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BAHCESEHIR UNIVERSITY

GRADUATE SCHOOL

ELECTRICAL AND ELECTRONICS ENGINEERING HEAD OF THE DEPARTMENT

OPTIMAL POWER FLOW SOLUTION USING FULLY CONNECTED NEURAL NETWORKS WITH DISCRETE WAVELET TRANSFORM

MASTER'S THESIS

RESUL ÇALIŞKAN

ISTANBUL 2024

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THESIS ADVISOR

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ABSTRACT

OPTIMAL POWER FLOW SOLUTION USING FULLY CONNECTED NEURAL NETWORKS WITH DISCRETE WAVELET TRANSFORM

Resul Çalışkan
Master's Program in Electrical and Electronics Engineering

Supervisor: Assist. Prof. Dr. Gürkan Soykan

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The Optimal Power Flow (OPF) is one of the most valuable tools for operational and planning strategies in power systems. Traditional methods for solving OPF have faced problems such as complexity and computational difficulties in large-scale systems. This thesis proposes a Fully Connected Neural Network (FCNN) supported by the discrete wavelet transform to handle the problems. By using discrete wavelet processing, FCNN provides better solutions for non-stationary data and extracts features in both temporal and frequency details. These features can enhance the parameter prediction capability of the FCNN for optimal power distributions. The proposed models are compared with conventional FCNN method to demonstrate a considerable improvement in predictive accuracy as well as computational efficiency. The performance tests were conducted for the IEEE-24 bus system, IEEE-57 bus system, and IEEE-118 bus system cases. The performance was evaluated based on mean squared error analysis related to generator outputs and bus voltages. The discrete wavelet processing technique positively affects the performance of FCNN.

Keywords: AC Optimal Power Flow, Neural Networks, Discrete Wavelet Transform

ÖZ

AYRIK DALGACIK DÖNÜŞÜMÜ İLE TAM BAĞLI SİNİR AĞLARI KULLANARAK OPTİMUM GÜÇ AKIŞI ÇÖZÜMÜ

Resul Çalışkan
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Optimal Güç Akışı (OPF), güç sistemlerinde operasyonel ve planlama stratejileri için en değerli araçlardan biridir. OPF'yi çözmek için kullanılan geleneksel yöntemler, büyük ölçekli sistemlerde karmaşıklık ve hesaplama zorlukları gibi sorunlarla karşılaşmıştır. Bu tez, problemlerin üstesinden gelmek için ayrık dalgacık dönüşümü ile desteklenen bir Tam Bağlantılı Sinir Ağı (FCNN) önermektedir. FCNN, ayrık dalgacık işleme yöntemini kullanarak durağan olmayan veriler için daha iyi çözümler sunmakta ve hem zamansal hem de frekans detaylarında özellikler çıkarmaktadır. Bu özellikler, optimum güç dağılımları için FCNN'nin parametre tahmin kabiliyetini artırabilir. Önerilen modeller, tahmin doğruluğunda ve hesaplama verimliliğinde önemli bir gelişme göstermek için geleneksel FCNN yöntemiyle karşılaştırılmıştır. Performans testleri IEEE-24 bara sistemi, IEEE-57 bara sistemi ve IEEE-118 bara sistemi durumları için gerçekleştirilmiştir. Performans, jeneratör çıkışları ve bara gerilimleri ile ilgili ortalama karesel hata analizine dayalı olarak değerlendirilmiştir. Ayrık dalgacık dönüşüm tekniği FCNN'nin performansını olumlu yönde etkilemektedir.

Anahtar Kelimeler: AC Optimal Güç Akışı, Sinir Ağları, Ayrık Dalgacık Dönüşümü,

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OPF	Optimal Power Flow
FCNN	Fully Connected Neural Network
WPT	Wavelet Packet Transform
WOA	Whale Optimization Algorithm
WOA-WM	Whale Optimization Algorithm with Wavelet Mutation
MDL	Minimum Description Length
DFT	Discrete Fourier Transform
MSE	Mean Squared Error
ACOPF	Alternating Current Optimal Power Flow
SC-DCOPF	Security-Constrained Direct Current Optimal Power Flow
ML	Machine Learning
DER	Distributed Energy Resources
IPM	Interior Point Method
ALADIN	Augmented Lagrangian Alternating Direction Inexact Newton
ADMM	Alternating Direction Method of Multipliers
SQP	Sequential Quadratic Programming
SLP	Sequential Linear Programming
GNN	Graph Neural Network
MLOPF.jl	Machine Learning Optimal Power Flow Julia package
JuMP.jl	Julia for Mathematical Programming
PG-Lib-OPF	Power Grid Library for Optimal Power Flow
IEEE	Institute of Electrical and Electronics Engineers
ReLU	Rectified Linear Unit
RGA	Real-Coded Genetic Algorithm
NR	Newton-Raphson

Chapter 1

Introduction

In today's world, where the demand for energy is increasingly growing and the efficient use of resources is emphasized, the electricity produced by thermal, hydroelectric, natural gas, and renewable energy power plants, being delivered to consumers with minimal loss and maximum efficiency continuously and in high quality, has transformed from a luxury to a mandatory necessity. In this context, the nature of electrical energy, which cannot be stored, necessitates balancing production and distribution processes, and makes instantaneous, demand-based production strategically significant in the energy sector. This situation has brought to the forefront issues such as the modernization of energy infrastructure and the integration of smart grid technologies, playing a critical role in achieving energy efficiency and sustainability goals. The necessity, which underscores the importance of instantaneous production and transmission, has also paved the way for innovative solutions and technological advancements in energy management systems. Thus, the energy sector, while aiming to provide high-quality service to consumers, also promotes practices that support environmental sustainability and takes steps towards the future.

During the process of energy production and transmission, the distribution of energy produced with the demand, and the need to ensure that power plants are operated within their capacity limitations while maintaining a balance in-between is understood. It is only possible if this balance is maintained, which is a crucial prerequisite for the sustainability of the optimal power flow. Because if power plants are forced to operate fuzzy alterations or given the freedom to operate in alterations above their design values, then this results in the uneven sharing of the load by generators, and the entire energy system is exposed to the risk of collapse. Consequently, operational variables are pushed far beyond acceptable limits, and penalties are imposed, in addition to the substantial increase in the cost of fuel being used . Effective and efficient operation of power plants within their respective values of capacity is not only vital for the energy system to remain fit and healthy. It is through this principle that energy management strategies are built, thus, central to policy formulation for enhancing energy sustainability and efficiency. Deterministic Optimal Power Flow models were finally fostered by works initiated by Carpentier as early as

1962. Originally, they focused on the minimization of operational costs related to power systems without considering uncertainties.

His first formulations as nonlinear programming problems were developed to include active reactive power and transformer tap ratios; the scope of studies expanded over the decades to include security constraints using advanced methods, such as sequential linear and quadratic programming. Improvements have been made to increase reliability while reducing the cost of power distribution, especially when integrating renewable sources and embedding security measures reflecting ongoing adaptations in modern power systems optimization. Carpentier's approach has mainly formulated OPF as a nonlinear NLP problem for minimizing the total operational cost of the power systems(Mohagheghi et al., 2018).

The most important factor contributing to the development of OPF solutions in the 1970s, the gradient approach has brought efficiency in power systems engineering. Developed initially for the optimization of generation cost with considerations of system constraints and stability, this approach utilizes the derivatives of the objective function in order to implement adjustments so that a qualitative minimum of operational costs may be reached. It is possible that an update of power system variables in the direction of negative gradient may allow engineers to reduce fuel consumption and further enhance the reliability of electric grids. The gradient method realized high improvement in the management and planning of generation and distribution of electricity, which indicated the movement toward more severe yet cost-effective power system management(Carpentier, 1985).

Important to the work done in OPF solutions in the late 19th century, the Newton-Raphson method provided the strong algorithmic approach needed to enhance power system operations. Essentially, the method has been used for solving nonlinear equations in the analysis of power flow, one way through which the adjustment of settings in power systems can be done efficiently to obtain optimum operating conditions. The applications of the Newton-Raphson method allowed them to converge on solutions that met power generation requirements and system constraints on items such as voltage levels and power flow limits. This step is indispensable in the automation and optimization of the distribution of electricity, hence giving way to more reliable and economically feasible power grids. It marked a very important development in electrical engineering and supported the advances in automation for the analysis and operational efficiency of power systems (Eltamaly et al., n.d.).

Important developments in optimization algorithms beyond the classic gradient and Newton-Raphson methods have been made, particularly in nonlinear programming, since the 1980s. The emergence of the Conjugate Gradient (CG) method was a significant improvement over the Reduced Gradient (RG) method, when non-interfering search directions that speed up the convergence and reduce the computational steps were put forward. Simultaneously, the Generalized Reduced Gradient method was refined in a way that could handle both equality and nonlinear constraints more directly, by slack variables and dynamic changes of the constraints while optimizing. Interior Point Methods (IPMs) were gaining strength as methods capable of delivering robust solutions for large-scale linear and nonlinear optimization problems, guiding a path in the interior of the feasible region using barrier terms, and often performing better than classic methods like the Simplex Method for complex problems. Further evolution saw the emergence of Sequential Quadratic Programming (SQP) and Sequential Linear Programming (SLP), where a series of quadratic or linear approximations are iteratively solved, improving the model of the objective function and efficiency in finding the optimal solution, especially in the case of a tightly constrained optimization problem. The preceding development represents an important evolution in optimization techniques, driven by increased computing power and increased complexity of systems being modelled (Frank et al., 2012).

Traditional methods in the power systems sector have been taken over by innovative solution techniques since the early 1990s. Fuzzy modelling in the power systems was done in 1991 to model uncertainties in loads and power generation by treating such uncertainties as fuzzy variables. In that way, the optimum power flow was achieved with maximized power production and distribution in uncertain situations. Fuzzy set theory is one which offers a method to handle imprecision in data and incomplete information which cannot be modelled probabilistically. The application of fuzzy modelling was a means of deriving the power generation and load distribution in a more effective way, even in indeterminate scenarios (Miranda & Saraiva, 1992).

Stochastic OPF was first introduced during the early 1980s, when new and complex difficulties started to arise regarding the operations of the electric power systems, particularly issues related to the planning and handling of uncertainties in renewable energy sources. In other words, stochastic OPF drew significant attention in the 1990s. This technique was proposed to face the intrinsic variability characterizing RESs, such as wind and solar, to ensure reliable and economical operation of power systems in the presence of such uncertainty. Deregulation, together with a strong drive for decarbonization, has heightened the need for the integration of a large share of renewable resources; the necessity for Stochastic OPF has become very high. Stochastic OPF uses probability density functions and scenario generation to model and mitigate the risks posed by the stochastic nature of renewable energy sources. It guarantees a more rigid framework than the traditional deterministic methods by optimizing the power flow considering the anticipation and planning of different possible future states. It is, therefore, increasingly enhancing the flexibility and resilience of power grids against the unpredictable nature of renewable energy inputs (Maheshwari et al., 2023).

Over time, the introduction of distributed and decentralized OPF techniques has increasingly taken place in the handling of complex power systems. In particular, the development of the Augmented Lagrangian Alternating Direction Inexact Newton (ALADIN) method has significantly enhanced OPF computation efficiency. Designed for non-convex AC optimal power flow problems, ALADIN has outstanding performance when compared to the older methods such as the Alternating Direction Method of Multipliers (ADMM). Besides, it attains locally quadratic convergence rates and significantly reduces the number of iterations. This method especially stands out within those systems with large bus systems; it has shown better performance in 300-bus test cases. The distributed OPF, including ALADIN, is leveraging the fast increase in the computational abilities of system devices such that they can locally solve subproblems while a coordinator synthesizes these local solutions. This approach does not only cut computational overhead but also offers solutions to enhance scalability and resilience in power systems operations, which remain key, especially in a setting with a high penetration of renewable sources (Engelmann et al., 2019).

Against the modern scientific research landscape, many other fields have emerged due to the revolution brought about in the field of Artificial Intelligence and heuristic optimization algorithms. One such newly emerged field comprises the optimal power flow problem. These swarm intelligence techniques and nature-inspired algorithms work better because they have fast convergence, can handle multi-variable problems, and have a large search space. These are capability factors for which it is particularly fit to deliver solutions within seconds on nonlinear complex challenges thanks to advances in computation.

For example, AI optimizes OPF solutions using advanced modelling and adaptive systems to improve the efficiency and stability of grids. Swarm intelligence, on the other hand, attempts to optimize power flow with inspiration from the emergent collective behaviours of completely decentralized, self-organizing systems, such as flocks of birds or colonies of ants. This would do well in this distributed environment where a set of agents, all performing in unison to solve OPF problems give way to resilient energy networks. Besides, evolutionary algorithms take their inspiration from the principles of genetic evolution, using mechanisms of mutation, selection, and crossover toward efficient exploration and exploitation of the search space. Such algorithms are useful in that they are basically robust and flexible, with the capability of adapting to new or changing conditions without human interference. Heuristic algorithms rely on methods of trial and error guided by intuitive logic rather than rigid rules; thus, they always come up with practical solutions through educated guesses that hasten convergence toward optimal solutions. These are essential in real-time applications where decisions should be made in the quickest and most efficient way.

This ranges from efficient management in power systems to the fostering of development for increased integration of renewable energy sources into the grid. As this technology continues to evolve and integrate, there is more that is yet to be expected in terms of development in energy system optimization and management. Advanced computational techniques taken contribute to the field of OPF by making it efficient in the management of power systems and consequently allowing developments that enable more integration of renewable energy sources into the grid. Their continuous development and integration further lead to greater advancements in energy system optimization and management. Some of the techniques used in the analysis of the Optimal Power Flow problem include Newton's Method, Gradient Method, Linear Programming Method, Nonlinear Programming, QP, and AI Methods. Each of these techniques is shown in the Figure 1 (Singh Rana et al., 2019).

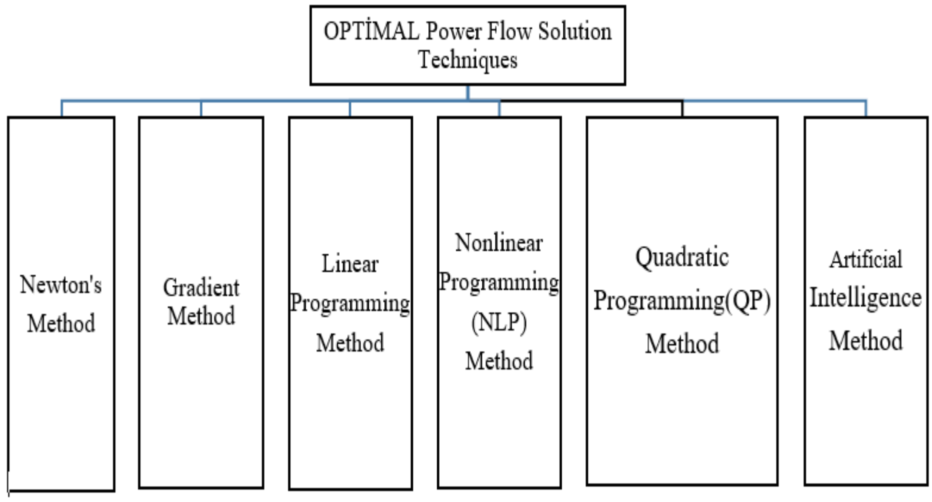

Figure 1. Optimal Power Flow Solution Techniques (Singh Rana et al., 2019).

1.1 Challenges and Limitations in OPF

Against the backdrop of changing demands on electrical power systems and in the complexity of modern electricity markets, bring several found challenges in the realm of optimal power flow. The OPF models necessary to regulate the power flows in order to optimize some objectives, such as the minimization of production cost or losses, are not trivial tools and possess profound complexities. This is further driven by the restructuring of the electrical supply industry, along with increased load demands and constraints by environmental advocacy against new transmissions, which gives a stronger urge to maximize the capability of existing networks. This in turn leads utilities to delay new infrastructural projects and rely more on OPF models to manage and plan under these conditions.

OPF tools are increasingly critical for engineers in the management of increased power flows in these networks. However, their usage presents several difficulties, especially for newer users who may find the convoluted technology of OPF difficult to master. A fundamental difference in the way OPF tools work from other non-OPF tools, like classical economic dispatch, is that OPF fundamentally uses a model of the power network. This difference is very critical because it highlights the unique offering of OPF in contributing to the optimization of the network but also reveals an inherent steep learning curve and misuse if not well understood.

However, the application of OPF tools in the restructured electricity supply industry has additional problems. Proper strategic application of OPF is of prime importance since improper use may lead to suboptimal operation and planning. For example, it is a matter of good judgment that may dramatically alter the effectiveness of OPF applications, such as the distinction between global optimization control and local regulation, understanding the levels of network security, and the priority of control variables.

These challenges, therefore, call for an approach that is both rigorous on training and familiarization with OPF tools for new users. They must sort through these complexities if they are to employ OPF in a way that works for them in the betterment of the operation and planning of power systems. The industry is evolving, and so are the strategies and understandings of how these powerful tools are applied in order to ensure that power systems are efficient but also robust and resilient in the face of forthcoming demands and potential contingencies (Cheng, 1998).

1.2 Benefits of OPF

The application of Optimal Power Flow (OPF) programs gives profound advantages when operating and planning power systems, especially to enhance efficiency, reliability, and economic outcomes. These benefits will be increasingly critical as utilities try to meet growing demands and regulatory pressures using extant infrastructures.

First and foremost, OPF allows the accomplishment of better economic efficiency. OPF will be able to pick out the best from among a set of possible options, optimizing the flow of power within the network for predefined objectives such as minimizing production costs or losses. These solutions will be selected considering engineering requirements and economic factors; therefore, operational decisions would not only be technically feasible but also economically viable.

Another important advantage is the uniqueness of optimal solutions that meet all operational constraints, irrespective of the experience of the user. This systematic approach not only yields the best solution but also effectively traces the binding constraints within the network, as the bottlenecks are identified by the transfer limits. This clarity is important for strategic planning and mitigation of the potential problems before they impact system performance.

Moreover, OPF enables the in-depth scenario studies possible through its automated processes. It permits consideration of literally an infinite number of alternative configurations. For example, this functionality will be useful when decisions need to be made, such as identification of best locations and size for addition of new equipment. Comparing these alternatives against common criteria can result in better decisions that are in confluence with the utilities' long-run strategic objectives.

Besides, the conditions of optimality and the associated mathematical expressions provided by OPF also carry significant insight into the impact brought about by the change in the control variables or easing several constraints-a process termed sensitivity analysis. These may pertain only to the vicinity of the computed optimum solution but do yield very helpful information for adjusting in the operations so that efficiency and stability of the system are enhanced. Where systems constraints lead to infeasible physical solutions, the OPF can formulate solutions with redundancies. This not only identifies conflicting constraints that have caused infeasibility but also suggests possible remedial measures to make the system operations viable. In certain cases, mild violations of constraints are tolerable, which OPF can accommodate to maintain system integrity without major redesigns.

Furthermore, in the context of a restructured electricity supply industry, OPF provides a reference case for benchmarking. This is increasingly important as different stakeholders may use these benchmarks to negotiate new transactions or address contentious issues, ensuring that all parties have a common understanding based on optimized system performance.

Overall, the use of OPF in power system operations and planning not only enhances the economic and operational efficiency but also aids in strategic decision-making and system robustness. As such, it plays a critical role in enabling utilities to adapt to and thrive in the evolving energy landscape, where optimization and strategic foresight are key to maintaining system reliability and meeting future challenges (Cheng, 1998).

During the operation and planning of energy systems, intensive studies have been conducted to solve the Economic Dispatch (ED) problem with the aim of ensuring the initial power (load) flow at the lowest possible cost, to avoid unwanted high costs and capacity overruns. These studies aim to ensure that generators produce power within permitted limits and that the sum of demanded power and power losses is balanced with the total generated power. Successfully achieving economic load distribution requires fulfilling these two fundamental conditions. These conditions related to active power management make the solution of the ED problem straightforward and comprehensible, resulting in a structure that is simple and free of complexity. This approach is critically important for optimizing the cost of energy production and distribution, making more efficient use of energy resources, and enhancing the overall sustainability of the system.

1.3 Objective of the Thesis

The purpose of this thesis is to solve the OPF problem using a discrete wavelet transform and an FCNN. Utilizing the discrete wavelet transform to preprocess input data created by OPF will help the FCNN working model represent the underlying characteristics of both the time and frequency domains and better capture non-stationary patterns characteristic of power system data. The performance of the discrete wavelet transformed FCNN against a standard FCNN model is evaluated by using mean squared error. Overall, this thesis showcases how utilizing discrete wavelet transform incorporated into the neural network used for OPF modelling decreases computational load and generally increases overall prediction quality and performance, ultimately creating another contribution to the ongoing research enduring in OPF modelling using data science principles.

Chapter 2

Literature Review

Optimal Power Flow (OPF) is an essential optimization problem in the energy sector, aimed at determining the optimal operating parameters for power generation to minimize costs and satisfy demand constraints. The problem is highly non-linear and non-convex, particularly in the Alternating Current OPF (ACOPF) form. Recently, machine learning techniques have proven effective in reducing the computational complexity of OPF problems.

Machine Learning (ML) and power systems are increasingly intersecting, particularly in the field of Optimal Power Flow (OPF). OPF is central to many power system operation tools and market clearing processes. Initially approached through mathematical and heuristic methods, the advent of machine learning algorithms, combined with the increase in computational resources and data availability, has encouraged the power systems community to explore the potential of ML. Machine learning has found applications in power systems operation, planning, monitoring, and economics

Although ML techniques are studied for many power system problems, their application to OPF is still emerging. From the early classical Lagrangian methods in the 1960s to today's machine learning techniques, the OPF problem has remained a significant challenge. Various approximation, relaxation, and decomposition methods have been used to find feasible OPF solutions. ML techniques are potential solutions to tackle variants of OPF with the goal of finding cost-effective solutions and reducing solver computational burdens. Figure 2 illustrates how ML techniques are currently used for OPF problems (Hasan et al., 2020).

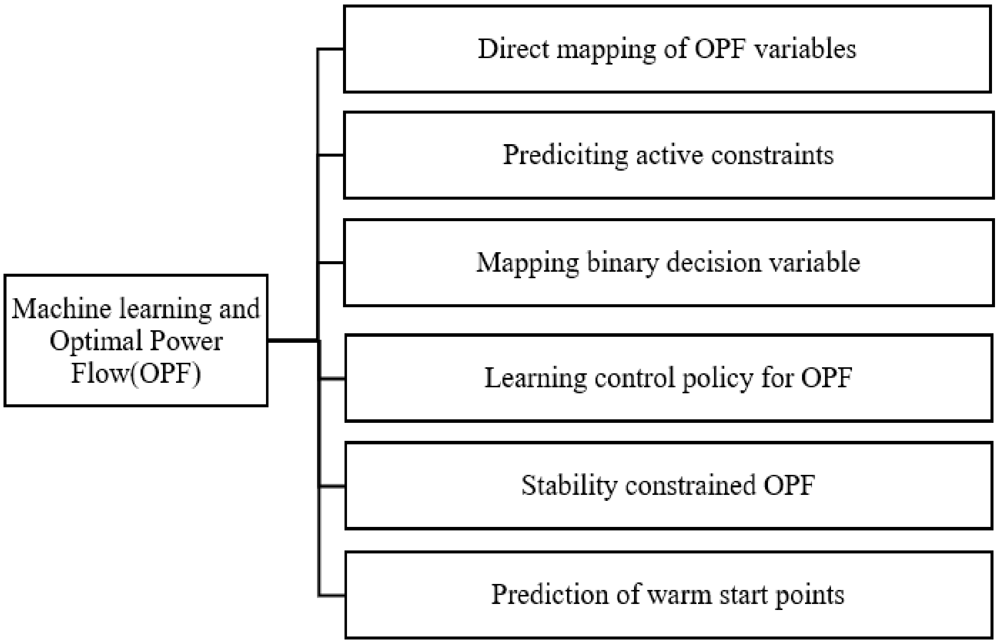

Figure 2. ML Techniques in OPF Solutions
(Hasan et al., 2020).

The direct mapping of OPF variables is done by the direct prediction of OPF solutions with a dataset of historical data or simulated scenarios, providing a framework for supervised learning in training models on input parameters that yield OPF results, voltages, line flows, and power generation. For example, it is found that boosting regression yields a better choice when considering time reduction or improving solution accuracy. However, this method results in infeasible or suboptimal solutions with small errors in the prediction. Prediction of active constraints: The machine learning models classify active and inactive constraints to improve the OPF formulation in this approach. This simplifies the learning task since the focus shifts to identifying critical constraints, rather than mapping continuous variables directly. For example, it has been realized that a fully connected neural network for the classification of constraints develops computational efficiency by a great margin. Binary decision variables mapping: This approach is very critical in learning unit commitment approximations for reducing computational costs. With nearest-neighbour classification algorithms or techniques alike, the models can approximate unit commitment solutions to market clearing without requiring computationally expensive solvers. Learning the control policy for OPF: It uses local measurements in an attempt to emulate the centralized control policies by means of decentralized reactive power controllers. This is especially important in distribution networks with high penetration of Distributed Energy Resources where decentralized decision-making greatly improves grid stability and efficiency. Stability-Constrained OPF: Stability constraints are included in OPF by data-driven approaches in a way that small-signal and transient stability margins are bounded within an optimal solution. Then, decision trees and machine learning models classify the operating scenarios between stable and unstable, and this knowledge can then be integrated into OPF formulations. Put all together, this can substantially reduce computational time and yield reliable solutions of OPF problems.(Hasan et al., 2020).

2.1 Direct Mapping of OPF Variables

The most popular method is the direct prediction of OPF solutions by machine learning. It basically trains a learner with input parameters provided OPF results as voltages, line flows, and power generation outputs. For example, the various algorithms used by Navidi et al. have demonstrated that the gradient boosting regression algorithm enhances time in computation along with accuracy in the solution. Along this line, Sun et al. (2018) have recently proposed a Security-Constrained OPF framework with the integration of multi-target regression based supervised learning. (Hasan et al., 2020).

In this context, it was shown in Ng et al (2018) that an OPF solution is defined by a set of active constraints corresponding to a certain uncertainty occurrence and that such basic solutions can be used in order to create affine policies. It has been said in some literature that these affine policies may be sufficient in certain cases, but in the more complex scenarios of uncertainty, the general policies like PWA policies should be used instead. Furthermore, the direct mapping of OPF variables that define critical regions and monitoring of an optimal solution by switching between those regions have also been studied. It is in this connection that the selection of important bases through the techniques of statistical learning and utilizing them in OPF solutions are oft-repeated themes in the literature. (Ng et al., 2018).

In the paper of Sun at et al. (2018), a study on the adequacy of direct mapping and local features for the estimation of security-constrained generation distribution is conducted. As traditional optimization approaches are not good enough in terms of time in large-scale power systems to solve the problems related to SCOPF, therefore usage of only local features along with local measurements is considered. In this work, it has been shown that local generation distribution estimation can be done rather accurately with local data. Also, the local estimates provide similar results compared to estimates that were based on global data. This approach is highly significant in real-time applications such as large and complex electrical systems (Sun et al., 2018).

In the article by Canyasse, a study on direct mapping OPF was conducted by investigating supervised learning algorithms to quickly estimate costs and feasibility of ACOPF. The authors then focused on this approach because of its benefits in making fast estimates instead of simulating the OPF solution, especially in long-term planning and control applications. This approach has been applied to large test systems such as IEEE RTS-96 and allowed the estimation of the OPF cost with an error rate less than about 1%. Besides that, the proposed approach enables the detection of spatial clusters caused by different modes of congestion due to the presence of multimodal structures. The solution of the cost estimation problem in large-scale power systems is therefore very efficient, as its execution is extremely fast with high accuracy (Canyasse et al., 2017).

2.2 Predicting Active Constraints

Active set classification methods learn active constraint sets corresponding to uncertainty realizations. The work of Deepjyoti Deka and Sidhant Misra will try to learn the relationship of these realizations to optimal active sets instead of directly mapping uncertainty realizations to optimal solutions. Neural network classifiers create a mapping from uncertainty states to active sets. Hence, these classifiers can predict optimum solutions in real time efficiently and quickly. The work shows the performance of this approach on various systems of the IEEE PES PGLib-OPF benchmark library. Active set classification simplifies the learning task and makes accurate predictions by taking advantage of the system and problem structure (Deka & Misra, 2019).

A study by Kyri Baker and Andrey Bernstein introduced an alternative data-driven method to account for joint chance constraints in AC optimal power flow (OPF) problems. The authors look at distribution systems with a significant penetration of distributed renewable generation resources, allowing a more formal mathematical model of uncertainty in the OPF problem. Then the authors use statistical learning tools to reduce the computational burden of the OPF optimization problem by allowing the user to classify given constraints as active or inactive and concisely substitute the joint chance constraint with a string of independent (to minimize conservativeness) chance constraints. In this case, the authors choose support vector classifiers from the statistics learning motor. There are bounds on conservativeness relative to models with single chance constraints (like Boole's inequality) and considerable reduction in conservativeness using an off-the-shelf support vector machine solver to further disaggregate standard models for optimization in power systems dealing with significant uncertainty. The framework is tested within the IEEE 37-node test feeder. The study concludes with an interesting evaluation of optimization procedures to mitigate voltage regulation related challenges in distribution networks (Baker & Bernstein, 2019).

Slightly erroneous predictions of the OPF results may lead to infeasible or suboptimal solutions from direct mapping of results. Prediction of active constraint sets has attracted a lot of attention in recent years. A new concept proposed a methodology to determine optimal active constraint sets using the advantages in statistical learning. It ensures probabilistic guarantees for output sample scenarios by identifying and learning important bases (Misra et al., 2021).

2.3 Learning Control Policy for OPF

ML can decentralize such control policies. A few linear regression learners have so far implemented decentralized OPF-based reactive power controllers. The learners leverage advanced metering infrastructure, coupled with simulations, to prepare a dataset for a range of scenarios and further map the local measurements to the optimal power injection of Distributed Energy Resources-DERs. In other words, machine learning techniques have indeed proven immensely promising in solving OPF problems. This has been an area of continual maturity with new learning techniques, with effective handling of the associated computational challenges, and with associated issues of robustness and reliability related to power system operation. (Hasan et al., 2020).

Another contribution that could be taken into consideration has to do with Federica Bellizio et al., where there is an approach to active distribution grids by decentralized control, embedding principles of machine learning. The authors seek, the optimal solution for local control of DERs under the assumption of limited monitoring and communication infrastructure. Results will be detailed, resting on a two-step approach. First, it develops a dataset of optimal DER setpoints represented under various weather and electrical network conditions through a centralized optimal power flow algorithm. Next, using the OPF dataset, local controllers at each DER resource are trained by the machine learning model, in this case, Support Vector Regression. The idea behind this is to surely attain real-time operations considered near optimal through designing DER controllers to measure quantities locally, and to use historical data from the local controllers to emulate the optimized settings and operating conditions from a centralized basis, yet still assure the security and efficiency of the whole distribution system. This operational framework was applied to a low-voltage distribution feeder and extended by conducting more comparisons against existing centralized and decentralized operational approaches, considering uncertainties and concerns that may arise from modern distribution systems.(Bellizio et al., 2018).

Stavros Karagiannopoulos, Petros Aristidou, and Gabriela Hug introduce a Machine Learning control policy for active distribution grids that emulates the outcome of the optimum behaviours in case of absence of a high degree monitoring and communication architecture. The authors have proposed a data-driven algorithm that would make use of historical data in conjunction with an offline OPF model to compute the optimal setpoints of DERs and further train the machine learning models like SVM, and regression-based models required to realize the machine learning solution. This paper designs an online machine learning-based control policy that enables real-time operations of DERs using only local measurements to efficiently approximate a centralized OPF solution and guarantee stability of the grid and operation costs. It is applied to the control simulation of a three-phase unbalanced low-voltage distribution network. Results are indicative that the approach can realize better outputs compared to other traditional local control strategies: it manages to track the optimal control outputs commonly achieved under centralized control strategies.(Karagiannopoulos et al., 2019a).

2.4 Mapping Binary Decision Variables

In the paper "Unit Commitment using Nearest Neighbour as a Short-Term Proxy," the authors propose a machine learning methodology for mapping binary decision variables within unit commitment issues, a classic problem that usually occurs within power systems. In this paper, a nearest neighbours algorithm is employed to approximate the optimum unit commitment solution achieved from problems that have previously been solved. The authors have developed a database of solved unit commitment scenarios that is useful to estimate binary decision variables, i.e., the on/off state of generation units, from solved mixed-integer linear programs, without requiring the full solution of the latter in each occasion. That amounts to enormous saving in computation time with the same level of accuracy, so machine learning can be used in real time for hourly commitment/dispatch in large-scale power systems and also can be used normally while planning for a long-term reliable operation. In practice, this would represent a state-of-the-art use of supervised learning in operational decision-making for power networks. This is to outline, through examples, how machine learning applied to a previously obtained dataset goes to make energy management even more effective and reliable. (Dalal et al., 2016).

2.5 Stability Constrained OPF

The problem of stability-constrained OPF is mostly pointed out in the paper "Data-Driven Local Control Design for Active Distribution Grids using off-line Optimal Power Flow and Machine Learning Techniques". This paper is providing one approach for developing the local control policies of DERs in a data-driven manner by using historical data and machine learning techniques in approximating OPF outcomes in a centralized OPF framework. With this work, OPF models did not consider stability, and neither is there any discussion on methods of OPF operating under stability constraints. The goal of the research work is to study the local actions in such a way that they would be assured of maximum efficiency and security in the operation of a studied distribution grid, given implications of DER availability under contingencies (Karagiannopoulos et al., 2019).

The stability-constrained OPF is discussed in the next paper: "Efficient Database Generation for Data-driven Security Assessment of Power Systems." Correspondingly, the authors go on to propose a method toward generating, in a modular and scalable fashion, the datasets needed for dynamic security assessment. In particular, the present methodology will organically make use of convex relaxation techniques and complex network theory, whereby it manages to reduce the computational burden when computing the security boundaries, including those imposed by small-signal stability. It brings forth an avenue of methodology that, though focused on N-k security and small disturbance stability, the researcher enables the fast discard of big infeasible regions and finds secure/insecure operating points about stability. In this direction, especially, stability-constrained OPF analysis is presently being drastically reduced, compared to the effort of traditional techniques, with efforts in time used in quite a different way, for both off-line security assessment and real-time operation.(Thams et al., 2020).

2.6 Prediction of Warm Start Points

Ziyou Zhang, Qianchuan Zhao & Fa-An Dai published a study in 2023 that suggested an integral-point inner shrinking horizon variable step discretization (SWITS) model predictive control (MPC) using warm-start. The paper wanted to do that in a way that also dramatically cut down on computation time, so it went even further and built the initial guess using parts of prior solutions. This led to an approximately 80% cut in iterations when implemented for fuel-efficient planetary descent guidance in the context of second-order cone programming (SOCP) problems. Pubathon results showed that the warm-start strategy outperforms cold-start methods(Zhang et al., 2023).

2.7 FCNN and DWT Related Studies

In addition to the literature mentioned above, the following works have been included on Fully Connected Neural Networks (FCNN) and Discrete Wavelet Transform (DWT) in the context of optimal power flow.

The role of FCNN in power system analysis has gained prominence due to their ability to model non-linear, complex relationships in the power system. They predict bus voltages and line flows under varied load conditions, hence have been applied for load flow analysis, and contribute to security assessment by mapping the operational states to secure or insecure categories. In OPF problems, FCNNs provide high accuracy in approximating the traditional OPF solution, directly predicting OPF variables using historical data or simulated scenarios, hence reducing the computational time of the classical optimization method considerably. Furthermore, some approaches predict active constraints directly, hence improving the computational efficiency of the OPF formulation.

In fault detection and diagnosis, FCNNs utilize historical fault data to identify fault locations and classify fault types; hence, they can be used in transient stability assessments by predicting the fault's effect on system stability. They also contribute to the security assessment by classifying system states as secure or insecure with high accuracy; the robustness is improved as more diverse training data becomes available.

FCNNs in OPF, load flow, and security assessment show the scalability, high representational power, and speed of prediction compared to traditional methods. However, the challenges need to be addressed, such as the requirement of large datasets, which are always not available, and when not properly regularized, overfitting may occur. In addition, the interpretability of the FCNN models is an area of concern compared to the classical methods.

Guha et al. (2019) showed that while FCNNs can predict ACOPF solutions, they mostly lack generalization. On the contrary, GNNs, as presented by Owerko et al. (2019), exploit the graph structure of power systems and reduce the RMSE by up to 213% compared to FCNNs on larger networks because GNNs can process localized information with high efficiency. Moreover, GNNs have the capability to scale and provide stability against graph perturbations, making them suitable for large-scale power system analysis. Although FCNNs offer fast approximations to load flow and security assessment compared to the classical methods, the localized processing capability of GNNs and their scalability make GNNs the preferred choice, as they provide more accurate and robust solutions in OPF and other power system optimization problems (Owerko et al., 2019).

In the paper "DeepOPF: A Deep Neural Network Approach for Security-Constrained DC Optimal Power Flow", Pan et al. (2021) introduce how to apply a new solution framework-using a fully connected neural network-to solve the Security-Constrained Direct Current Optimal Power Flow problem. The authors realize very well that the solution to the SC-DCOPF problem is intrinsically a mapping problem: it maps the power load input to the optimal generation output and voltage phase angle. DeepOPF leverages the universal approximation capability of FCNNs for effective and efficient learning of this high-dimensional mapping. It includes two major steps: prediction and reconstruction. First, DeepOPF applies an FCNN which predicts generation values based on the load inputs. Then FCNN calculates the phase angles by straightforward solution of power flow equations with the use of predicted generation values. This predict-then-reconstruct approach reduces the dimension of the problem; the FCNN needs to predict only the generation values. After being trained on historical data, DeepOPF can approximate the optimal solution with less than 0.2% optimality loss. On the other hand, it maintains feasibility and accelerates the computation time up to two orders of magnitude compared to conventional interior-point solvers. The contribution of this approach to scalability and efficiency makes it quite appropriate to solve large-scale SC-DCOPF problems in real-time applications; that is, it can achieve an optimal balance between speed and accuracy in power system operation. In all, DeepOPF shows how FCNNs can significantly improve the computation of optimal power flow solutions. It provides a robust and practical alternative to traditional methods in the computation of optimal power flow solutions (Pan et al., 2021).

In an analysis conducted by S. A. Saleh and M. A. Rahman in 2005, the wavelet packet transform has been applied to a novel algorithm for the differential protection of three-phase power transformers. The algorithm uses WPT to extract features from the differential current signals for distinguishing between magnetizing inrush and internal fault currents. Optimal wavelet and resolution levels were selected in light of the MDL criteria. Extensive offline testing using laboratory data revealed that the proposed method outperforms the traditional DFT-based method regarding speed and accuracy. In this paper, it is revealed that WPT is effective in bringing improvement to transformer protection with reduction in computational burden (Saleh & Rahman, 2005).

In the research of Amin Shabanpour-Haghighi, Ali Reza Seifi, and Taher Niknam, a modified teaching-learning-based optimization algorithm was applied to solve the optimal power flow problem. The algorithm was analysed to deal with the Mult objective OPF problem concerning total fuel cost and total emissions of generators. It adds up the modified phase with a self-adaptive wavelet mutation strategy. The algorithm performance was shown for IEEE 30-Bus and 57-Bus systems, where the results were compared with those in the literature. It was proved that such an approach can increase the search space to reach the best solutions with good convergence speed (Shabanpour-Haghighi et al., 2014).

In the study "Whale Optimization Algorithm with Wavelet Mutation for the Solution of Optimal Power Flow Problem," V. Mukherjee, Aparajita Mukherjee, and Dharmbir Prasad have developed a novel approach for the solution of the AC optimal power flow problem. Wavelet mutation strategy is added to the WOA for enhancing its effectiveness. This wavelet mutation applied in the basic iterations of WOA enhances the exploration-exploitation capability of the algorithms to escape the local optima and converge to globally optimal solutions. The performances of the proposed method are studied in different standard power systems like IEEE 30-bus, 57-bus, and

118-bus systems and found giving superior performance for fuel cost minimization, transmission loss minimization, and voltage deviation minimization compared to the traditional optimization methods. The incorporation of wavelet theory in the optimization algorithm is an effective way to solve challenging OPF problems efficiently. (Mukherjee et al., 2018).

The study "Optimal Power Flow Pursuit" by Dall'Anese, E., & Simonetto, A. presents a development of distributed feedback controllers that solve OPF problems in distribution networks with inverter-based distributed energy resources. These controllers iteratively adjust the powers of the inverter outputs based on real-time voltage measurements and time varying OPF targets. The control architecture leverages linear approximations of the AC power-flow equations and employs Lagrangian regularization to ensure effective performance. The authors provide analytical proofs of the convergence and OPF-target tracking properties of the proposed controllers. By rendering optimization in real time, the method overcomes the limitations of traditional hierarchical setups where the time scales of feedback control and optimization are very different, hence allowing for a far more effective and responsive management of distribution systems (Dall’anese & Simonetto, n.d.).

Chapter 3

Optimal Power Flow

Generators producing electrical energy, transmission systems carrying the generated energy at high voltage levels, distribution systems supplying the energy to the end user, and the loads consuming the energy are the sections that comprise a power system. The connection infrastructure of this power system is shown by means of a single line diagram. It is used in the analysis of the given power system. Single-line diagrams are generally named according to the total number of busbars. Figure 3 shows an example of single line diagram of the IEEE 24 bus system.

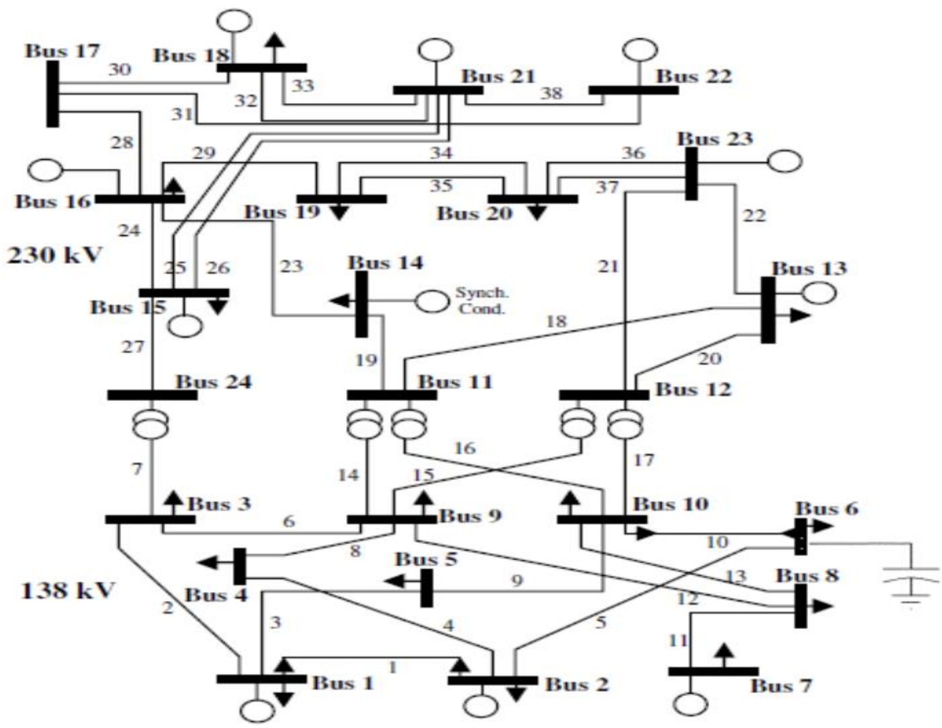

Figure 3. Single Line Diagram of IEEE 24 Bus System

(Hameed et al., 2020).

Since the early 1900s, academic research on load flow has initially focused on Economic Distribution and Power Flow. In the 1960s, the first mathematical formulations of OPF revolutionized how electrical grids were managed. Today, it has evolved into a multi-parameter and complex structure where the power system's goal-oriented objective function yields optimal results. OPF involves solving a constrained optimization problem that balances power supply and demand while minimizing generation costs or transmission losses.

Key challenges include ensuring voltage stability, maintaining system security, and adhering to regulatory limits on generation and transmission capacity. With the growing integration of renewable energy sources, OPF is crucial for ensuring efficient and sustainable operation of modern power grids. Various algorithms, such as Newton-Raphson, Linear Programming, and Interior-Point methods, have been developed to solve OPF problems efficiently. Before the complex and computer-aided OPF problem, the Economic Dispatch (ED) problem was frequently solved to reduce fuel costs in power systems. In comparison to OPF, Economic Dispatch focuses simply on minimizing fuel costs. The only inequality constraint is that the active power output of generators must remain within specified limits, while the equality constraint requires that the total output power of the generators, including transmission line losses, matches the total power demand. The equations required for OPF are given below. In this study, the objective function is used to minimize the total generation cost of the power system. The following equation represents the formulation of the optimization problem for OPF.

$$\min_{P_G\,, Q_G, V\,, \theta} \sum_{i\,\in G} Ci(P_{Gi}) \tag{3.1}$$

Where $C_i(P_{Gi})$ is the cost of generated power P_{Gi} by generator i.

OPF fundamentally involves ensuring that power generation in power systems meets the equality and inequality constraints within specified limits, that load flow is balanced and of high quality, and that the power system is operated under nominal conditions, avoiding faults. The primary distinction that sets OPF apart from the Economic Dispatch and load flow problems is that, within specified limits, OPF optimally manages the power system's operation and load distribution while meeting mandatory requirements and essential criteria for load flow, simultaneously optimizing the objective function's outcome. Equality constraints include power balance equations that ensure the sum of generation equals the sum of demand plus losses, while inequality constraints involve limits on generator outputs, voltage levels, and line flow capacities.

Active and reactive power balance equations given by:

$$Q_i = \sum_{\mathrm{j}=1}^{\mathrm{n}} \left(\mathrm{V_i\, V_j}\ (\mathrm{G_{ij}}\, sin\, \Theta_{\mathrm{ij}} + \mathrm{B_{ij}} \cos \Theta_{\mathrm{ij}})\right) \tag{3.2}$$

$$P_i = \sum_{\mathrm{j}=1}^{\mathrm{n}} \left(\mathrm{V_i\, V_j}\ (\mathrm{G_{ij}} cos\, \Theta_{\mathrm{ij}} + \mathrm{B_{ij}} \sin \Theta_{\mathrm{ij}})\right) \tag{3.3}$$

Where P_i is an active power injected to bus i. $\mathrm{V_i}$ and $\mathrm{V_j}$ are the voltage magnitudes at bus i and j. Θ_{i} and Θ_{j} are the voltage angles at bus i and bus j. $\mathrm{G_{ij}}$ and $\mathrm{B_{ij}}$ conductance and susceptance of the line between i and j respectively. A total number of buses also shown by n.

Inequality constraints are defined as keeping the generator, transformer, compensation, and transmission line parameters within specified limit values in the power system. For OPF to be implemented as desired, all system component values must remain within the given range. This criterion is an absolute requirement that must be fulfilled to ensure optimal power flow. Generators need to maintain their active and reactive power outputs within specified minimum and maximum limits, while transformers must control tap changer positions and phase shift angles to avoid voltage violations. Additionally, transmission lines should not exceed their thermal limits to prevent overheating and potential failures. The boundary equations for decision and state variables are listed below. Generator constraints limit the output of the generators in term of active and reactive power.

Active generation limits:

$$\mathrm{P_{Gi}^{min}} \leq \mathrm{P_{Gi}} \leq \mathrm{P_{Gi}^{max}} \tag{3.4}$$

Where $\mathrm{P_{Gi}^{min}}$ and $\mathrm{P_{Gi}^{max}}$ are the minimum and maximum active power outputs of generator i respectively.

Reactive generation limits:

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \tag{3.5}$$

Where Q_{Gi}^{min} and Q_{Gi}^{max} are the minimum and maximum reactive power outputs of generator i respectively.

Voltage magnitude constraints ensure that the voltage magnitude at each bus stays within specified limits.

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{3.6}$$

Where V_i^{min} and V_i^{max} are the minimum and maximum allowable voltage magnitudes at bus i respectively.

Line flow constraints ensure that the power flowing through each transmission line does not exceed its thermal limit:

$$S_{ij}^{min} \leq S_{ij} \leq S_{ij}^{max} \tag{3.7}$$

Where S_{ij}^{min} and S_{ij}^{max} are the minimum and maximum apparent power that line can handle at bus i to j.

Together, these equations and constraints form the core of the AC OPF problem, guiding the optimization process to determine the best operating conditions for a power system.

Chapter 4

Methodology

OPF is an important task within modern power systems, which involves the minimization of operating costs with respect to all system constraints on, for example, generator limits and voltage stability. These traditional optimization methods, including linear programming, non-linear programming, and interior-point methods, are usually too computationally expensive to handle the high non-linearities that appear in the equations of power flow. These conventional methods are computationally intensive, especially for large-scale systems.

In the past years, machine learning methods and, particularly, neural networks have indicated the potential for accurate and computationally efficient solutions to OPF problems. Specifically, FCNNs can approximate the complex relationships between input loads and optimal generator outputs. However, conventional neural network models suffer from problems caused by high dimensionality and non-stationarity of OPF input data. These problems lead to increased training times and possibly result in reduced accuracy in estimating optimal generator outputs and bus voltage levels.

OPF is a very crucial activity in modern power systems, which basically entails minimizing operating costs without violating system constraints like generator limits and voltage stability. Classical optimization techniques, such as linear programming, nonlinear programming, and interior-point methods, normally have very high computational complexity, influenced by power flow equations being nonlinear. The traditional methods are computationally intensive, especially for large-scale systems.

Machine learning techniques, especially neural networks, have obtained good results in recent years as accurate and computationally efficient solutions for the OPF problem. Specifically, fully connected neural networks can be used to approximate the highly nonlinear relationships between the input loads and the optimal generator outputs. However, conventional neural network models suffer from high-dimensional and non-stationary OPF input data, leading to longer training times and potentially reduced accuracy while predicting optimal generator outputs and bus voltage levels.

In the methodology section, we describe the structured approach followed to evaluate the effectiveness of Fully Connected Neural Networks and their enhancements through wavelet transformations in this thesis. This section describes in detail all the steps taken, from data preprocessing to the deep analysis and evaluation of the model performance. The order and justification for each methodological decision are included for clarity on how the study was conducted. To facilitate an understanding of the logical sequence of these steps, a flowchart has been provided, which is shown in Figure 4.

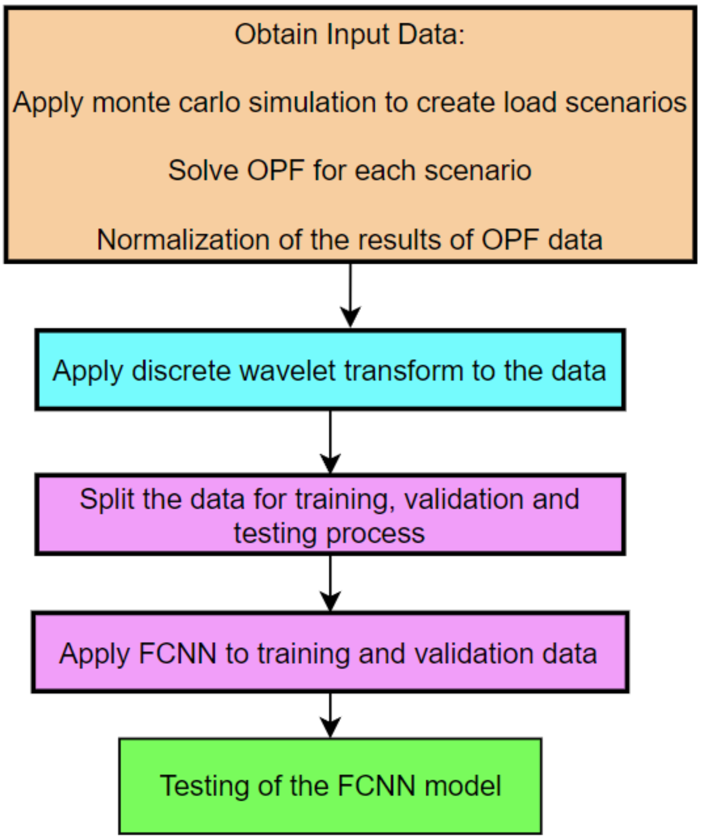

Figure 4. The steps of the proposed method for OPF

4.1 Data Preparation

The data set required as input for the proposed method is prepared in this section. Initially, various loading scenarios are generated for the power system using Monte Carlo simulation. Subsequently, OPF analysis is conducted for each scenario to determine the active power output of the generators and the voltage magnitudes of the buses. Finally, these values undergo a normalization process to obtain the input data.

4.2 Discrete Wavelet Transform Integration

4.2.1 Discrete Wavelet Transform. The Discrete Wavelet Transform (DWT) is an effective, powerful mathematical tool to analyse signals in the time and frequency domains. The Fourier transform only provides frequency-based information, while DWT provides simultaneous transitory and continuous signal information. DWT allows one to use varying elementary functions referred to as "mother wavelets" to filter the signal based on scale(s) and local regions of the signal. Therefore, one can then examine the signal features or characteristics in detail.

The DWT allows one to analyse the signal f(t) at different resolutions using two different foundational functions namely the mother wavelet ψ(t) and the scaling function ϕ(t). The mother wavelet captures the high frequency components of the signal while the scaling function captures the low frequency components. DWT transforms a signal by scaling and shifting mother wavelet functions according to scale and translation parameters as shown below:

$$\psi_j, k(t) = 2^{\frac{j}{2}}\psi\left(2^j t - k\right) \tag{3.8}$$

Where j is scale parameter which allows analysis of the signal at various resolution levels. Translation parameter represented by k that shifts over time. 2^jt represents the normalization factor.

The decomposition of a signal using DWT is represented by wavelet coefficients ($c_{i,k}$), calculated based on the scale and translation parameters:

$$c_{i,k} = \int_{-\infty}^{\infty} f(t)\ \psi_{j,k} t dt \tag{3.9}$$

These coefficients provide time-frequency characteristics of the signal with different resolutions

4.2.2 Applying DWT to Input Data. In this study, discrete wavelet Transform was incorporated in the data processing of the FCNN model to further advance the representation of its features in obtaining the optimal generator set points and bus voltage magnitudes. For training, both the input load data, active load `$P_D$` and reactive load `$Q_D$`, and output labels, bus voltage magnitude `$V_M$` and active power generation `$P_G$`, are normalized to unify scaling. This mainly involves incorporating a few DWTs into decomposing the `$P_D$` and `$Q_D$` inputs into their respective wavelet coefficients. The latter step often aids in catching the unstructured localized variations in the signals, besides denoising them. Therefore, using discrete wavelets, the resulting wavelet coefficients yielded a more detailed structured representation of the input features and enhanced the capacity of the network to learn and generalize. This in turn improves this set of features that feeds into the FCNN model, improving predictive performance and providing more accurate solutions to the optimal power flow.

4.3 FCNN Network and Training Process

In this thesis, Fully Connected Neural Network (FCNN) architecture is presented to aid in solving the Optimal Power Flow (OPF) problem. A Fully Connected Neural Network (FCNN) is a form of artificial neural network in which every neuron is connected to every neuron in the previous layer. This model typically has an input layer, one or more hidden layers, and an output layer. A conventional FCNN consists of an input layer, one or more hidden layers, and an output layer. The input layer accepts the data while the hidden layers extracting and performing features from the data. Each neuron processes signals that receives information from other neurons with weight and a bias term. The neuron produces output values that is determined use an activation function. An activation function enables the neural network to acquire non-linear relationships. FCNN network are an effective structure to allow the neural network to learn patterns, as the neurons are fully connected in all layers with flexible and powerful structures. A totally connected and dense format can enable a model to learn very complex relationships between inputs and outputs. FCNNs are often employed in applications, such as: classification, regression and pattern recognition. Benefits of FCNNs include capability to generalize across datasets, flexibility with inclusion of different data, and learn non-linear relationships. However, due to the large number of connections, FCNNs can be numerical expensive, and have issues with overfitting, that is the model may fit training data very well but generalizes lower with new data. Moreover, as data grows larger and the number of features increases, training these models will become even more difficult. In Figure 5, the overall structure of the Fully Connected Neural Network (FCNN) architecture is presented (Tonello et al., 2019).

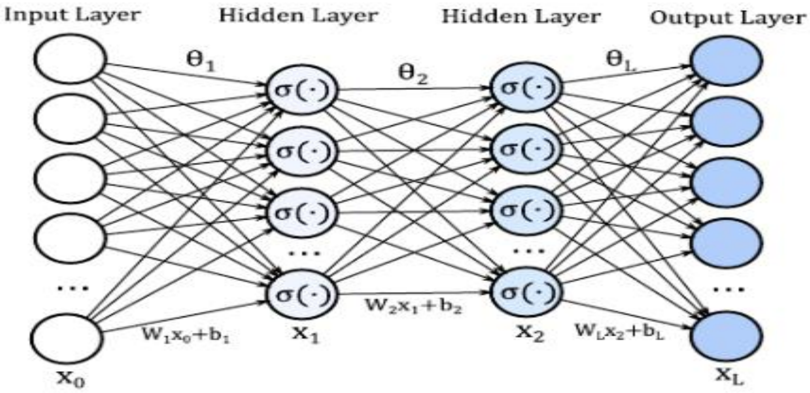

Figure 5. FCNN Architecture

(Tonello et al., 2019).

The input features will consist of grid parameters like active and reactive power components of the loads presented in per-unit values (P_D and Q_D), and the output labels will consist of optimal generator set points, active and reactive power injections (P_G and V_M), and bus voltage magnitudes which are represented in per-unit values. The data will be used for model fitting, and the hyperparameters will be tuned based on the validation data; they are also useful in overfitting. While the test data provides a realistic and unbiased evaluation of the final model. The foregoing procedure is reliable and true ways of assessing the models. The FCNN has been developed to predict the optimum generator set points along with the bus voltage magnitudes directly, reducing the computational complexity for OPF problem solutions. Performance for the Fully Connected Neural Network was measured by training and testing independently five times, recording average performance for results. Each independent run meant training from scratch and then testing on a separate test set. Then, mean and standard deviation of the performance metrics were calculated to get the measure of the consistency. Results obtained, therefore, give assurance of the reliability of predictive performance. This will ensure that there will not be any skew in random initialization and variability in the data that might make the model perform well.

Chapter 5

Simulations and Results

5.1 Simulations

Julia, a high-level, high-performance language, is the best for generating OPF data because it has speed and advanced optimization capabilities. With Just-In-Time compilation through the LLVM-based compiler and built-in support for multi-threading and parallel computing, Julia achieves execution speeds comparable to those of C and Fortran and is extremely efficient at solving large-scale OPF problems. The speed of Julia in various domains is benchmarked against other languages. This language's performance, which rivals or even outdoes that of C, Python, and MATLAB. Its high capability to solve nonlinear problems through JuMP.jl and Ipopt.jl is also critical to solving the difficult, non-convex power flow equations in the problems of OPF analysis. (Bezanson et al., 2012)

MLOPF.jl is a Julia package for machine learning assisted OPF that utilizes Julia's high-performance computing and flexible modelling capabilities. Building upon PowerModels.jl, MLOPF.jl provides a complete framework for efficient generation of the training data through Monte Carlo simulation and preprocessing; the package supports AC and DC power flow formulations. It integrates with the machine learning libraries like Flux.jl for direct training models such as Fully Connected Neural Networks (FCNNs). Other facilities in MLOPF.jl include normalization, feature engineering, and model evaluation tools. That makes it a complete solution for a researcher to handle, preprocess, and analyse large OPF datasets efficiently. Combining Julia's computational speed, a flexible modelling language with powerful optimization capabilities, MLOPF.jl enables researchers to take on large-scale OPF problems with confidence, thereby making Julia the best language for OPF data creation and analysis. (Falconer & Mones, 2023)

First, power system case studies are imported using the PowerModels.jl package in Julia, such as benchmark IEEE 24-bus, IEEE 57-bus, and IEEE-118-bus networks. Utilizing Monte Carlo simulation, varying load values, both active and reactive power, are changed within a ±20% range from their base load values to generate 10,000 different feasible data for each case system. This will provide a wide number of feasible solutions, which will accurately model the variability in real-world power systems. The optimal power flow data was generated and trained using an Asus Vivobook equipped with an AMD Ryzen 9 5900HX processor with Radeon Graphics. The system also had 16GB of RAM, providing adequate computational resources for the tasks.

In this study, various kinds of discrete wavelet transforms have been tried: Coiflet, Haar, and Daubechies Wavelet Transforms, each for different capabilities to analyze the data. After evaluating the performance of each type of wavelet, Coiflet 8 wavelet showed the best results. Among all these cases, the performance of Coiflet 8 was found to be better, hence Coiflet 8 wavelet transform has been selected to carry out this analysis. Coiflet 8 DWT will henceforth capture low-and high-frequency components of the signal for more accurate and detailed modeling in OPF analysis. Additionally, noise reduction and multi-resolution ability will enhance the reliability and comprehensiveness in the data evaluation in OPF problems. The detailed analysis of FCNN and their wavelet-transformed counterparts have been analysed FCNN with Wavelet, on three different cases IEEE 24 bus, IEEE 57 bus, IEEE 118 bus systems. Cross validation tests for each case have been conducted to present the reliability of the results which is derived from these runs. Dataset will be randomly divided into training, validation, and test subsets in the ratio 70%, 20%, and 10%, respectively. These models are trained with the Adam optimizer using a learning rate of 10^{-4} and the mean squared error acts as the main loss function. For efficient convergence during training, a mini-batch size of 100 is used.

5.2 Results of Simulations

The generation of 10,000 optimal power flow solution datasets took approximately 8 minutes for the IEEE 24-bus system, around 13 minutes for the IEEE 57-bus system, and about 28 minutes for the IEEE 118-bus system. Training, validating and testing of these systems with 10000 data samples took an average of 15 seconds for the IEEE 24-bus system, 5 seconds for the IEEE 57-bus system, and 12 seconds for the IEEE 118-bus system. The table below presents the average IPOPT durations required to generate feasible data for different cases, as well as the training, validation, and test for the data.

Table 1

IPOPT Durations and Model Training, Validation and Testing Durations for Different Bus Systems

Model	IPOPT Durations	Training, Validation and Testing Durations
IEEE 24 Bus System	8 Minutes	15 Seconds
IEEE 57 Bus System	13 Minutes	5 Seconds
IEEE 118 Bus System	28 Minutes	12 Seconds

In the simulations, FCNN models have been investigated as 2, 3, and 4 hidden layers to evaluate their performance across different datasets. The number of hidden layers in a neural network can significantly influence the model's ability to learn and generalize from the data. Following the analysis of the results, 3-hidden-layer model was chosen to be implemented for the final evaluations. The model with 3 hidden layers, regardless of training data, consistently produced lower loss values than that with 2 hidden layers suggesting the 3-hidden-layer model had superior learning capability and better generalization across learning datasets. It also performed comparably to the model with 4 hidden layers despite lower training and validation losses suggesting the 3-hidden-layer model was less vulnerable to overfitting and yet effectively learned complex data patterns. In the table below MSE loss values have been shown.

Table 2

FCNN Architecture Results with Different Hidden Layer Sizes

Case	MSE Loss	2 hidden layers	3 hidden layers	4 hidden layers
IEEE 24 Bus System	Training	0.010734	0.009706	0.009489
	Validation	0.010417	0.009389	0.009162
	Testing	0.010879	0.009830	0.009549
IEEE 57 Bus System	Training	0.004638	0.004086	0.004011
	Validation	0.004733	0.004210	0.004138
	Testing	0.004289	0.003836	0.003777
IEEE 118 Bus System	Training	0.012964	0.012152	0.011992
	Validition	0.013053	0.012380	0.012373
	Testing	0.013452	0.012810	0.012949

Before the training and testing the data cross-validation is performed to ensure that our model generalizes well to unseen data by testing it on multiple subsets of the dataset. By using a 7-fold cross-validation approach, we can assess the model's performance more reliably across different portions of the data. Below is the table showing the results for IEEE 24 bus system using 7-fold cross-validation.

Table 3

Cross Validation Analysis of FCNN and the Proposed Method of IEEE 24 Bus System

Method	Average MSE in Training	Average MSE in Validation	Minimum and Maximum MSE in Training	Minimum and Maximum MSE in Validation
FCNN	0.01041	0.010491	0.010070 0.010990	0.009698 0.011847
The Proposed Method	0.009891	0.009989	0.009640 0.010347	0.009295 0.011478

Below is the table showing the results for IEEE 57 bus system using 7-fold cross-validation.

Table 4

Cross Validation Analysis of FCNN and the Proposed Method of IEEE 57 Bus System

Method	Average MSE in Training	Average MSE in Validation	Minimum and Maximum MSE in Training	Minimum and Maximum MSE in Validation
FCNN	0.004770	0.004891	0.004559 0.005008	0.004457 0.005444
The Proposed Method	0.004348	0.004458	0.004156 0.004745	0.003960 0.004929

Below is the table showing the results for IEEE 118 bus system using 7-fold cross-validation.

Table 5

Cross Validation Analysis of FCNN and the Proposed Method of IEEE 118 Bus System

Method	Average MSE in Training	Average MSE in Validation	Minimum and Maximum MSE in Training	Minimum and Maximum MSE in Validation
FCNN	0.012956	0.013379	0.012539 0.013286	0.012919 0.013564
The Proposed Method	0.011601	0.012249	0.011476 0.011742	0.011609 0.012814

For IEEE 24 bus system, as depicted by the corresponding tables, the integration of wavelet transformations in the FCNN model improved the loss metrics in all three phases of training, validation, and testing. This improvement suggests that wavelet transformations could help to effectively reduce overfitting and improve the generalization capabilities of neural networks dealing with complex datasets. The predicted values and the actual values of generator parameters are shown in Figure 6 for 24 bus system.

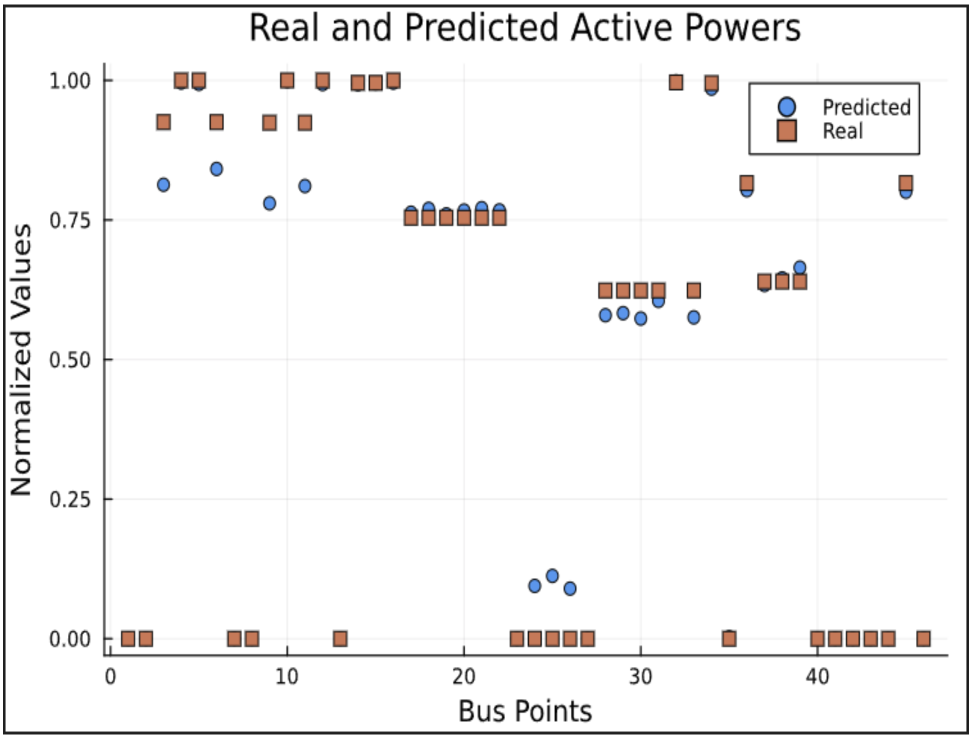

Figure 6. Predicted and Real Generator Parameters in IEEE 24 Bus System

The figure 7 below shows the predicted and actual bus voltages for the IEEE-24 bus system

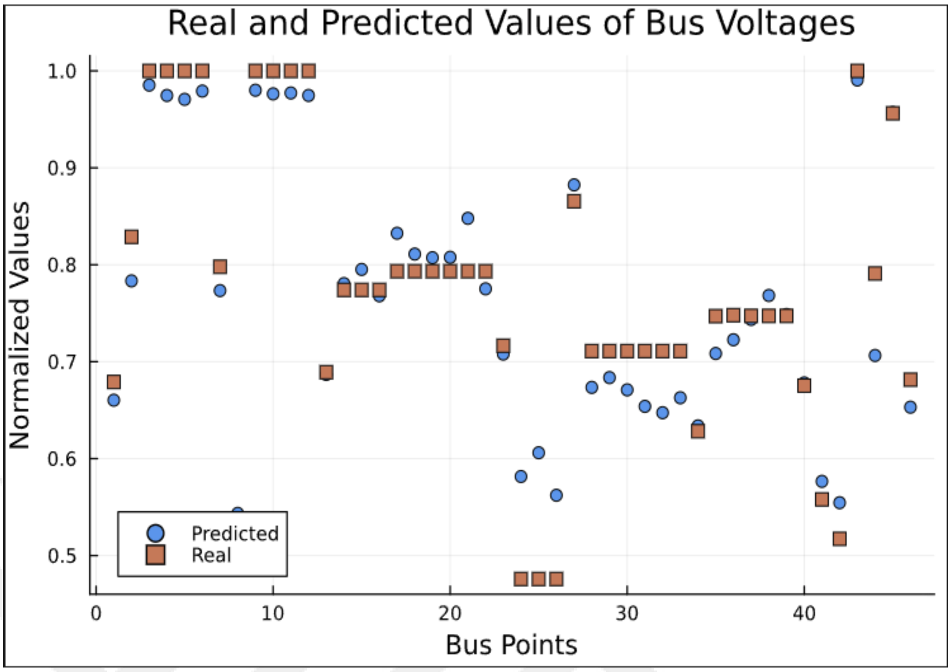

Figure 7. Predicted and Real Bus Voltages in IEEE 24 Bus System

Notice that an outlying MSE value was noted for the wavelet model; this can be a subject of further research for understanding the impact of such outliers or conditions on the model performance. The figure 8 below shows the average training loss over epochs, highlighting a steady decrease in MSE loss as training progresses, indicating improved model performance and convergence.

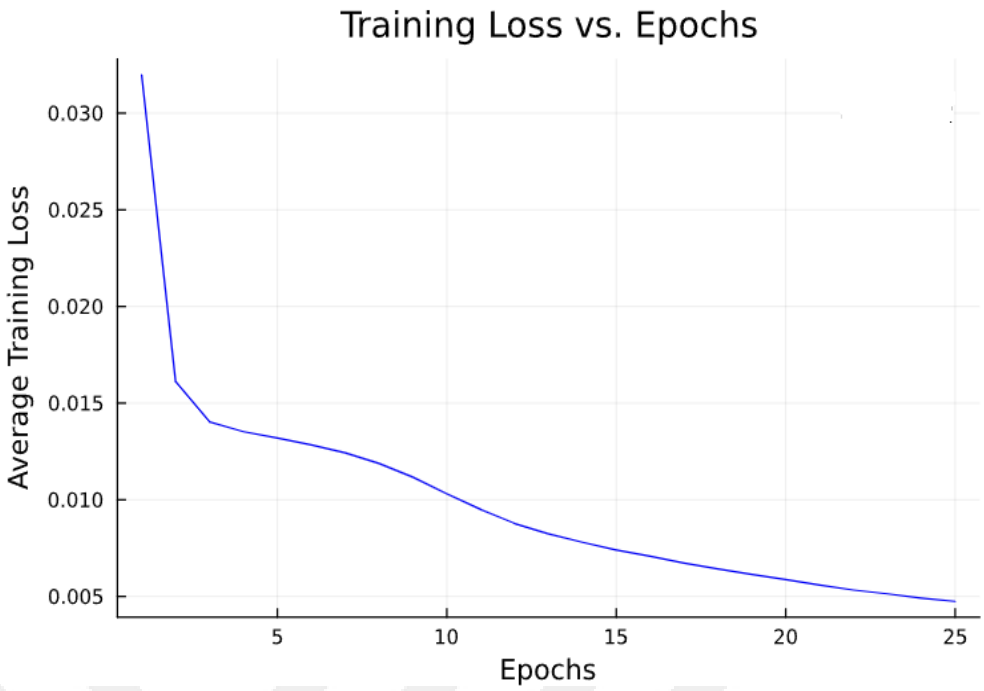

Figure 8. Model Performance of Training Process for IEEE 24 Bus System

The model performance improvements and the detailed statistical analyses are well documented in Table 6, for a view on the average losses and MSE values for each case and model configuration.

Table 6

Comparative Analysis of FCNN and the Proposed Method of IEEE 24 Bus System

Method	Average MSE in Training	Average MSE in Validation	Average MSE in Testing	Average MSE with Actual Values in Testing
FCNN	0.009706 ±0.000348	0.009389 ± 0.000532	0.009880 ± 0.000508	0.000836 ± 0.000017
The Proposed Method	0.009086 ± 0.000175	0.008744 ± 0.000145	0.009225 ± 0.000257	0.000738 ± 0.000028

The results in IEEE 57 bus system show the clear benefits of wavelet transformation, the loss values are considerably lower for the wavelet-enhanced model and the deviations are very small. The predicted values and the actual values of generator parameters are shown in Figure 9 below.

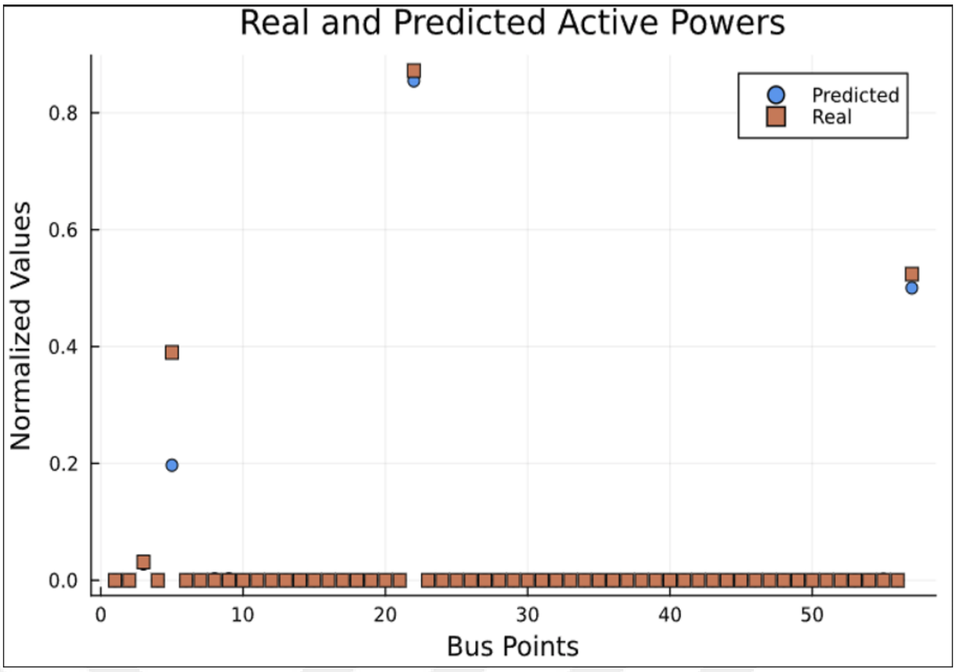

Figure 9. Predicted and Real Generator Parameters in IEEE 57 Bus System

The figure 10 below shows the predicted and actual bus voltages for the IEEE-57 bus system.

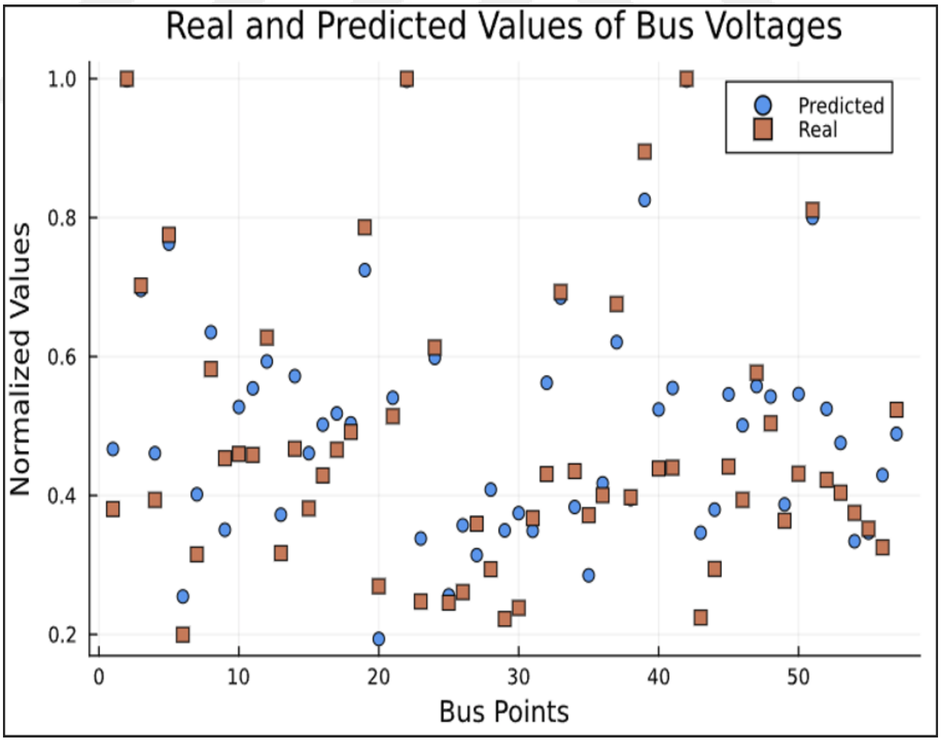

Figure 10. Predicted and Real Bus Voltages in IEEE 57 Bus System

This reflects a very stable and consistent model performance for runs with this case, reflecting the value of wavelets in capturing important features in the data necessary for achieving the highest accuracy with dynamic systems like power networks. The figure 11 below shows the average training loss over epochs, highlighting a steady decrease in MSE loss as training progresses, indicating improved model performance and convergence.

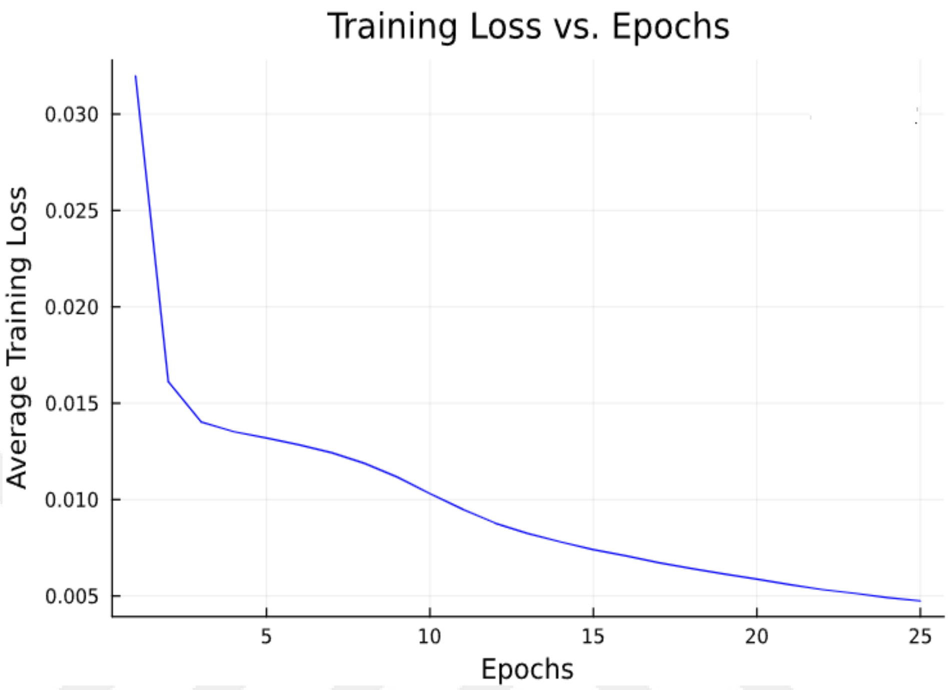

Figure 11. Model Performance of Training Process for IEEE 57 Bus System

Detailed results in the form of statistical analyses are given in Table 7, displaying the average losses and MSEs for each case and each model configuration.

Table 7

Comparative Analysis of FCNN and the Proposed Method of IEEE 57 Bus Systems

Method	Average MSE in Training	Average MSE in Validation	Average MSE in Testing	Average MSE with Actual Values in Testing
FCNN	0.004060 ± 0.000520	0.004250 ± 0.000136	0.003859 ± 0.000114	0.002536 ±0.000129
The Proposed Method	0.003674 ± 0.000519	0.003864 ± 0.000525	0.0034621 ± 0.000052	0.002283 ±0.000126

Finally, IEEE 118 bus system put our models to the test under more stringent conditions. The tables show that, while the standard FCNN model showed higher losses, the FCNN with wavelet model yielded lower average losses and at the same time kept the variability of the results tighter than the standard model. IEEE 118 bus system underlines that the wavelet-transformed model is better when it comes to controlling complex and fluctuating data inputs; it is thus a strong argument for its application in advanced neural network architectures for optimal power flow analysis. The predicted values and the actual values of active generator parameters are shown in figure 12 below.

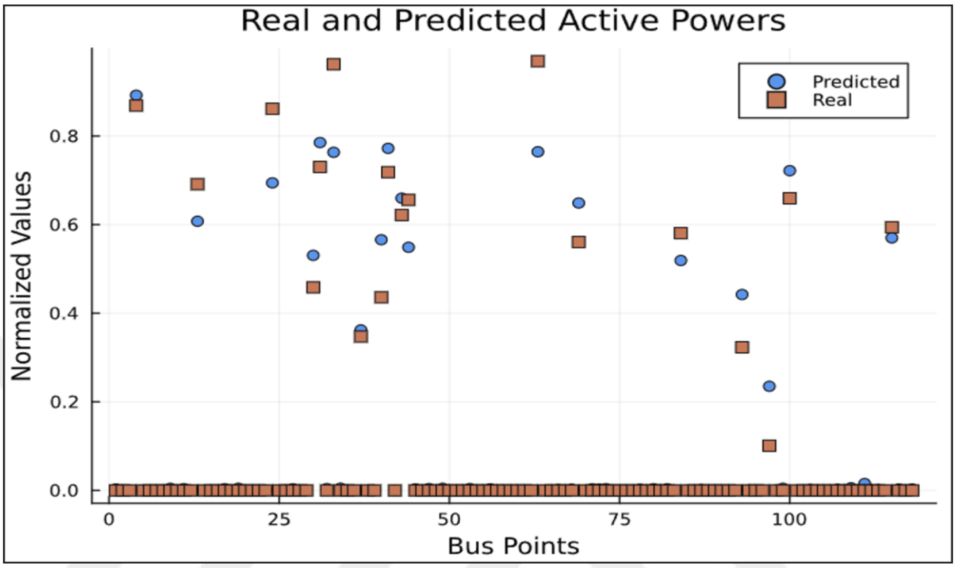

Figure 12. Predicted and Actual Bus Parameters in IEEE 118 Bus System

The figure below shows the predicted and actual bus voltages for the IEEE-118 bus system.

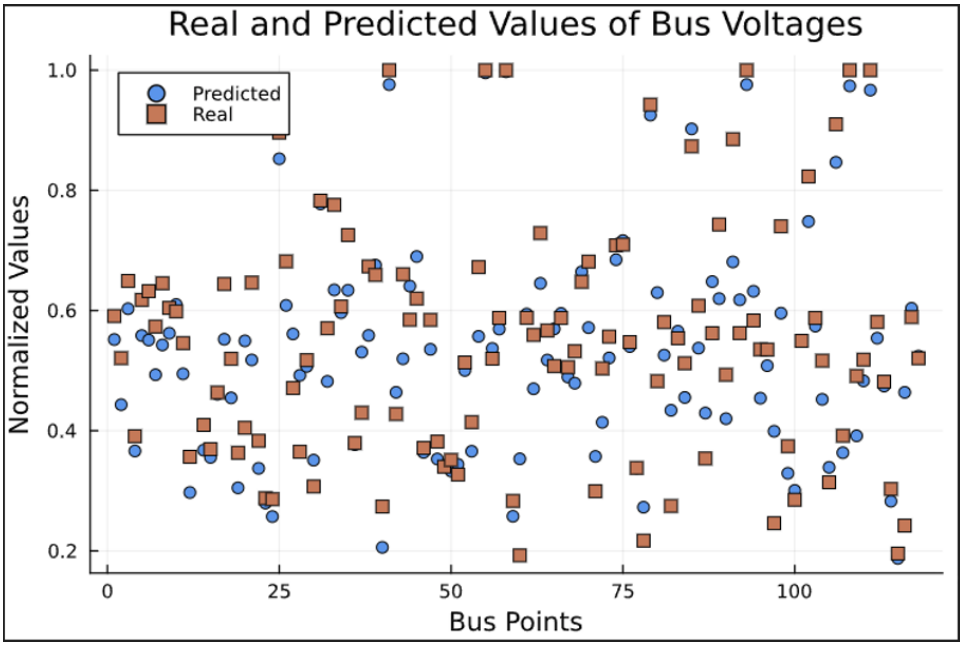

Figure 13. Predicted and Real Bus Voltages in IEEE 118 Bus System

The figure below shows the average training loss over epochs, highlighting a steady decrease in MSE loss as training progresses, indicating improved model performance and convergence.

Figure 14. Model Performance of Training Process for IEEE 118 Bus System

The improvements in model performance and the detailed statistical analyses are well-documented in Table 8 and, which represents the average losses and MSE values for all the cases and all model configurations.

Table 8

Comparative Analysis of FCNN and the Proposed Method of IEEE 118 Bus System

Method	Average MSE in Training	Average MSE in Validation	Average MSE in Testing	Average MSE with Actual Values in Testing
FCNN	0.012151 ±0.000041	0.012388 ±0.000072	0.012812 ±0.000291	0.000645 ± 0.000031
The Proposed Method	0.011148 ± 0.000016	0.011671 ± 0.000029	0.012060 ± 0.000211	0.000588 ±0.000024

Note that this study performed the calculations in MSE error using true labels, while the loss function was computed using normalized data. This distinction is important since it reflects how normalization affects the way the model is assessed in terms of performance, giving more subtle insights into the performance of the configurations of the neural network model used.

This research performed a sensitivity analysis utilizing an optimized and confirmed model for optimal power flow (OPF) in the IEEE-24 bus system. A dataset consisting of 1000 instances was utilized to accurately predict active power (P_G) and voltage (V_M) values of generators using this model. Subsequently, these predicted results along with loading values (P_D and Q_D) formed input into OPF solution. From the study findings, all obtained P_G and V_M were local optimal or global optimal in OPF hence resulting in high success rate of %100. The large success rate on the IEEE-24 bus system signifies how sensitive and dependable can be the model when it comes to solving OPF problems. A similar analysis should also be done for both IEEE-57 and IEEE-118 bus systems. With their resulting numbers from IEEE-24 being successful, if it applies to others like IEEE-57 and 118, then that would validate its general applicability across various bus systems in general OPF analysis. Such sensitivity analysis contributes significantly towards assessing and enhancing performance of models during energy systems assessment.

Overall, these results show that wavelet transformations improve the performance of FCNNs, allowing them to deal with the intricacies and variations of power system data. The fact that improvement can be seen regularly across the different cases and metrics indicates great potential for wavelet-transformed neural networks in devising strong solutions for complicated engineering problems.

Chapter 6

Conclusions

In this study, the OPF problem is solved with one of the machine learning-based methods. Considering existing literature, discrete wavelet transformation is integrated into the FCNN method as a data preprocessing step. The inclusion of wavelet transforms into the architecture of FCNN significantly increased its capabilities for dealing with large datasets, as was shown by the reduced loss metrics and Mean Squared Errors across different cases. The number of generators in the system affects the performance of the proposed method.

The discrete wavelet model continues to display superior performance by keeping the average loss lower and the results stable across the simulations. This not only points to the potential of wavelet transformation in enhancing the predictive capabilities of the neural network but also speaks to practical applicability in dynamic systems like power networks where variability and complexity of data are the rule. Further, the difference in MSE calculations with the use of true labels and the loss function with normalized data gave insight into the influence the normalization process has on model performance evaluation. This aspect serves to underline how important it is to take into consideration some techniques of data preprocessing in the development and assessment of neural network architectures.

For future studies, results from this study encourage research into the integration of advanced techniques of data processing, such as wavelet transforms, into the body of neural network-based methods to solve the OPF problem for power systems. In addition, in methods other than FCNN, this data preprocessing step can be added, and its effects on the solution can be examined in different analyses.

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