective function values in milliseconds within 0.01% of optimality, while representing the problem constraints.

The author in [21] presents a Quasi-Newton approach based on ML that provides iterative updates for possible optimum solutions without calculating a Jacobian or approximation Jacobian matrix, using a feedback-based DNN. The model could be transformed into a proper contraction mapping if the correct selection of weights and activation functions accommodated, hence the convergence can be ensured. The outcomes for systems with up to 1,354 buses demonstrate that the proposed approach is capable of rapidly finding approximate solutions to ACOPF.

In [22], an ML technique is used to enhance the execution time of complex power grids simulations (PGSim) while maintaining accuracy. Specifically, the authors construct Smart-PGSim, a framework that builds multitask-learning NN (MTLNN) models to forecast the starting values of variables crucial to the problem's solution. The MTLNN model utilizes data for predicting numerous dependent variables while using customizable layers to predict specific variables. They demonstrate that embedding domain-specific restrictions obtained from the individual power-grid components into the MTL model is crucial for achieving the needed precision. The Smart-PGSim framework then uses the anticipated beginning values as a high-quality initial condition for the power-grid numerical solver (warm start), resulting in improved execution time (by an average factor of 2.6) while maintaining the same accuracy comparing to the state-of-the-art solvers.

In [23], the authors introduce the OPFLearn package for Julia and Python, which employs a computationally efficient method to generate representative datasets that cover a broad range of the ACOPF feasible solution area. The load profiles are evenly sampled from the ACOPF feasible set contained in a convex set. For each identified infeasible point, the convex set is decreased using infeasibility certificates, which are derived from the attributes of a relaxed formulation. It is shown that the framework generates datasets that are more representative of the complete possible space than previous methodologies, hence enhancing the performance of ML models.

The authors in [24] provide an MTL-trained DNN-based OPF predictor. The main idea behind this method is to identify a universal initialization vector that permits rapid training for any system architecture. The designed OPF-predictor is verified by simulations using IEEE bus benchmark networks. The findings demonstrate that the MTL strategy produces considerable training speedups, taking only a few gradient steps and a small number of data samples to reach high OPF prediction accuracy, and outperforms existing pre-training strategies.

The authors in [25] compare several NN architectures for inferring ACOPF solutions in a systematic manner. By creating abstract representations of electrical grids in the graph domain for both Convolutional Neural Network (CNN) and Graph Neural Network (GNN), they illustrate the effectiveness of exploiting network structure in the provided models using Fully Connected Neural Network (FCNN). The performance of different NN architectures is finally compared for regression (predicting optimum generator set-points) and classification (predicting the active set of constraints).

A DNN-based voltage-constrained technique (DeepOPF-V) is suggested in [26] to efficiently address ACOPF. The innovative architecture of this method anticipates the voltages of all buses and reconstructs the remaining variables without solving nonlinear AC power flow equations. In addition, a rapid post-processing procedure is created to enforce the box limitations. Simulations using IEEE 118/300-bus systems and a 2000-bus test system are used to evaluate DeepOPF-V efficiency, which are delivering an execution time enhancement by a factor of four and equivalent performance in optimality gap, while maintaining the feasibility of the solution, compared to previous research.

The authors in [27] suggest a DNN-based policy, anticipating the generator dispatch choices in real time in order to deal with the uncertainties in the power system. The weights of DNN are learned via stochastic primal-dual updates, solving the Stochastic OPF without requiring the production of training labels beforehand and may explicitly account for the SOPF's feasibility limitations. On a variety of test situations, the benefits of the DNN policy over simpler policies and their effectiveness in enforcing safety restrictions and producing near-optimal solutions are proven within the framework of a chance constrained formulation.

The authors in [28] create a novel topology-aware GNN technique for predicting the best solutions of real-time ACOPF. The new GNN for OPF framework uses the localization feature of locational marginal pricing and voltage magnitude to add grid topology into the NN model. In addition, they create a physics-aware AC flow feasibility regularisation method for OPF learning in general. The suggested approaches provide decreased model complexity, more generalizability, and assurances of feasibility. By giving an analytical knowledge of the graph subspace's stability under changing grid topologies, the authors demonstrate that the suggested GNN can rapidly adapt to varying grid topologies via an effective retraining technique. The proposed GNN-based learning framework's prediction accuracy, enhanced flow feasibility, and adaptability to topology have been proven by numerical experiments conducted on a variety of test systems of differing sizes.

In [29], the authors propose a method (DeepOPF-NGT) for addressing ACOPF that does not need training datasets containing ground truth. Instead, it employs a correctly constructed loss function to guide the tuning of NN parameters in order to directly learn a single load-solution mapping. Their numerical results, on the IEEE 30-bus test system, indicate that the unsupervised DeepOPF-NGT technique may attain optimality, feasibility, and execution time efficiency equivalent to an existing supervised learning approach.

The study in [30] proposes a CNN-based regression method for determining the least amount of load curtailments of sampled states without solving OPF except during the training phase. Then, minimum load curtailments are utilised to assess power and energy indices (e.g., projected demand not provided) and probability and frequency indices. The proposed method is applied on multiple systems, including the IEEE Reliability Test Systems (The IEEE RTS and IEEE RTS-96) and Saskatchewan Power Corporation in Canada. Calculating the most prevalent composite system dependability indices is shown to be quick and accurate using the suggested method.

Using a one-dimensional CNN, the research in [31] proposes a novel approach for rapidly estimating OPF outcomes (1D-CNN). In this research, the authors constructed and trained a 1D-CNN to discover the mappings between system loads and generator outputs, and evaluated the model using the IEEE 30, 57, 118, and 300 Bus systems. Extensive testing and sensitivity analysis have proven the accuracy of the 1D-CNN for estimating OPF outcomes.

The research in [32] offers a real-time (RT) OPF strategy using deep RL (DRL) in the continuous action space. For the RTOPF, DRL technique generates an enhanced action-value function with a penalty on constraint violation and derives DNN updating rule based on deep deterministic policy gradient. The performance of the suggested RTOPF with safety limitations is shown via numerical simulations.

1.2.6 ML-based models for learning OPF solutions

In [33], a learning-augmented optimization method for solving the security-constrained optimal power flow (SCOPF) problem is devised. Specifically, a multi-input, multi-output random forest model is created to solve the magnitudes and angles of bus network voltages. Then, system equations based on physics of the network are used to estimate the current injection and complex/real power injection at various buses. To examine the efficacy of the proposed ML-assisted method, two benchmark models using the standard MATPOWER Interior Point Solver and an end-to-end ML algorithms are used. The results of the study on a 500-bus system demonstrate that the suggested ML-assisted solution greatly improves the computational efficiency compared to the MATPOWER solver, while effectively satisfying all network constraints.

The research in [34] provides a data-driven method for obtaining the solution of OPF problem based on the architecture of the stacked extreme learning machine (SELM). Compared to deep learning methods, SELM has a faster training speed and does not need the time-consuming parameter adjustment procedure. Due to the complex interaction between the system operating state and OPF solutions, straight application of SELM to OPF is not feasible, and therefore the authors design a data-driven OPF regression framework decomposing the OPF model's characteristics into three steps. This approach not only minimises the difficulty of learning, but it also helps to correct learning biases. In addition, a sample pre-classification technique, based on active constraint identification is also suggested to improve the attractiveness of feature elements. Numerical findings on IEEE and Polish benchmark systems indicate that the suggested technique outperforms other approaches. It is also shown that the suggested technique could be adapted to various test systems by modifying a few of the hyper-parameters.

The work in [35] presents a learning-enhanced technique for solving ACOPF power system equations with ML techniques to provide near-optimal solutions. Specifically, ML models are first created to anticipate the magnitudes and angles of bus voltages. Then, power system equations based on physics are used to determine the power injection at each node. The random forest, multi-target decision tree, and extreme learning machine (ELM) algorithms are investigated and compared against each other. MATPOWER Interior Point Solver is used as a benchmark for evaluating the performance of the proposed learning-augmented ACOPF solver. Case studies on 500-bus and 4918-bus test systems demonstrate that the proposed learning-augmented strategy reduces computing time by 15–100 times, based on system size, with minimum loss of optimality.

In [36], an RL-based OPF solution generator is provided. The solution process of OPF is characterised as a Markov Decision Process (MDP) with a single step and is solved using the Twin Delayed Deep Deterministic policy gradient (TD3) method. A warm-up training approach is implemented to improve NN initialization. Parallel computing is used to broaden the scope of a search and increase the efficiency of the model training. Using the IEEE-39 system, numerical tests are performed. The results demonstrate the accuracy and effectiveness of the suggested algorithm. The well-trained agent's actor (policy) network may serve as a quick generator of OPF solutions for online situations.

In [37], the authors suggest approximating a given optimum solution using GNNs (which are localised, scalable parametrizations of network data) trained under the imitation learning paradigm. While the best solution is shown to be expensive to calculate, it is only necessary for network states in the training set. During testing, GNN learns how to calculate the OPF solution effectively.

The authors in [38] investigate how ML may assist in accelerating the convergence of the Alternating Direction Method of Multipliers (ADMM) while solving ACOPF. It presents a unique technique to decentralised ML, ML-ADMM, in which each agent utilises deep learning to learn the consensus parameters on the coupling branches. In addition, the research addresses the concept of learning exclusively from ADMM runs with high-quality convergence qualities and provides filtering algorithms to pick these runs. Experimental findings on test cases based on the French system illustrate the approach's ability to greatly accelerate the convergence of ADMM.

The authors in [39] explore two kinds of techniques, end-to-end learning and learning to optimise, for solving OPF problem. The End-to-end learning method aims to provide optimization proxies which closely resemble the optimum solutions to OPF problem. In contrast, the applied learning-to-optimize strategy aims to increase the speed of current optimization algorithms for OPF problem solution.

1.2.7 ML for predicting active constraints

The authors in [40] investigate ML techniques for solving ACOPF problem, by maximizing power production in a transmission network while taking into account the physical and technical constraints. The study offers two formulations of ACOPF as an ML problem: an end-to-end prediction job in which the optimum generator settings are predicted directly, and a constraint prediction task in which the active constraints in the optimal solution are predicted. The authors verify their methods using IEEE 30 and 118 bus system.

The authors in [41] present a brief structure for generalising methodologies for ML aided OPF and evaluate the performance of numerous FCNN, CNN, and GNN models for two fundamental approaches in this domain which are regression (predicting optimal generator set-points) and classification (predicting the active set of constraints). For a number of synthetic power systems with linked utilities, the author shows that locality properties between feature and target variables are rare and could highlight the marginal value of using CNN and GNN architectures in comparison to FCNN for a given grid topology.

However, with varied topology (such as simulating transmission line contingency), GNN models are able to easily adjust for the change in topological data and beat both FCNN and CNN models.

The researchers in [42] provide a hybrid supervised regression-classification learning-based approach for predicting inactive and active inequality constraints prior to addressing ACOPF using just nodal power demand data. The suggested approach is composed of a combination of classifiers and regression-based algorithms. In lieu of mapping OPF output, resulted directly from demand, the proposed approach eliminates inactive restrictions to produce a reduced ACOPF. This reduced optimization problem can be addressed more quickly and with less computer resources than the original problem. The efficiency of the proposed technique for estimating active and inactive constraints and creating a shortened ACOPF is shown by simulation solution on many test cases.

1.3 Contributions

The current proposed ML-based methods in literature do not guarantee the convergence of their solutions under general circumstances which is an important criterion for operationalizing such methods. Since ML algorithms learn from data to provide results, regardless of their convergence status, there should be an underlying method to investigate the convergence of the solution, in order to enhance their credibility, as the system operators must know the probability of of convergence and legitimacy of the output results, acquired by DNN.

Therefore, the contributions of this thesis are as follows:

• First, a DNN algorithm is introduced to classify loads, based on yielding converging or non-converging solutions. The added classification will support the system operators to acknowledge the convergence of the current load configuration before feeding it to DNN to predict system variables such as generator voltages and active power output.

• Second, another DNN is used to predict the desired output of the OPF problem for each converging pair of active and reactive power demand. In this stage, a method is suggested to satisfy the constraints on generation and voltage limits within the OPF problem. To satisfy such constraints, a MinMax normalization method is used to normalize the voltage and generation outputs and furthermore, a Sigmoid function is used to generate normalized outputs within 0 and 1. The output will be later converted to pre-normalized values.

• Finally, the proposed DNN for OPF (DNN-OPF) method is benchmarked against optimization-based methods to solve ACOPF and DCOPF problem in order to compare its accuracy and speed.

The outcomes of this thesis is published in [43].

Chapter 2

Application of ML for OPF problem in Power System

In this section, the concept of end-to-end learning is explained to provide background on solving optimization problems using optimization, and then a background on DNN is given as it is used as primary solution methodology for solving OPF problem. Finally, a background on the formulations of the OPF problems including ACOPF and DCOPF is given to familiarize readers with the application of ML in power systems.

2.1 End to end learning for optimization problems

The field of ML has grown at a phenomenal rate, attracting a large number of researchers and practitioners. It has grown to be one of the most popular research areas, with applications in a variety of fields such as machine translation, speech recognition, image recognition, recommendation systems, and so on. In order to use ML for optimization, the ML algorithms are trained to output a solution using data. The effectiveness and efficiency of numerical optimization algorithms have a significant impact on the popularity and application of ML models in the age of massive data. In order to promote the development of ML, a number of effective optimization methods have been implemented [44].

From the standpoint of gradient information in optimization, prominent optimization techniques may be split into three categories: first-order optimization methods, which are illustrated by the commonly used stochastic gradient techniques; high-order optimization methods, which include Newton's method; and heuristic derivative-free optimization methods, which include the coordinate descent method [44].

As a representative of first-order optimization methods, the stochastic gradient descent method and its derivatives have become increasingly popular and are advancing rapidly in recent years. However, many users disregard the features and application scope of these techniques. They frequently utilise them as black box optimizer, which may restrict the effectiveness of the optimization techniques [44].

In comparison to first-order optimization techniques, high-order algorithms converge at a quicker rate, with the curvature information making the search direction more efficient. High-order optimizations garner a great deal of interest, but present greater obstacles. In high-order techniques, the operation and storage of the inverse matrix of the Hessian matrix provide a challenge. Many adaptations of Newton's approach have been devised to handle this issue, the majority of which attempt to approximate the Hessian matrix using various ways. The stochastic quasi-Newton approach and its variations are developed in following research to extend high-order methods to large-scale data [44].

Derivative-free optimization approaches are often used when the derivative of the objective function does not exist or it is difficult to be determined. There are two fundamental concepts in derivative-free optimization techniques: One does a heuristic search based on empirical principles, while the other fits samples to the objective function. In addition to being compatible with gradient-based optimization techniques, derivative-free optimization techniques may also be used in tandem with gradient-based techniques [44].

Once defined, the majority of ML problem may be addressed as optimization problems. Optimization in the disciplines of DNN, RL , meta learning, variational inference, and Markov chain Monte Carlo faces a variety of obstacles, and therefore specific ML domains have evolved distinct optimization approaches, which might serve as inspiration for the creation of universal optimization methods [44].

For example, in pattern recognition, DNN have shown significant success. There are two extremely prominent NNs, namely CNNs and Recurrent Neural Network (RNN)s, which play crucial roles in several ML domains. The CNNs are Feed Forward Neural Network (FFNN) that calculate convolution [44].

The CNN models have been used well in several domains, including image processing, video processing, and natural language processing (NLP). They are a type of sequential model that is widely used in NLP. Additionally, the RNN models are prominent in the domains of image and video processing, and in the realm of restricted optimization, the RNN models are capable of achieving outstanding outcomes. In developing such models, the parameters of weights in RNNs are learnt using analytical approaches, and these methods may locate the best solution based on the trajectory of the state solution.

In DNN models, stochastic gradient-based techniques are commonly used. When using stochastic gradient-based algorithms, however, a number of issues are appearing. In the later training stage of certain adaptive techniques, for instance, the learning rate would oscillate, which may lead to the issue of non-convergence. Consequently, further optimization strategies based on variance reduction were developed to enhance the convergence rate. In addition, integrating stochastic gradient descent with the features of its variations is a potential strategy for enhancing optimization. Particularly, moving an adaptive algorithm to the stochastic gradient descent approach may increase the algorithm's precision and convergence rate [44].

The RL method is a sub-field of ML in which an agent interacts with its environment via a trial-and-error method and discovers an optimum policy by maximising cumulative rewards. Combining RL and deep learning methods, deep reinforcement learning allows the RL agent to have an accurate view of its surroundings. Recent studies have shown that deep learning may be used to acquire a suitable representation for reinforcement learning challenges. In RL and deep RL models, stochastic optimization strategies are often used [44].

Recently, meta learning has gained popularity in the area of ML. The objective of meta-learning is to create a model that can effectively adapt to a new environment with the fewest available examples. Therefore, the lack of data, could be resolved with the use of meta-learning in supervised learning methods. In general, meta-learning approaches may be broken down into three categories: metric-based methods, model-based methods, and optimization-based methods [44].

2.2 Deep neural network

The DNN model constitutes the basis for the majority of contemporary Artificial Intelligence (AI) applications. Since the DNN models were first used in voice recognition and picture recognition applications, the number of other applications that employ DNNs has skyrocketed, including self-driving automobiles, cancer detection, and playing difficult games. In several of these fields, the DNN models can currently surpass human accuracy. The DNN exceptional performance is a result of its capacity to extract high-level features from raw sensory data using statistical learning on a large quantity of data to get an accurate representation of an input space. This differs from previous techniques that used hand-crafted features or rules created by professionals [45]. The DNN models' increased accuracy comes at the expense of tremendous computational complexity. While general-purpose compute engines, particularly graphic processing units (GPUs), have been the basis for most DNN processing, there is a growing interest in offering more specific DNN computation acceleration [45].

A DNN is a form of Artificial Neural Network (ANN) with more than one hidden layer. The number of layers depends on the complexities associated with the model. A typical DNN is depicted in 2.1, which is indicating a DNN architecture with three hidden layers.

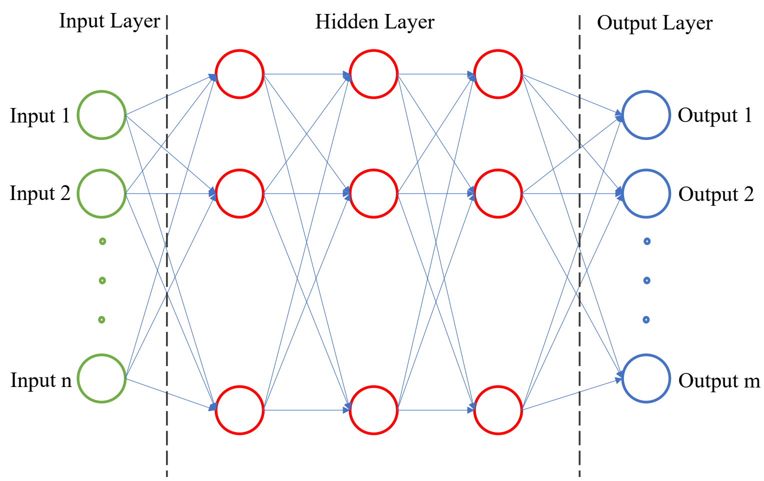


Figure 2.1: A typical DNN.

The DNN model consists of neurons and weights W on each layer l, derived from each layer's activation functions, f_l, which is resulting the predictions in the output layer, y, as shown in (2.1) for layers 1 to 3 and the output layer. Note that the output of each individual layer is calculated by the product of the weights and the values from input layers.

$$y = f_4(f_3(f_2(f_1(x.W_1).W_2).W_3).W_4). \tag{2.1}$$

Such mapping of the input to the output layer is a form of matrix multiplication which can be done much faster than traditional iterative methods. Therefore, it is apparent that DNN solution method could be utilized to facilitate several runs of complex models for sensitivity analysis in a short time.

The Universal Approximation Theorem in DNN methodology proves that DNN-based models could approximate any function to the desired accuracy after tuning the models by adjusting the number of neurons and the activation functions [46, 47]. Cybenko was the first person to successfully demonstrate a universal approximation theorem for typical DNNs. It asserts that when the width is increased to infinity, a typical neural network with a single hidden layer has the ability to estimate any continuous function with compact support and can do so with arbitrary precision. Even if his theory could only be applied to sigmoid activation functions, there are more advanced versions of this theorem that can be used to apply it to other classes of activation functions [48].

The training of the proposed method is done using backpropagation, which is the most commonly implemented method in ANN. This method stands for "backward propagation of error" and is the main algorithm of supervised learning in ANN which is based on gradient descent. This algorithm calculates the error of the gradient of loss function of an ANN in regards to ANN weight which is a general form of delta rule of perceptrons in MLP [49].

The "backward" section of the name origins from gradient backward calculation in ANN by calculating the gradient of the last weight layer in the first stage and the gradient of the first weights layer in the last level. Then, the algorithm calculates the partial gradient of the each layer and uses it to compute the weight gradient of the next layer. The backward error information flow leads to effective calculation of gradient at each weight layer [49].

The goal of this paper is to leverage this aspect of DNN to estimate the output of OPF problem by training the models using labeled datasets, achieving faster and more accurate results than DCOPF. It is important to note that the output resulted from DNN is not explainable and requires further studies to obtain optimal solutions. Therefore, another goal of this research is to improve the accuracy of the output and provide insights on the distance of the output from optimality [50].

2.3 Power system background

An overall view of the power system is shown in figure 2.2. A power system network includes generation, transmission, and distribution systems. Generation system accounts for all the traditional power plants satisfying the load. Transmission system relates to the connections of wires and cables that deliver the energy from the generators to the loads. Distribution system deals with distributing the energy in lower voltages to the loads [51].

There are different problems in the power system planning, operation, and control, some of which are shown in table 2.1. These problems require the power system operators to solve OPF to be able to determine the amount of power required to be generated by

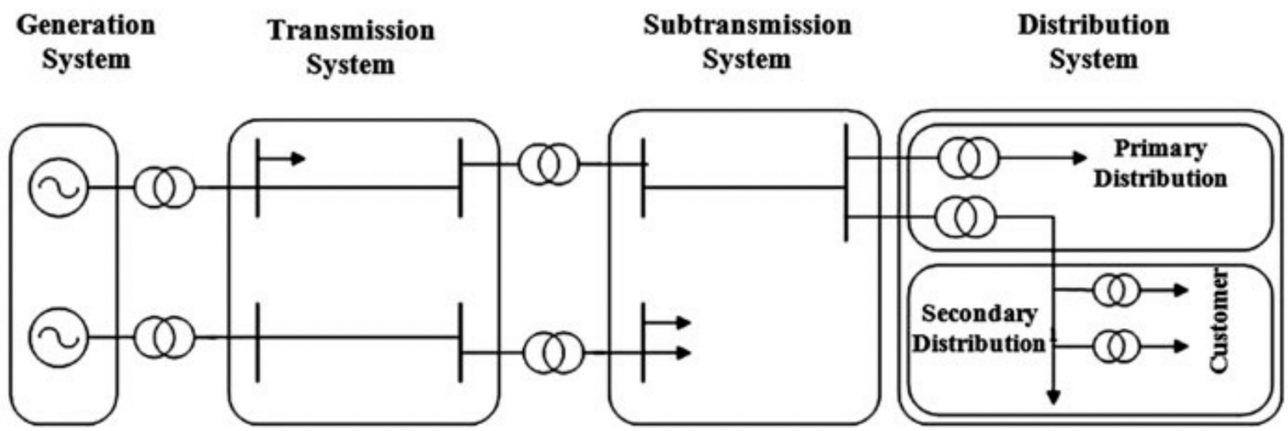


Figure 2.2: The structure of the power system. Reprinted/adapted by permission from [the Licensor]: [Springer] [Introduction and Literature Review of Power System Challenges and Issues] by [Ali Ardeshiri, Amir Lotfi, Reza Behkam, Arash Moradzadeh, and Ashkan Barzkar] [COPYRIGHT] (2021)

generators to satisfy demand. Engineers use approximations to achieve reasonable results which are not the optimal solution, leading to loss of billions of dollars each year [3].

In [51] a brief explanation of the problems and issues of power system in planning, operation, and control applications is provided. Power system planning means the act of making the decision for the developments and expansions in the power system including construction, designation, and expansion of power system devices in order to supply the electrical energy demand in near or far future. This can be done by forecasting the future demand. The decision-makers concern about decreasing the investment costs, pollution, and power outages. After power system devices and elements are constructed, these devices should be properly operated to meet the demand without violating the technical, environmental, and economical constraints. Meanwhile, in a short time prior to the power delivery to the demands, power system control will deal with maintaining the robustness and security of the power system against contingencies, outages, and other events in the system. The OPF problem is a subset of power system operation, dealing with delivering the electrical energy to the loads, considering the technical constraints and economical objective function.

Table 2.1: Different problems in the power system.

Problem name	ACOPF	DCOPF	Decoupled OPF	Security Constrained Economic Dispatch (SCED)	Power flow	Economic dispatch	Security constraint OPF
Consider voltage angle constraint?	Yes	No	Yes	Yes	No	No	Yes
Consider voltage magnitude constraint?	Yes	No	Yes	No	Yes	No	Yes
Consider transmission constraint?	Yes	Yes	Yes	Yes	No	No	Yes
Consider loss?	Yes	No	Yes	Yes	Yes	It can	Yes
Consider generator cost?	Yes	Yes	Yes	Yes	Yes	No	Yes
Consider contingency constraints?	No	No	No	Yes	Yes	No	No

2.4 Optimal power flow

Even after sixty years of efforts to improve solution methodologies, the ACOPF is still regarded as an exceptionally challenging non-convex optimization problem, and it is still not employed in the majority of market operations and planning. Although the ACOPF simultaneously manages real power demand along with voltage and reactive power management, the DCOPF problem, which is a linearized approximation of the real power injections, has been extremely helpful in calculating the locational marginal prices (LMPs) for market operations. This is due to the fact that the DCOPF is an approximation of the real power injections. These clearing prices are thus derived from the shadow price of the actual power balancing constraint, and they are modified according to whether or not the revenues are sufficient to pay the bid expenses. This method of optimization ignores voltage and reactive power management on a basic level, and this is true even after losses have been taken into account in the DCOPF problem. Using the ACOPF model, the value that is contributed may be quantified to a greater extent when smarter grid controls and technologies are gradually included into the power system. As a result, the ACOPF problem has the potential to promote more efficient use of resources, as well as to encourage price-based competition and the maximum of welfare across a wide range of market activities [52].

In more than fifty years that have been spent on researching and testing various formulations, approximation techniques, algorithmic methodologies, and other modelling components of the ACOPF, a lack of rigorous experimental design for assessing rival approaches has persisted. Studies on ACOPF that have been published up to this point typically provide a solution strategy and claim that the suggested approach is either quicker or converges more robustly compared to alternatives. These assertions are made on the basis of a small number of tests and a small number of reports of the findings. However, theoretical findings are rarely adequate proxies for the actual performance of an algorithm since such broad principles often fail to explain the events that occur in the real world [52].

2.4.1 AC optimal power flow

The ACOPF problem is used in power system studies to obtain generator voltages and active power output considering the limits of the system. It is formulated as a non-linear optimization problem which is categorised as NP-hard problem. A formulation of ACOPF is shown in (2.2)-(2.8). The objective function (2.2) of the ACOPF problem is to minimize the total cost of generation subject to constraints shown in (2.3)-(2.8). The overall power system generation cost is $c(\mathcal{P}^{\mathcal{G}})$ in which is the sum of the generation cost at each bus n and $\mathcal{P}^{\mathcal{G}}$ is the vector of generators' active output power. The active and reactive power balance at each bus is shown in (2.3) and (2.4) which p_n^D, p_n^G, q_n^D, q_n^G v_n, $G_{i,n}$, $B_{i,n}$, and $\Theta_{i,n}$ are the active demand, active generation, reactive demand, reactive generation, and the voltage at bus n, conductance, susceptance, and the angle difference between bus i and n. Moreover, the line current limit constraint is shown in (2.5), where $I_{i,n}^l$ is the current limit of line i to n. The active power limits at each bus are depicted in (2.6) where $\underline{p}_n^G$ and $\overline{p}_n^G$ are the minimum and maximum limits of active power generation at bus n. The limits of reactive power at each bus are demonstrated in (2.7) where $\underline{q}_n^G$, $\overline{q}_n^G$, and q_n^G are the minimum limit, maximum limit, and actual value of reactive power generation at bus n, respectively. The equation in (2.8) indicates the limits of voltages at each bus in which $\underline{v}_n^G$, $\overline{v}_n^G$, and v_n^G are the minimum limit, maximum limit, and actual value of voltage at bus n, respectively. Lastly, (2.9) shows the limits of voltage angle at each line in which $\underline{\Theta}_{i,n}^{G}$ and $\overline{\Theta}_{i,n}^{G}$ are the minimum and maximum limit of the voltage angle difference of the transmission line connecting i to n.

$$c(\mathcal{P}^{\mathcal{G}}) = \sum_{n=1}^{N} c_n(p_n^G). \tag{2.2}$$

$$\text{s.t.:} \sum_{n=1}^{N} V_i V_n (G_{i,n} cos\Theta_{i,n} + B_{i,n} sin\Theta_{i,n}) = p_n^D - p_n^G. \tag{2.3}$$

$$\sum_{i=1}^{N} V_i V_n (G_{i,n} sin\Theta_{i,n} - B_{i,n} cos\Theta_{i,n}) = q_n^D - q_n^G. \tag{2.4}$$

$$(V_i G_{i,n} cos\Theta_{i,n} - V_i B_{i,n} sin\Theta_{i,n})^2 + (V_i B_{i,n} cos\Theta_{i,n} + V_i G_{i,n} sin\Theta_{i,n})^2 \leq (I_{i,n}^l)^2 \tag{2.5}$$

$$\underline{p}_n^G \leq p_n^G \leq \overline{p}_n^G. \tag{2.6}$$

$$\underline{q}_n^G \leq q_n^G \leq \overline{q}_n^G. \tag{2.7}$$

$$\underline{V}_n^G \leq V_n^G \leq \overline{V}_n^G. \tag{2.8}$$

$$\underline{\Theta}_{i,n}^G \leq \Theta_{i,n}^G \leq \overline{\Theta}_{i,n}^G. \tag{2.9}$$

2.4.2 DC optimal power flow

Due to the difficulties in solving ACOPF, the DCOPF solution methodology was introduced as a linearized model of ACOPF problem to simplify the network by assuming the voltage magnitudes as unity and neglecting resistance in transmission lines. Therefore, the DCOPF problem does not consider line losses in calculations. Even though DCOPF is faster than ACOPF, neglecting some of the network features leads to approximated solutions with lower accuracy. Due to the remaining concerns with current approximation solution methodologies for solving OPF, there is still a need to provide faster, more flexible, and more accurate solution [3]. As a result of the underlying assumptions, the linearized DCOPF is formulated as shown in (2.10)-(2.14) which are the objective function, active power balance, transmission lines current limits, and active power limits, respectively.

$$c(\mathcal{P}^{\mathcal{G}}) = \sum_{n=1}^{N} c_n(p_n^G). \tag{2.10}$$

$$\text{subject to: } \sum_{i=1}^{N} B_{i,n}\Theta_{i,n} = p_n^D - p_n^G. \tag{2.11}$$

$$B_{i,n}\Theta_{i,n} \leq I_{i,n}^l. \tag{2.12}$$

$$\underline{p_n^G} \leq p_n^G \leq \overline{p_n^G}. \tag{2.13}$$

$$\underline{\Theta}_{i,n}^G \leq \Theta_{i,n}^G \leq \overline{\Theta}_{i,n}^G. \tag{2.14}$$

Chapter 3

Methodology and numerical results

In order to achieve the goals of this research, outlined in chapter 1, two fully connected neural networks are trained by datasets, constructed from executing ACOPF simulations. The suggested approach benefits from two pre-processing and post-processing steps in order to achieve better results and guarantee the convergence of solutions. As shown in Fig 3.1, $\mathcal{P}^L$ and $\mathcal{Q}^L$ are fed into a convergence classifier and if the results are determined to be converging, they are fed into a prediction algorithm to produce $\mathcal{V}^G$ and $\mathcal{P}^G$. In the post processing approach, the resulted values are studied for convergence in power flow equations.

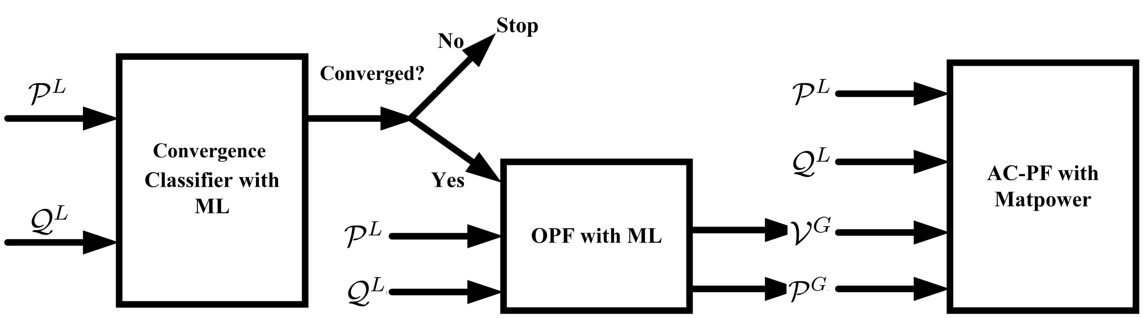


Figure 3.1: Proposed novel method for OPF with DNN.

In the following sub-sections, the pre-processing, the implemented DNNs, and post-processing steps are explained.

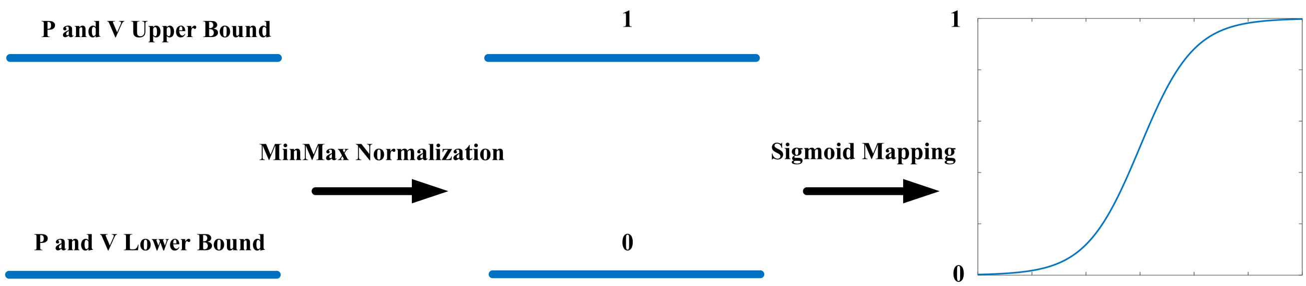


Figure 3.2: Pre-processing using Sigmoid function.

3.1 Pre-processing

After generating the data from ACOPF simulations, pre-processing is required to convert the data to the desired format, to increase the accuracy of the results obtained from DNN. As the implemented data in this paper are simulated using traditional optimization models, it is assumed that the collected data are exact solutions.

In order to restrict the voltage and generated power remain within the required limits, a MinMax normalization method is utilized to scale the voltage and output power values between 0 and 1. The details of the pre-processing method are displayed in Fig 3.2. As shown in (3.1) and (3.2), V_n^g, $\overline{V}_n^g$, $\underline{V}_n^g$, $\hat{V_n^g}$ are the actual voltage , maximum voltage limit , minimum voltage limit , and the normalized voltage of generator at bus n. Also, p_n^g, $\overline{p}_n^g$, $\underline{p}_n^g$, $\hat{p_n^g}$ are the actual output power , maximum output power limit , minimum output power limit , and the normalized output power of generator n.

$$\hat{V_n^g} = \frac{V_n^g - \underline{V}_n^g}{\overline{V}_n^g - \underline{V}_n^g}. \tag{3.1}$$

$$\hat{p_n^g} = \frac{p_n^g - \underline{p}_n^g}{\overline{p}_n^g - \underline{p}_n^g}. \tag{3.2}$$

3.2 Implementation of DNN model

The implemented DNN models for both classification and prediction of OPF solutions, as shown in Fig 3.3 and Fig 3.4, have an input layer, three hidden layers, and an output layer.

The input layer in the provided DNN contains active and reactive loads, $\mathcal{P}^L$ and $\mathcal{Q}^L$, and the output vector contains voltage and active power generation, $\mathcal{V}^G$ and $\mathcal{P}^G$. The simulated dataset is split into three sets: training, validation, and testing. The training dataset is implemented to train DNN by calculating the weight of each neuron using back-propagation, while minimizing the loss function. Assuming the number of buses and generators to be N and G, respectively, meaning that the input layer has $2N$ nodes, indicating active and reactive loads at each bus. After manual tuning, using trial and error, it is found that three hidden layers can the most accurate results. The size and activation functions of the implemented DNN algorithm is depicted in Table 3.1, in which characteristics of the two models, OPF convergence and OPF solution prediction are shown. The reason to select three hidden layers is that increasing the number of layers leads to a more complex NN, causing network training to be time-consuming and overfitting. On the other hand, using less number of layers will lead to underfitting and high training error. After trying two, three, and four hidden layers, the network with three hidden layers shows the best accuracy as well as reasonable training time. This architecture is also confirmed in [15] and [21].

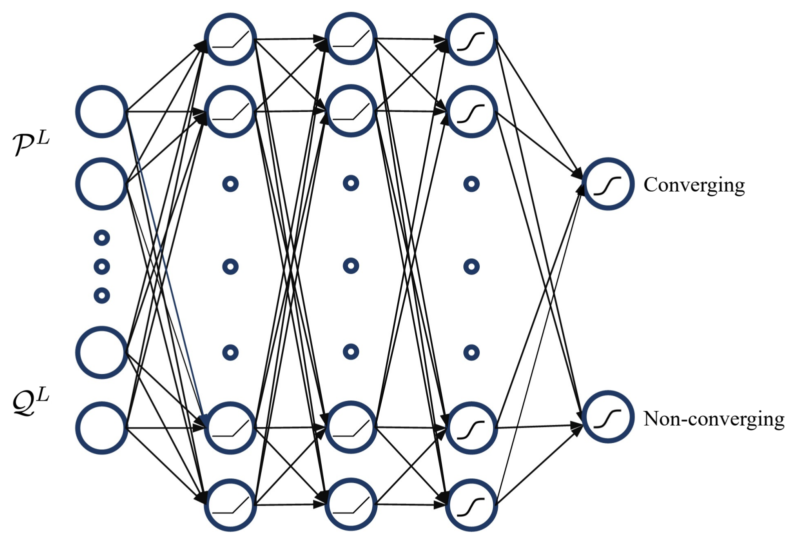


Figure 3.3: DNN implemented for OPF convergence classifier.

In this research, Adam optimizer, which is a modified version of the gradient descent algorithm has been used as the main optimizer for backpropogation of weights. It is used to adjust the weights of the network using the training data. While gradient descent holds a single learning rate which is determined before the start of the algorithm and does

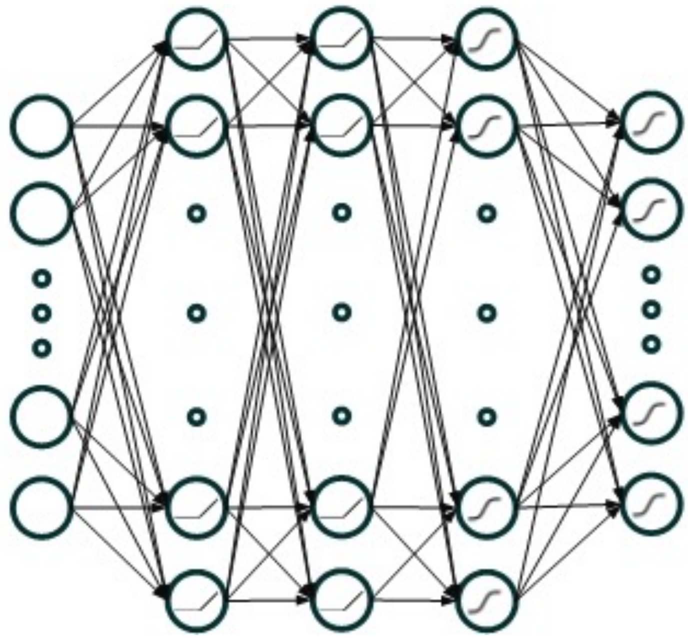


Figure 3.4: DNN implemented for OPF solution prediction.

not change during the iteration, Adam optimizer leverages the advantagous of Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp), meaning that Adam optimizer uses the average of the first and second moments of the gradients to avoid being trapped in a local minimum and to get faster results.

The MAE (Mean Absolute Error) criterion is implemented as the loss function in this thesis which is depicted in (3.3), where m, M, X_m, $\widehat{X}_m$ are output neuron index, number of output neurons, predicted output neuron, and actual output neuron, respectively.

$$MAE = \frac{\sum_{m=1} |X_m - \widehat{X}_m|}{M}. \tag{3.3}$$

3.3 Post-processing

After training the described DNN model, a post-processing approach is implemented to check for the violations of the network constraints. In this step, the optimal voltage and output power values from DNN are fed into Power Flow equations using PF function in

Table 3.1: Size and activation function of DNN for each model.

	OPF Convergence	**OPF Solution Prediction**
Input Layer	2N nodes	2N nodes
1st hidden layer	6N nodes, Relu	6N nodes, Relu
2nd hidden layer	6N nodes, Relu	6N nodes, Relu
3rd hidden layer	4 nodes, Sigmoid	$2(G)$, Sigmoid
Output layer	2 node, Sigmoid	G nodes, Sigmoid

MATPOWER to investigate whether the obtained values are converging for OPF problem. This extra steps reassures the system operators that the obtained output is converging for the power system.

3.4 Advantages of DNN-OPF

Power system operators use DCOPF approximation as the solution to OPF problems, as it converges faster than ACOPF formulation. Since the power system operators need to have an estimate of the solution of the OPF problem in a short time, solving OPF problem using DNN-OPF method could provide more accurate solutions in a very short time.

The solution of DNN-OPF considers the line losses, voltages, and generators' reactive power, which are missing in the DCOPF formulations. The fast and accurate solutions obtained from DNN-OPF could also support uncertainty analysis studies, such as scenario based uncertainty planning. Since this method allows the decision makers to consider the possible outcomes and their occurring probability, including the extreme conditions, the system operators can modify an uncertain parameter numerous times to study the system results for both planning and operational applications [53, 54].

3.5 Case studies

The data required for the suggested method is generated using MATPOWER which is a Matlab-based open source program used to run PF and OPF, utilized by power system researchers to implement power system planning and operation. The first system is IEEE 24 reliability bus system which was introduced by IEEE reliability subcommittee in 1979 as a base widely-used system for reliability assessment.

Algorithm 1 Matpower flag data generation

while Converging-count $\leq$ 2500 **do**
  Generate random load configurations.
  Run OPF for load configuration $\pi_{s_{iteration}}$
  if flag=1 **then**
    Converging-count+=1
  end if
end while
while Non-converging-count $\leq$ 2500 **do**
  Generate random load configurations.
  Run OPF for load configuration $\pi_{s_{iteration}}$
  if flag=0 **then**
    Non-converging-count+=1
  end if
end while

The IEEE 24-bus reliability test system was developed by the IEEE reliability subcommittee and published in 1979 as a benchmark for testing various reliability analysis methods. The three reliability test systems are IEEE one-area, IEEE two-area, and IEEE three-area.

Three test systems, namely, IEEE-24 (fig. 3.5), IEEE-300 (fig. 3.6), and PEGASE 1354 bus are used as case studies to collect data.

In order to create different scenarios for each case, the base parameters are implemented, then a random uniform value, between 0 and 1.4 is chosen for each load to be multiplied by the load. For example, the active and reactive load of bus 3 in 1354 bus case is 151 MW and 48.8 MVA. Then, a random value, e.g. 0.6 is generated to create a different load value at bus 3 for a new scenario leading to 90.6 MW and 29.28 MVA. In each scenario, a different random value is generated for each bus to create various set of loads. Note that the power factor of each load in each scenario is the same as the base case.

Since the suggested approach needs two datasets and for convergence classifier and another one for predicting network parameters. In order to generate data for the convergence classifier, after generating the subset of loads, the convergence of ACOPF for each scenario is checked using MATPOWER, through which 2500 converging and 2500 non-converging scenarios are generated for IEEE 24 and 300 bus system (overall 5000 scenarios). Then, this dataset is labeled as 0 for non-converging and 1 for converging scenarios. This dataset will be used for training DNN to detect converging and non-converging cases.

The second dataset is used to predict the results of OPF using DNN approach. To generate data, the same approach as explained for the first dataset is implemented, while only the converging scenarios are considered. For the converging scenarios, the voltage and output active power of the generators are collected as the output of ACOPF. Also, DCOPF results of the same scenarios are collected to compare with the output of DNN. Two set of 5000 and 50000 converging data are generated to be used in the proposed DNN method.

Algorithm 2 Matpower converging data OPF results generation

while Converging-count $\leq$ 50000 **do**
    Generate random load configurations.
    Run OPF for load configuration $\pi_{s_{iteration}}$
    if flag=1 **then**
        Save the load configuration and the generators' voltage and output power
    end if
end while

3.6 Numerical results

3.6.1 Case studies and model description

Three case studies (IEEE 24 bus, IEEE 300 bus, and PEGASE 1354 bus system) are implemented in this paper to study the performance and accuracy of the proposed DNN-OPF. The number of buses, number of generators, and average loads in MW are shown in Table 3.2. The parameters of the DNN-OPF for each network are shown in 3.3.

Table 3.2: Number of buses and generators and the average loads of each case study.

Case study	No. of buses	No. of Gen	Ave loads (MW)
IEEE 24 bus	24	33	1,995
IEEE 300 bus	300	69	16,467
PEGASE 1354 bus	1354	260	51,141

3.6.2 Generators' cost function

The cost function of each generator, $c_n(p_n^g)$,is a quadratic function, shown in (3.4), in which generation cost at each bus $c_n(p_n^g)$ is a quadratic function of p_n^g where c_1, c_2, and c_3 are the coefficients of the generator cost function and p_n^g is active power output of generator n.

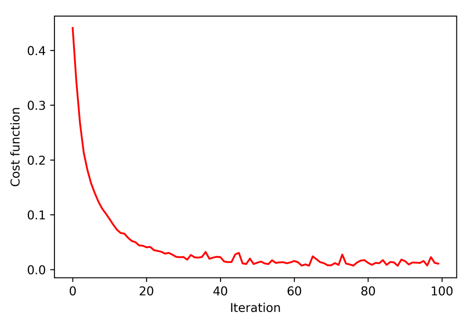
$$c_n(p_n^g) = c_{1n} + c_{2n} \times p_n^g + c_{3n} \times p_n^{g2}. \tag{3.4}$$

Table 3.3: Number of buses and generators and the average loads of each case study.

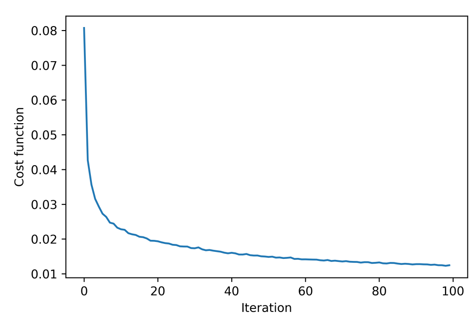
Case study	Batch size	epoch	Optimizer	Loss function
IEEE 24 bus	20	100	Adam	MAE
IEEE 300 bus	20	100	Adam	MAE
PEGASE 1354 bus	20	100	Adam	MAE

3.6.3 Training error

The training error of IEEE 24 bus, IEEE 300 bus, and PEGASE 1354 bus system are depicted in 3.7, 3.8, and 3.9, respectively. The x axis depicts the number of iterations (epochs) which is set to 100 and the y axis shows the training error. As shown in the figures, the training error reduces as the number of iterations increase.

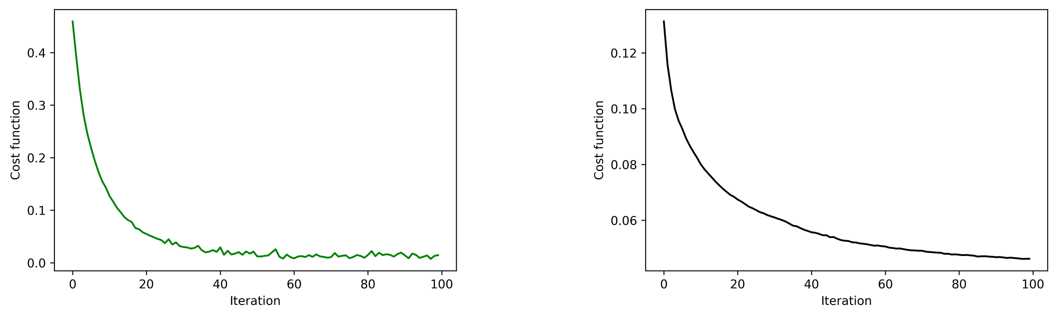


(a) Training cost of convergence checker



(b) Training cost of P and V predictor

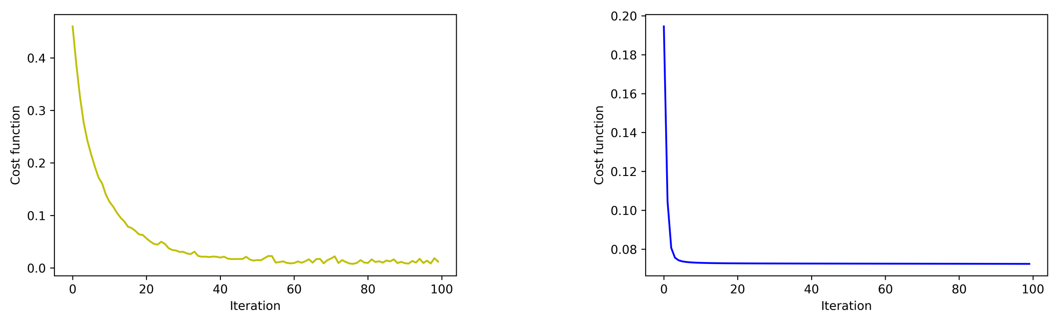
Figure 3.7: Training cost of convergence checker (a) and voltage and power predictor (b) of IEEE 24 bus system



(a) Training cost of convergence checker

(b) Training cost of P and V predictor

Figure 3.8: Training cost of convergence checker (a) and voltage and power predictor (b) of IEEE 300 bus system



(a) Training cost of convergence checker

(b) Training cost of P and V predictor

Figure 3.9: Training cost of convergence checker (a) and voltage and power predictor (b) of PEGASE 1354 bus system

3.6.4 Convergence Classifier

This algorithm allows the user to predict whether the current load combination will lead to a converging or non-converging solution. The accuracy of the convergence classifier is denoted as the ratio of correctly classified test cases relative to all cases. Table 3.4 shows the accuracy of classification method on of IEEE 24 and 300 bus systems. It can be seen that the accuracy for IEEE 24 bus, IEEE 300 bus system, and PEGASE 1354 is 98.8%, 94.0%, and 89.4% respectively.

Table 3.5: Voltage and active power error of the proposed DNN-OPF.

Case study	V (MAPE % correction)	P (MAE correction)
IEEE 24 bus	95%	87%
IEEE 300 bus	80%	21%
PEGASE 1354 bus	81%	82%

Table 3.4: Accuracy of convergence check algorithm.

Case study	Accuracy %
IEEE 24 bus	98.8
IEEE 300 bus	94.0
PEGASE 1354 bus	89.4

3.6.5 Prediction Error and Distance to Optimality

Five type of measurements errors considered in this paper to compare the solutions of DNN-OPF to ACOPF, which is MAE (3.5) and (3.6) that is implemented for voltage and power error as:

$$V_{MAE} = \frac{\sum_{g=1}^{G} |V_i - \widehat{V}_i|}{G}. \tag{3.5}$$

$$P_{MAE} = \frac{\sum_{g=1}^{G} |p_g - \widehat{p}_g|}{G}. \tag{3.6}$$

where V_g, $\widehat{V}_g$, P_g, $\widehat{P}_g$, and G are the voltages and powers obtained from DNN-OPF and ACOPF at bus g and the number of generators, respectively.

The second error estimator is MAPE (Mean Absolute Percentage Error) shown in (3.7) which is implemented to calculate the voltage only.

$$V_{MAPE} = \frac{1}{G} \sum_{g=1}^{G} |\frac{V_g - \widehat{V}_g}{\widehat{V}_g}| \times 100. \tag{3.7}$$

The main reason for choosing MAPE for voltage is that the voltage value is between 0.95 and 1.05. The difference of the predicted value and real value can be divided by the real value, but this is not the case for the output power, as the output power can be zero in some cases, leading to the denominator to be zero. Instead, RAE is used for active power error measurement.

In order to depict the active power error, another error metric called Relative Absolute Error (RAE) (3.8) is introduced as follows:

$$P_{RAE} = \frac{\sum_{g=1}^{G} |p_g - \widehat{p}_g|}{\sum_{g=1}^{G} |\widehat{p}_g|} \times 100. \tag{3.8}$$

The cost function error is defined as the total deviation of the objective function values from the one in ACOPF, as shown in (3.9):

$$C_E = \frac{|\sum_{g=1}^{G} c_g - \widehat{c}^g|}{\sum_{g=1}^{G} |\widehat{c}^g|} \times 100. \tag{3.9}$$

3.6.6 Comparison of DCOPF and ACOPF results

As depicted in Table 3.6, the error of DCOPF solver is calculated for voltage, output power, and generation cost for different case studies. The voltage error using MAPE index is 2.864% and 2.745% for IEEE 24 and 300 bus system, respectively. The error is relatively large as DCOPF assumes that the voltages are set to 1 p.u. in all buses, while it can be any value between 0.95 and 1.05 p.u. The active power generation error, resulted from DCOPF formulation error in MAE are 1.958, 28.85, 100.625 MW for IEEE 24, IEEE 300, and PEGASE 1354 bus system, respectively. As shown, MAE error of larger networks are significantly larger than smaller networks. The RAE errors of the active power are 0.09499, 0.12228, and 0.19560% for IEEE24, IEEE 300, and PEGASE 1354 network, respectively, which can provide a better comparison point, as it is independent of the size of the system. As the size of the network grows, RAE error tend to increase in general. Finally, the cost error of DCOPF are 1.4515, 2.1637, and 1.468% for 24, 300, and 1354 bus system.

Table 3.6: Voltage and active power error of DCOPF.

Case study	V (MAPE %)	V(MAE p.u.)	P(RAE%)	P (MAE MW)	C (%)
IEEE 24 bus	2.864	0.02949	0.09499	1.958	1.4515
IEEE 300 bus	2.745	0.02818	0.12228	28.85	2.1637
PEGASE 1354 bus	2.404	0.02461	0.19560	100.625	1.468

3.6.7 Comparison of DNN-OPF and ACOPF results

Table 3.7 indicates the errors obtained from the solution of DNN-OPF compared to ACOPF. MAPE voltage error for IEEE 24, IEEE 300, and PEGASE 1354 bus networks are 0.147, 0.552, and 0.501%, respectively, while MAE error of voltage are 0.00148, 0.00557, and 0.00529 (p.u.). MAE errors of active power are 0.251, 22.762, and 17.697 MW for IEEE 24, IEEE 300, and PEGASE 1354, respectively. RAE error of active power are 0.01365, 0.13513, and 0.03462 for 24, 300, and 1354 bus system, respectively. The cost errors are 0.186, 7.241, and 0.08994% are for 24, 300, and 1354 bus system, respectively.

Comparing the errors of DCOPF and DNN with respect to ACOPF results, demonstrate that DNN leads to more accurate results than DCOPF. For voltage estimation, DNN-OPF method reduces MAPE error by 95%, 80%, and 81% comparing to DCOPF IEEE 24, IEEE 300, and PEGASE 1354, respectively. For active power prediction, DNN has less error in MAE measurement as the error correction in IEEE 24, IEEE 300, and PEGASE 1354 bus system are 87%, 21%, and 82%, respectively, as shown in Table. 3.5.

Table 3.7: Voltage and active power error of the proposed DNN-OPF.

Case study	V (MAPE %)	V(MAE p.u.)	P(RAE%)	P (MAE MW)	C (%)
IEEE 24 bus	0.147	0.00148	0.01365	0.251	0.186
IEEE 300 bus	0.552	0.00557	0.13513	22.422	7.241
PEGASE 1354 bus	0.501	0.00529	0.03462	17.697	0.08994

3.6.8 Time Comparison

The time needed to reach ACOPF solution using the proposed model and Matpower ACOPF solver for a a test case is denoted by τ_{NN} and τ_{AC}, respectively. To compare the computational run-time of two models, a Ratio Factor (RF) is defined as follows:

$$RF = \frac{\tau_{AC}}{\tau_{NN}} \tag{3.10}$$

Table 3.8 shows the run-time of DNN-OPF solution and Matpower ACOPF solver for different case studies. As shown, the obtained ACOPF results are faster than Newton-Raphson method. IEEE 24 bus, IEEE 300 bus, and PEGASE 1354 bus systems have RF of 1.74, 2.77, and 23.08, respectively. RF grows larger as the number of buses in

Table 3.8: Run-time of DNN and Matpower ACOPF for different case studies.

Case study	Run-time(s) 1 scenario			Run-time(s) 100 scenarios		
	DNN	Matpower	RF	DNN	Matpower	RF
IEEE 24 bus	0.085	0.148	1.74	0.0882	14.8	167.8
IEEE 300 bus	0.099	0.275	2.77	0.141	27.5	195.0
PEGASE 1354 bus	0.124	2.863	23.08	0.850	286.3	336.8

Case study	Run-time(s) 10000 scenarios		
	DNN	Matpower	RF
IEEE 24 bus	1.779	1480	831.9
IEEE 300 bus	4.484	2750	613.3
PEGASE 1354 bus	65.556	28630	436.7

the network grows, which makes the proposed model very effective in complex and more realistic networks.

In order to depict the performance of DNN-OPF for simulation In table 3.8, the run-time of different case studies is depicted for 1, 100, and 10000 scenarios. It is shown in table 3.8 that RF increases as the number of scenarios grow. RF for 10000 scenarios are 831.9, 613.3, and 436.7 for IEEE 24 bus, IEEE 300 bus, and PEGASE 1354, respectively. It is worth mentioning that the scenarios are all converging ACOPF datapoints which are fed to the second DNN.

Table 3.9: Run-time of DNN and Matpower DCOPF for different case studies.

Case study	Run-time(s) 1 scenario			Run-time(s) 100 scenarios		
	DNN	Matpower	RF	DNN	Matpower	RF
IEEE 24 bus	0.085	0.109	1.28	0.0882	10.9	123.6
IEEE 300 bus	0.099	0.142	1.43	0.141	14.2	100.7
PEGASE 1354 bus	0.124	1.346	10.85	0.850	134.4	158.1

Case study	Run-time(s) 10000 scenarios		
	DNN	Matpower	RF
IEEE 24 bus	1.779	1090	612.7
IEEE 300 bus	4.484	1420	316.6
PEGASE 1354 bus	65.556	13440	205.0

The run-time comparison of DNN-OPF against DCOPF for 1, 100, and 10000 converging scenarios is shown in table 3.9. It is also shown that RF ratio rises as the number and complexity of the network grows. RF for 1, 100, and 10000 scenarios for IEEE 24 bus system are 1.28, 123.6, and 612.7, respectively. However, RF for PEGASE 1354 bus system are 10.85, 158.1, and 205.0, respectively. These numbers show that DNN-OPF noticeably performs faster compared to ACOPF and DCOPF.

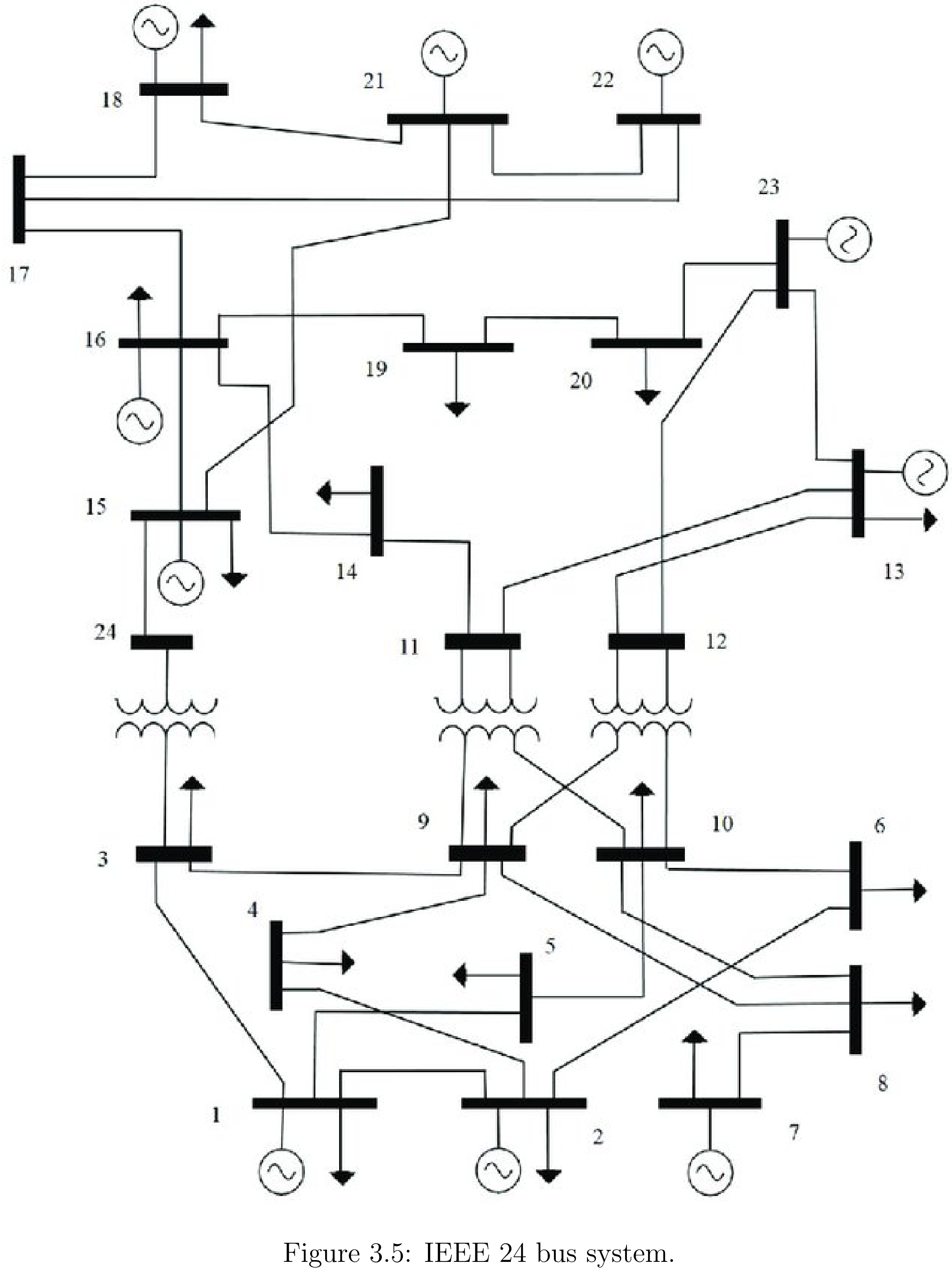


Figure 3.5: IEEE 24 bus system.

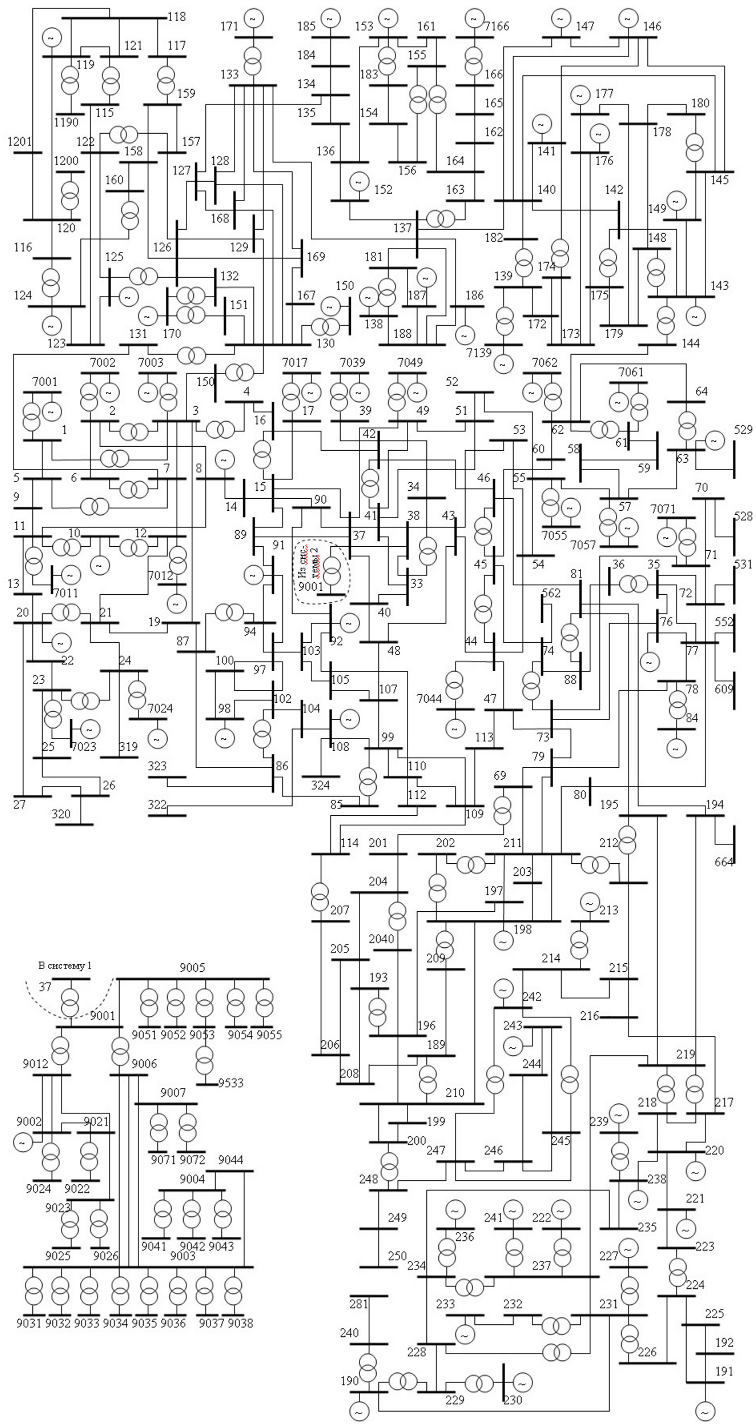


Figure 3.6: IEEE 300 bus system.

Chapter 4

Conclusion and future work

Since DCOPF approximation converges more quickly than the ACOPF formulation, power system operators choose to adopt it as the solution to issues involving OPF. Because the operators of the power system want an estimate of the answer to OPF issue in a short amount of time, OPF problem may be solved using the DNN-OPF approach, which has the potential to deliver more accurate solutions in a very short amount of time.

In this research, a novel ML-based DNN algorithm was introduced to estimate the solution of ACOPF with high accuracy and fast execution time. Two DNN models were described in which one was used to classify the converging and non-converging results and another one was to predict the solution of ACOPF for converging cases. The results of the proposed method provide faster execution time and high accuracy. Therefore, the proposed model was shown to be a perfect method replacement for widely-used DCOPF. Moreover, it was shown that the accuracy of DNN-OPF was very close to the solution of direct ACOPF method.

The solution provided by DNN-OPF takes into account line losses, voltages, and the reactive power generated by generators. These factors are not taken into account by DCOPF formulas.

The quick and precise answers that could be generated by DNN-OPF have the potential to additionally benefit studies that are concerned with uncertainty analysis, such as scenario-based uncertainty planning. System operators are able to modify an uncertain parameter numerous times in order to study the system's results for both planning and operational applications because this method enables decision makers to consider the possible outcomes and their occurring probabilities, including extreme conditions.

This work is planned to be expanded by deploying methods to guarantee the optimality of the solutions. Also, other feedback methods will be incorporated to reduce the size of the training set while producing robust solutions. Moreover, DNN can be used to run OPF in extreme situations, when a certain power system element is out due to maintenance or fault.

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