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The Application of Artificial Neural Networks to Pseudo Measurement Modeling in Distribution Networks

Scientific Students' Association Report

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Contents

Abstract

State estimation plays an important role in power system monitoring and control, which is in turn responsible for the stable, safe and efficient operation of the electricity supply system. It was originally developed and used in transmission networks, but because of the incorporation of renewable energy resources and the shift towards a smart, active network, the implementation of state estimation for distribution networks becomes a more and more pressing issue.

The realization of state estimation in distribution networks has its own unique challenges. One of the main problems is the limited number of real time measurements, since few measurements make the state estimation undependable and the system can even become unobservable. An attempt to solve this problem of lacking real time measurements is the employment of so-called pseudo measurements in order to ensure the observability of the system and a dependable estimation. Naturally, the accuracy of these generated pseudo measurements greatly affects the reliability of the state estimation.

Since the right modeling of pseudo measurements is a key ingredient for reliable state estimation, in this work I investigated possible solutions in order to achieve an accurate distribution system state estimation. For this purpose I utilized Artificial Neural Networks, which have become a widely popular tool for solving complex problems and have already found their applications in power systems as well. As a result, in this work I present an ANN based pseudo measurement generating algorithm, which not only enables the usage of state estimation in originally unobservable distribution networks, but also improves the accuracy of the pseudo measurement enhanced distribution system state estimation.

Keywords: state estimation, distribution networks, artificial neural networks, pseudo measurements

Absztrakt

Az állapotbecslés kulcsszerepet játszik az energia menedzsment rendszerek működésében, amelyek az áramellátó rendszer stabil, biztonságos és hatékony működéséért felelősek. Az állapotbecslést eredetileg az átviteli hálózatokban való alkalmazáshoz fejlesztették ki, de a megújuló energiaforrások egyre nagyobb térnyerése és az intelligens, aktív hálózat felé történő elmozdulás miatt az elosztó hálózatokban való alkalmazása egyre sürgetőbbé válik.

Az állapotbecslés megvalósításának az elosztó hálózatokban sajátos kihívásai vannak. Az egyik fő probléma a korlátozott számú valós idejű mérési adat, amely a becslést nem csak megbízhatatlanná teszi, de a rendszer maga akár megfigyelhetetlenné is válhat. A valós idejű mérések hiányának problémáját jelenleg az úgynevezett pszeudo-mérésadatok alkalmazásával igyekszenek megoldani, a rendszer megfigyelhetőségének és megbízható becslésének biztosítása érdekében. Természetesen a generált pszeudo-mérésadatok pontossága nagyban befolyásolja az állapotbecslés pontosságát.

Mivel a pszeudo-mérésadatok helyes modellezése kulcsfontosságú összetevő a megbízható állapotbecsléshez, a munkámban a pszeudo-mérésadatok modellezésének tökéletesítésén dolgoztam, a minél pontosabb elosztórendszer-állapotbecslés elérése érdekében. Ennek a célnak a megvalósításához mesterséges neurális hálózatokat alkalmaztam - amelyek széles körben elterjedtté váltak különböző komplex problémák megoldásában, és az energiarendszerekben is megtalálták már alkalmazási lehetőségeiket. Munkám eredményeként egy ANN alapú pszeudo-mérésadat generáló algoritmust mutatok be, amely nemcsak lehetővé teszi az állapotbecslést olyan elosztó hálózatokban is, amelyek eredetileg megfigyelhetetlenek voltak, hanem javítja a pszeudo-mérésadatokkal gazdagított elosztórendszer állapotbecslésének pontosságát is.

Kulcsszavak: állapotbecslés, elosztó hálózatok, mesterséges neurális hálózatok, pszeudo-mérésadatok

Chapter 1

Introduction

In our modern times, distribution systems play an increasingly important and active role in the power system network operation. It is expected that this tendency will not only continue, but it will also get stronger with the development of the smart grid. Some have even gone as far to state that "the distribution system of the future is going to be as much of a revolution to the electric energy industry as wireless telephony has been to consumer communications" [1].

With all the challenges of the "future grid" and the increased integration of Distributed Energy Resources (DERs), as well as the rise of electric vehicle charging and consumer participation, system operators need to be aware of the distribution system's exact state at all times [2]. Hence it is no wonder that a distribution system state estimation based real-time network model has become a crucial instrument in the control and protection of the distribution network [3]. Since the operation and planning philosophy of the distribution systems is different from transmission networks, the state estimation algorithms developed for the transmission network need to be adjusted in order to be implemented in distribution systems [3].

A significant problem in realizing the Distribution System State Estimation (DSSE) is the lack of real-time measurements in the distribution network. Distribution networks normally not only lack measurement redundancy, but when only using Supervisory Control and Data Acquisition (SCADA) measurements, they are highly unobservable [3].

To overcome this problem, pseudo measurements can be generated and utilized for the distribution system state estimation. A major benefit of using pseudo measurements in DSSE is that they can significantly reduce expenses which would otherwise be necessary in order to make a distribution system observable using only real measurements. Furthermore, in some cases additional problems can arise when some sensor locations prove to be either unfeasible or too expensive [4] [5]. When generating pseudo measurements, it is important to aim for good accuracy, since the better accuracy we can achieve for pseudo measurements, the higher the quality of the performed state estimation and the received output data will be [6].

In this work, I examine various pseudo measurement modelling approaches and introduce an artificial neural network based pseudo measurement generating algorithm (PMG-ANN), which I then compare to a reference model algorithm in a distribution system state estimation environment. As will be shown in detail later, my PMG-ANN algorithm made the state estimation on an otherwise unobservable network possible and also achieved significantly better accuracy results than the reference algorithm.

The continuation of this work is structured as follows: following the abstract and the introduction presented in Chapter 1, the theoretical background is summarized in Chapter 2, the practical background is discussed in Chapter 3, and the presentation of the results can be found in Chapter 4. Finally, a summary of my work is presented in Chapter 5.

The theoretical background (Chapter 2) involves state estimation (Section 2.1) and distribution system state estimation (Section 2.2), with special regard to pseudo measurement modeling (Section 2.3). In Section 2.4, I also describe in detail the theoretical background of the used Weighted Least Squares State Estimation method, and present a brief introduction to Artificial Neural Networks in Section 2.5.

In Chapter 3, I introduce the popular python programming language based *pandapower* package for power system modelling, analysis and optimization (Section 3.1), as well as the open source *SimBench* database (Section 3.2) which was utilized in my work for the modelling of networks.

Finally, Chapter 4 begins with the introduction of my pseudo measurement generating algorithm in Section 4.1, and the presentation of the pseudo measurement enhanced DSSE results can be viewed in Section 4.2.

Chapter 2

Theoretical Background

2.1 State Estimation

The power system can generally be divided into four subsystems: generation, transmission, sub-transmission and distribution system [7]. Transmission systems usually operate at high voltage levels (among other to reduce copper losses) and consist of a large number of substations which are connected by transmission lines, transformers and devices for system control and protection. At the receiving end, the transmission systems are connected to the distribution systems, which are typically operated at lower voltage levels and usually have a radial configuration [7]. The power system can be classified according to its operating conditions into so-called operating states, namely: normal, alert, restorative, emergency, and *in extremis* states [8]. A graphic representation of the operating states and the transitions between them can be seen in Figure 2.1. The goal of system operators is to keep or bring back the power system in the normal operating state.

The operation and monitoring of power systems is done by (transmission and distribution) system operators, using the energy management system. Energy management is the process which consists of monitoring, coordinating and controlling the generation, transmission and distribution of electrical energy. The core of energy management is the energy control center, which uses computer aided tools to monitor, control and optimize the generation, transmission and distribution of electrical energy [10]. In Figure 2.2, we can see a diagram about the state estimation's role in the modern energy management system.

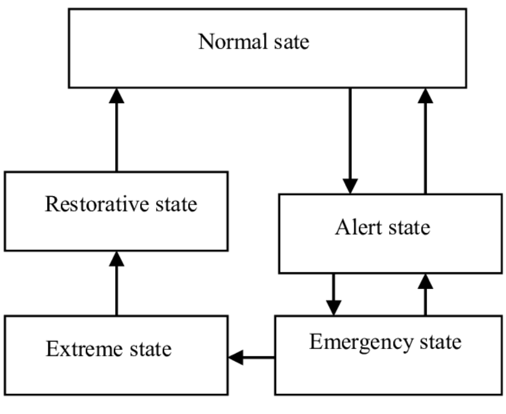

Figure 2.1: Power system operation states [9]

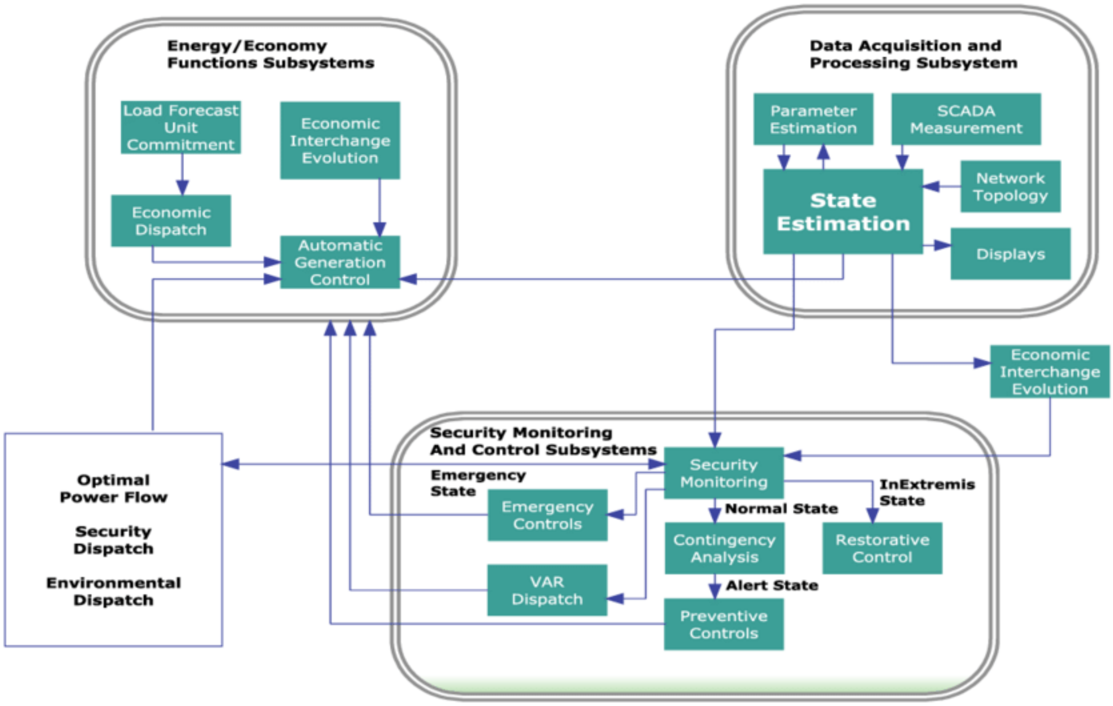

Figure 2.2: Illustration of the state estimations role in the power system management [11]

In order to be able to efficiently and precisely monitor and manage the power system, system operators must receive accurate information about the system state. This information about the operating conditions of the system can be determined – at any given instant in time – if the static state of the system is known [7]. The network model and the complex phasor voltages at every bus in the system fully specify the power system and are hence referred to as the static state of the system [7].

An important part in providing this much needed state information is played by the state estimation. The state estimator uses measurements (for instance from the SCADA system) to calculate the system states and provide the necessary information to the supervisory control system, which can then take the appropriate actions through for example the switchgears (circuit breakers) [2]. Basically, the state estimator acts like a filter between the raw measurements received from the data acquisition systems and all the applicatiosn that require the most reliable system data [7]. The conventional state estimator is based on the following four processes [2]:

1. Topology processor: Maintains a real-time database of the network model while tracking the network topology.

2. Observability analysis: It needs to verify that the measurement set is sufficient for carrying out the state estimation.

3. Bad-Data processing: It identifies gross errors in the measurements and also eliminates the bad measurements.

4. State estimation: It uses the “cleaned” measurement set and calculates the system state.

According to [2], state estimation schemes can be categorized into three types: Static State Estimation (SSE), Forecasting-Aided State Estimation (FASE) and Multiarea State Estimation (MASE).

The static state estimation is a group of computer programs which transform the received data into a reliable estimate of the transmission network structure and state, while taking into account the random metering-communication errors, uncertainties, bad data and errors in the network structure [12]. Classically, in power system state estimation the static approach (which uses a single set of measurements) based on the Weighted Least Square (WLS) method is used [13] According to the definition in [14], the static state of an electric power system is the vector of the voltage magnitudes and the angles at all network busses, and the static state estimator is used to calculate the static state vector of the power system.

Since the conventional static state estimation (SSE) relies only on a single set of measurements, all taken at one moment in time, it does not take the evolution of the state (over consecutive measurement instants) into account [2].

The process of estimating future values of a random process using the previously observed or estimated values is called priori estimation, prediction and forecasting [15]. In power systems, this ability can be incorporated with the help of the forecasting-aided state estimation (FASE) [15]. The underlying goal of the FASE is to provide a recursive update of the state estimation to be able to track the changes happening in the system [2].

The power grid is a very large network – this is why the computational complexity for a centralized state estimation would pose immense difficulties [2]. The over the years experienced large-scale incidents have also shown the need for a better real-time visibility beyond the extent which is covered by the traditional state estimator of a single county or company [16]. An alternative solution is presented by multiarea state estimation. In this scenario, the large power system is divided into smaller areas, each providing a local SE [2].

Multiarea state estimation decreases the amount of data that each state estimator must process and with the distribution of knowledge, it enhances the system robustness. The disadvantage of this method is the emerging additional communication overhead and the problem of asynchronous measurements [2].

2.2 Distribution System State Estimation

System operators – in the early 1960s – attempted to calculate the voltages at few selected busses using manually collected meter readings from geographically distributed transformers. However, due to timing, model uncertainties and measurement errors, the AC power flow equations were not solvable [17]. Shortly after (in the 1970s) the idea of applying state estimation to electric power networks emerged. The initial utilization was in transmissions networks, based on real-time SCADA measurements for the determination of the best estimate of all the generation, the loads, power flows and voltages at a particular moment in time [18]. Starting as a mathematical curiosity, over the years state estimation became the cornerstone of the modern power system control center [7].

Nowadays state estimation is mainly employed for transmission networks, but more and more research is focused on the implementation of state estimation in distribution networks. Since the operation and planning philosophy of the distribution systems is different from the transmission networks, the state estimation algorithms developed for transmission networks need to be adjusted in order to be implemented in distribution systems [2] [3]. In Figure 2.3, we can see an illustration of a transmission and a distribution network, together with the typical European voltages and loadings [19].

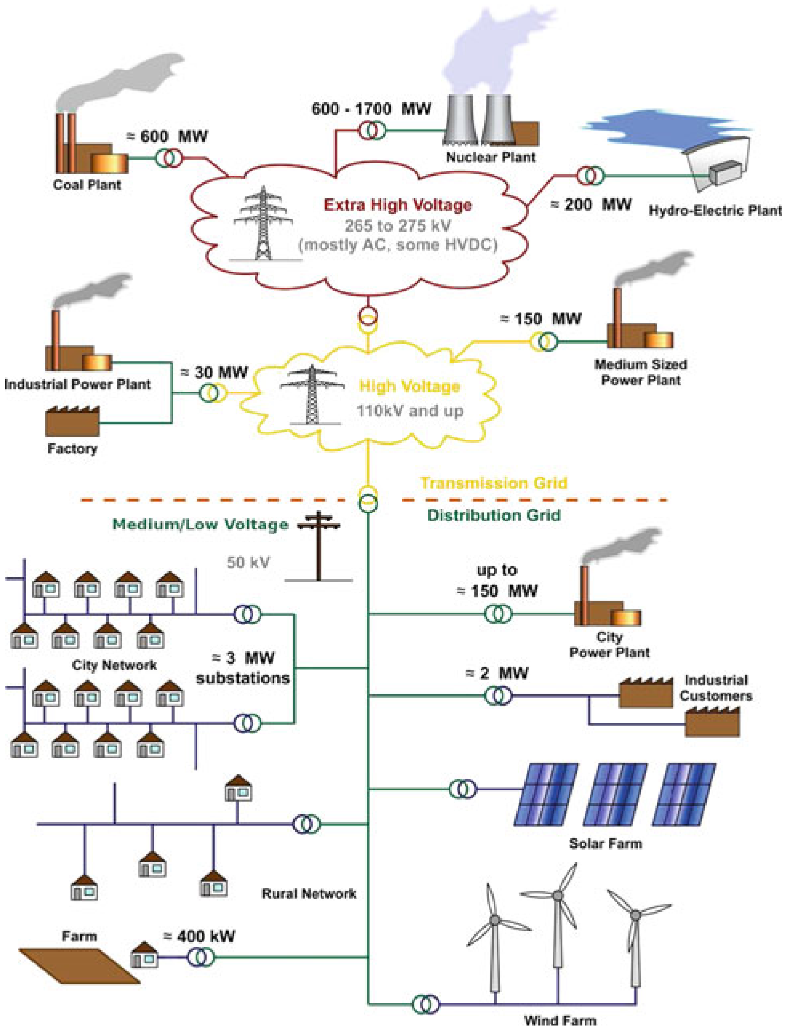

Figure 2.3: Illustration of transmission and distribution networks [19]

There are many differences between transmission and distribution networks which lead to the different requirements for state estimation, but probably the most eye catching one is the difference in network size. In transmission networks, the typical network size can range from a few hundred to a few thousand busses, while in distribution networks, the network size usually reaches up to around a thousand electrical nodes [18]. Not surprisingly, the topology of these two systems is quite different too. The topology of the transmission network is generally meshed and must be analysed as a whole, whereas the distribution networks can usually be separated for analysis into multiple islands and have a radial or three-like topology as well as an unsymmetrical construction [18] [20]. Distribution networks also have a larger resistance to reactance (R/X) ratio, and further complications in distribution systems can be caused by the unbalanced loading [20]. But perhaps the most troubling in terms of state estimation is the limited number of measurements in distribution systems. While transmission networks usually have enough measurement data so that the network is not only mathematically observable but there is also a redundancy, distribution networks normally not only lack measurement redundancy, but when only using SCADA measurements, they are also highly unobservable [3]. However, at the same time we know that state estimation is a great tool for dealing with missing, distorted and inconsistent data, so it may even be more of a necessity in distribution networks [20].

To overcome this problem, pseudo measurements can be generated and utilized for the distribution system state estimation. The better the accuracy of pseudo measurements, the higher the quality of the performed state estimation and the received output data will be [6]. More information about pseudo measurement modelling will be presented in Section 2.3.

Owing to the obvious differences between transmission and distribution networks, not all the state estimation algorithms usually used in transmission networks can be implemented for distribution systems. For example, the Weighted Least Absolute Value Estimator (WLAV) cannot be applied to distribution systems [21]. After careful consideration, I decided to use the Weighted Least Squares (WLS) estimation algorithm which is often used in transmission system state estimation, but can also be applied to distribution networks [21]. WLS are considered to be the most popular type of state estimators [3], and there are various research attempts to reduce the computational requirement of this method. The main focus of these attempts is the optimal choice of state variables, possible simplifications in order to speed up the estimation process and techniques of incorporation of heterogeneous measurements [3]. Weighted least square estimation is known to give a good accuracy even if less accurate measurements are utilized [22]. In the study of [21], it performed well in distribution systems as well.

2.3 Pseudo Measurement Modelling

Real-time voltage, current and power flow measurements can be acquired from the Distribution Automation (DA), the SCADA (Supervisory Control and Data Acquisition) systems, the IEDs (Intelligent Electronic Devices) and the PMUs (Phasor Measurement Units) [3]. Different measurement systems deliver data in different time intervals – for example, SCADA data is usually available every few seconds, while customer smart meters report data every fifteen minutes (or longer) [3]. The difference in time reference between the used measurements leads to the so-called time skew problem. To synchronize the various measurement types, a synchronization operator can be used [3].

Distribution systems have a significant lack of real-time measurements, which poses a serious obstacle for distribution system state estimation (DSSE) [3]. In distribution networks, real-time measurements are usually only found at the main substation, while line and load and even low voltage substations are not monitored [23]. As mentioned before, pseudo measurement can be created and used for state estimation to avoid this problem [3]. It is important to note that pseudo measurements are not only practical, but they are also economically advantageous – thanks to the otherwise high cost of the implementation and maintenance of modern measurement devices and their communication networks [4]. Exactly because DSSE needs so many added pseudo measurements, it is of utmost importance for them to be modelled correctly in order to represent the network's condition as realistically as possible [23].

One common category of pseudo measurement modelling methods is the statistical and probabilistic model [24]. It is common to model pseudo measurements with normal distributions – mostly to estimate the probability density functions of consumer load profiles – partly because of the compatibility with the weighted least squares (WLS) estimation (however, there were attempts to model with log-normal distributions too) [23] [24]. Another popular modelling method is the Gaussian Mixture Model (GMM) [23]. With the GMM, different types of load distributions can be represented as a convex combination of several normal distributions with their respective means and variances [23].

Some of the classical pseudo measurement generating methods also include pseudo power injection measurements at feeder busses defined as Gaussian distributions where the mean is half of the transformer rating and pseudo power injection measurements, established based on customer billing data and typical load profiles [3]. There are also attempts to model pseudo measurements using more modern tools and methods, like the load profile modelling using linear programming in [25] and testing of load allocation techniques on a fuzzy state estimator in [26].

The idea of using artificial neural networks for the modelling of pseudo measurements which can be applied to on-line estimations already appeared in 1996 in [5]. The idea to use artificial neural networks for pseudo measurement modelling has since been further explored from different angles. According to [24], machine learning based approaches for distribution system load estimation are able to further improve the accuracy of pseudo-measurements (compared to the statistical and probabilistic models) because they can utilize the available real-time data samples.

In [4], we can read about the usage of artificial neural networks for pseudo measurement modelling in low voltage distribution systems (here the GMM model is utilized with four separate ANNs). A methodology for allocating consumers' load profiles relying on probabilistic neural networks, wavelet multiresolution analysis and a FCM clustering algorithm can be found in [27]. For the reconstruction of missing SCADA measurements, offline trained autoencoders – neural networks able to store knowledge about a system in a non-linear manifold characterized by their weights – are used in [28]. In [29] a reduced model for power system state estimation is introduced, which also makes use of artificial neural networks and needs fewer measurement variables than conventional techniques. It additionally removes the need to carry out observability analysis on the system before running the state estimator [29]. One of the most recent works is a game-theoretic data-driven approach using relevance vector machines for generating weighted pseudo measurements [24]. This method relies on the parallel training of multiple machine learning units and is robust against bad data samples in the training set [24].

After exploring all these pseudo measurement modelling methods and approaches, we can conclude that pseudo measurement modelling is an important topic which provides an opportunity for many types of creative solutions and approaches. Similarly, one of the beauties of artificial neural networks lies in the fact that there is not only one good solution, but many possibilities and variations which can yield strong results. Still, the topic of pseudo measurement modelling with ANNs has been significantly better explored in transmission networks than in distribution networks, and for DSSE, there is still a lot of room for the testing of different ANN implementations, with special regard to the tuning of hyper parameters and the determination of the optimal ANN structure and output.

In my work, I created and tested a tuned multi-layer ANN based pseudo measurement generating algorithm, which generates pseudo reactive power values for the distribution system state estimation in unobservable networks, using time series data.

2.4 Weighted Least Squares State Estimation

As mentioned in Section 2.2, the Weighted Least Squares (WLS) estimation is a popular estimation algorithm which has proven to be suitable for distribution system state estimation [22]. That is why I decided to use a WLS state estimator for the testing of my artificial neural network based pseudo measurement generator (PMG-ANN).

The measurements for state estimation are usually defined according to the equation

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix} = \begin{bmatrix} h_1(x_1, x_2 \cdots, x_n) \\ h_2(x_1, x_2 \cdots, x_n) \\ \vdots \\ h_m(x_1, x_2 \cdots, x_n) \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_m \end{bmatrix} = h(x) + e \,, \tag{2.1}$$

where z is the measurement vector, x is the system state vector, $h_i(x)$ is the nonlinear function relating measurement i to the state vector x, and e is the vector of measurement errors [7].

The weighted least squares method aims to minimize the error e by minimizing the cost function described by equation 2.2, in which W is the weighting matrix (which is chosen to be the inverse of the covariance matrix of the measurement error vector) [4].

$$J(x) = [z - h(x)]^T W [z - h(x)] \tag{2.2}$$

For the minimization of the weighted difference between the calculated states and the measurements' values, the equation

$$Min\ J(x) = \left(\sum_{i=1}^{m} [z_i - h_i(x)]^T W [z_i - h_i(x)] \right) \tag{2.3}$$

is used [4].

For the equations 2.2 and 2.3 it is defined that [4]:

- $J(x)$ is the minimization function,
- x_i is is the state variables vector,
- m is the number of measurements,
- z_i is the measurement vector,
- h_i is the system of nonlinear power flow equations and
- W is the weighting matrix.

The best estimation – of the network states – is acquired when the gradient of $J(x)$ becomes zero. It has to be noted that the system power equations $h(x)$ must be solved iteratively with the equation [4]

$$\Delta x = (H^T W H)^{-1} H^T W [z - h(x)] \,. \tag{2.4}$$

In this case H is the Jacobian matrix of $h(x)$, and the equation converges when all elements of Δx are close to zero between two iterations.

2.5 Artificial Neural Networks: A Brief Introduction

Artificial Neural Networks (ANNs) are a subset of the artificial intelligence and machine learning concept. Machine learning describes the process where machines execute complex tasks (which would normally require human competence) without relying on constant instructions – but instead leaning on models and systems [30]. Artificial neural networks are complex problem solving systems inspired by the biological neural network. These system have the capability to "learn" to perform tasks or solve complex problems following a "learning process" [31].

In ANNs, the neurons of biological neural networks are realized in the form of nodes, and the connections between the inputs and outputs are weighted directed edges [31]. ANNs imitate the biological neurons, in the way that they accept different signals from the neighbouring neurons and process them. Then, depending on the outcome, they either fire an output signal or not [32]. While learning, the edge weights and the firing thresholds are changed in order to minimize the error between the output of the algorithm and the correct output [33]. Basically, this means that neural networks learn by iterating over given examples the way that we learn from our experiences [33]. In Figure 2.5, we can see a comparison of biological neural networks and artificial neural networks.

The learning process in artificial neural networks is usually categorized into three groups: supervised, unsupervised, and hybrid learning [31]. When we are talking about supervised

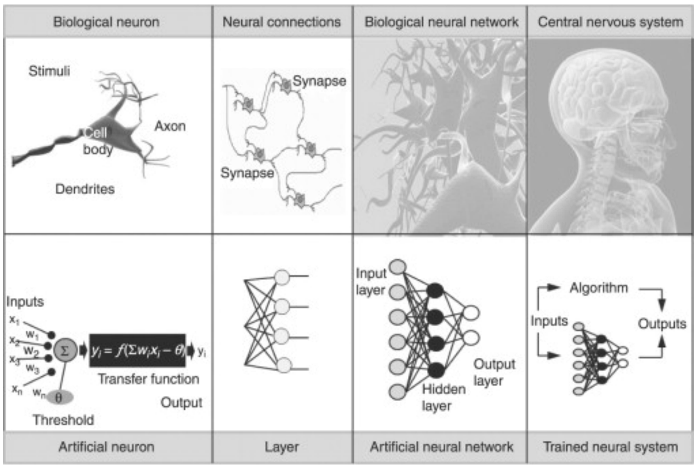

Figure 2.4: Comparison of biological neural networks and artificial neural networks [34]

learning, it means that the algorithm is first "trained" on a set of inputs and outputs, what makes it capable of predicting outputs based on inputs only [30]. Supervised learning includes regression and classification type algorithms. While regression algorithms predict a numerical value, classification algorithms predict labels [30]. Unsupervised learning relies on recognizing patterns in data (without providing solutions to the algorithm), and the hybrid category attempts to combine these two methods.

In Figure 2.4, we can see the three learning types of machine learning and their main implementations. As shown in the figure, supervised learning can for example be used for diagnostics, identity fraud detection and market forecasting, while unsupervised learning can be used for big data visualisation, targeted marketing, robot navigation and real time decision type problems [34].

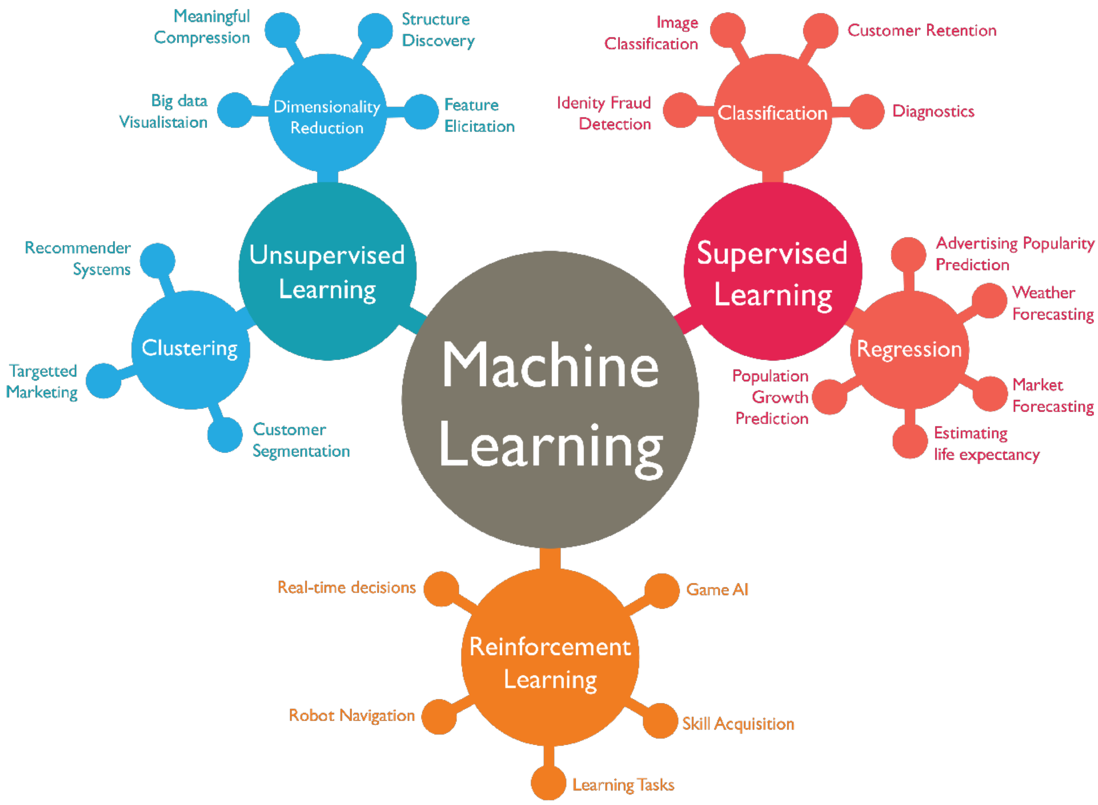

Figure 2.5: Learning process categories [35]

In my work, I used the principle of supervised learning to implement a regression algorithm, what means that the ANN received the correct answers for each input pattern during training and determined the weights so that the output (reactive power value in this case) is as close as possible to the received correct answer [31]. The results of this learning process were later tested on a testing set retained for this purpose.

Artificial neural networks have a very wide variety of applications and have many uses in a lot of fields, including power systems too. They can be used for the tuning of controllers, process identification, security assessment, load identification, load modelling, forecasting and fault diagnosis [36] [37]. And even if a topic was already studied with ANNs, there are still multiple other approaches and variations for solving the same problem because of the wide possibilities that artificial neural networks present.

Chapter 3

Practical Background

3.1 Pandapower: Power System Modelling and Analysis

Pandapower is a python based open source power system analysis tool which includes power flow, optimal power flow, state estimation, topological graph searches, and short-circuit calculations according to IEC 60909 [38]. Power systems in Europe are mostly designed symmetrically, up until the end consumer connection point in the low voltage level [38]. This is why *pandapower* was originally developed for the analysis of symmetrical distribution systems, but it has been upgraded with models for transmission systems and is now suited for the analysis of symmetrical distribution and transmission systems as well [38]. For my work, the most important *pandapower* features were the *pandapower* network model, the time series simulation module and the state estimation.

In *pandapower*, an element-based model (EBM) is used for the modelling of the electrical grid. Each element (for example lines, transformers etc.) is defined by its characteristic parameters and if it is connected to one or several busses [38]. Every element type is represented by a table that holds all parameters for a specific element and a result table which contains the results of the different analysis methods for each element [38]. This tabular data structure is based on the *pandas* library of python and is practical for expanding and customizing the data [38]. In Figure 3.1 we can see a schematic overview of the network representation in *pandapower*.

The *pandapower* time series module can simulate time based operations and is closely linked to the *pandapower* control module. When the time series simulation is executed, controllers are used to update the values of different elements for each time step [38]. In Figure 3.2, we can see the working mechanism of *pandapower's* time series loops, which is implemented in the time series module.

With the *pandapower* state estimation module, we can estimate the electrical state of the network even if we are dealing with inaccurate measurement data [38]. The used weighted least squares optimization (WLS) algorithm minimizes the weighted squared differences between measured values and the corresponding power flow equations [38].

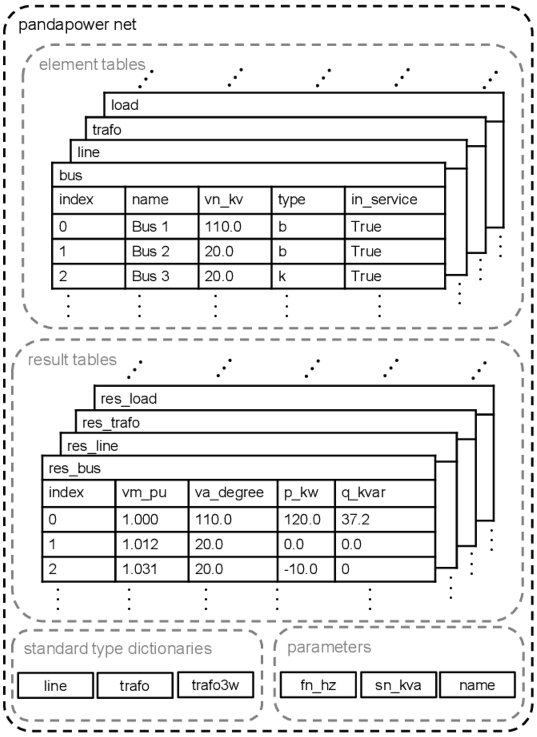

Figure 3.1: Pandapower's network representations, schematic overview [38]

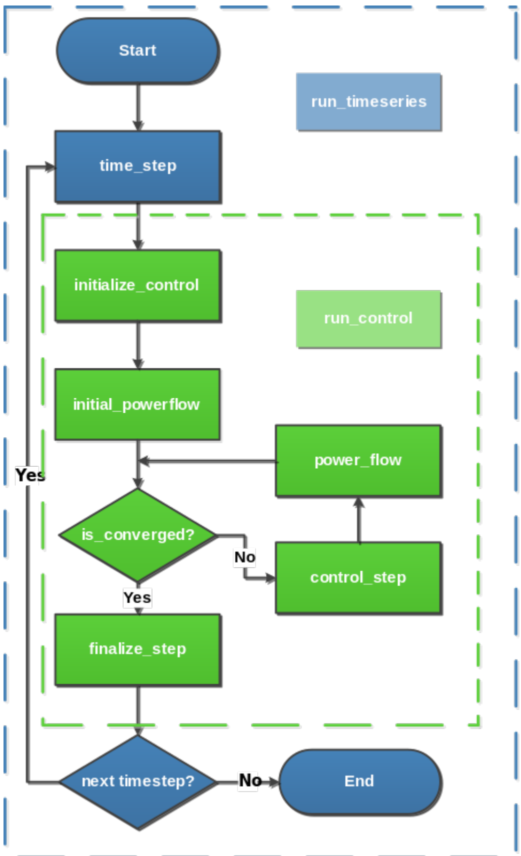

Figure 3.2: Illustration of the pandapower time series loop [39]

3.2 SimBench

SimBench is a thorough data set for low, medium, high and extra-high voltage levels, which is intended to be used for testing, publishing and comparing methods and algorithms for various use-cases, like for example grid planning, operation and simulation. It contains grids which can be combined across multiple voltage levels, but it also provides time series data for the time span of a year [40].

In *SimBench* load profiles are classified into categories according to their similarity to standard load profiles. In order to be able to represent a wide range of users and generation profiles, weather data and an agent-based simulation tool was used. The different one-year profiles contain commercial and household consumers, as well as storage and production units based on real measurements from Germany with a 15 minute resolution [41].

3.2.1 Implemented Networks

For my work I used a low voltage and a medium voltage grid from *SimBench* and the corresponding time series. I collected some basic information about the grids in Table 3.1.

Basic Grid Information		
	Low Voltage Network	Medium Voltage Network
Urbanization character	rural	rural
Rated voltage [kV]	0.4	20
No. supply points	13	92
Transformer types	1x160kVA	2x25MVA
Generation types	PV	Wind, PV, Biomass, Hydro

Table 3.1: Basic information of the used networks

The low voltage (LV) network consists of the following elements:

- 15 busses,
- 13 loads,
- 4 static generators,
- 28 switches,
- 1 external grid element,
- 13 lines,
- 1 transformer.

In Figure 3.3, we can see the graphical representation of the utilized low voltage network, plotted with the *matplotlib* and *pandapower* packages.

The medium voltage (MV) network consists of the following elements:

- 97 busses,

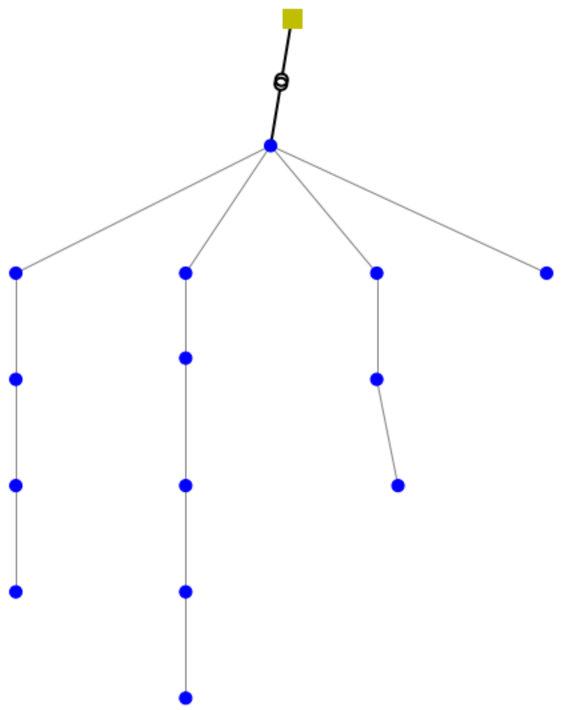

Figure 3.3: The low voltage network

- 96 loads,
- 102 static generators,
- 204 switches,
- 1 external grid element,
- 99 lines,
- 2 transformers.

In Figure 3.4, we can see the graphical representation of the utilized medium voltage network.

I chose the two networks in a way that ensures more diversity in order to be able to give a better overview of the ANN pseudo measurement generator's workings in different environments. The two networks not only have different voltage levels, but the low voltage network is also relatively simple while the medium voltage network has a significantly larger number of elements.

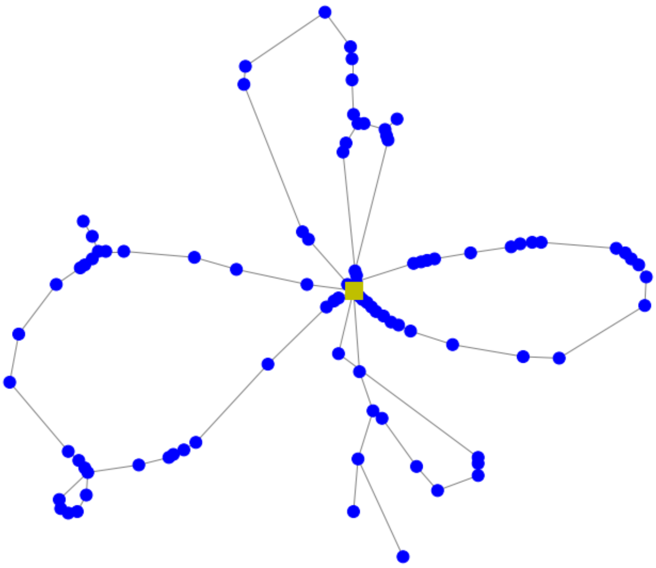

Figure 3.4: The medium voltage network

Chapter 4

Results

4.1 The Pseudo Measurement Generating ANN Algorithm

In my work I implemented a pseudo measurement generating Artificial Neural Network (PMG-ANN) algorithm which can be used for distribution system state estimations (DSSE).

Since it is crucial for system management to know the actual state of the system, it is necessary to implement state estimation in distribution systems [4]. However, the lack of real time measurements poses a big problem for the distribution system state estimation (in these networks there are only few measurement points compared to the number of nodes). A meter placement method used in transmission networks can also not be directly implemented for low voltage distribution networks because of the different network characteristics, what makes the problem even more complicated [4]. An improvement could be brought with the increased installation of smart meters, but this requires high investment costs, not just for the installation of the meters, but also for the upgrade of the communication infrastructure. Also, not all of the in distribution networks already available smart meters are equipped with communication ports, and hence they are not able to send their measurements [4]. This is why artificially created pseudo measurement could be not only a good practical, but also an economical solution for distribution system state estimation. In my work I used time series data for this purpose, which I also tested in a state estimation environment. I believe that artificial neural networks can find a good use in distribution system state estimation, especially because of the variable nature of the in distribution systems often used distributed energy resources.

4.1.1 The Data Set

With my algorithm, I generated reactive power measurements for all the busses in the network using the load and the static generator power profiles which I obtained from the *SimBench* time series database. The *SimBench* database includes various, real measurement based, one-year-profiles with a 15 minute resolution, containing commercial consumers, household consumers, storage, and production units mainly for medium voltage (MV) and low voltage (LV) networks [41]. Using the time series profiles (for an illustration see Figure 4.3) as a data source and the *pandapower ConstControl*, I calculated the bus active and reactive powers as well as the voltage absolute values and voltage angles for each time step. For the ANN training, I used *SimBench* time series profiles as inputs and the bus reactive power values as outputs. The from *SimBench* obtained time series have

35136 time steps, I used 7000 time steps for testing (approximately 20% of the data set) and the rest for the training of the ANN. I also made sure to only use data from the test set for the state estimation testing.

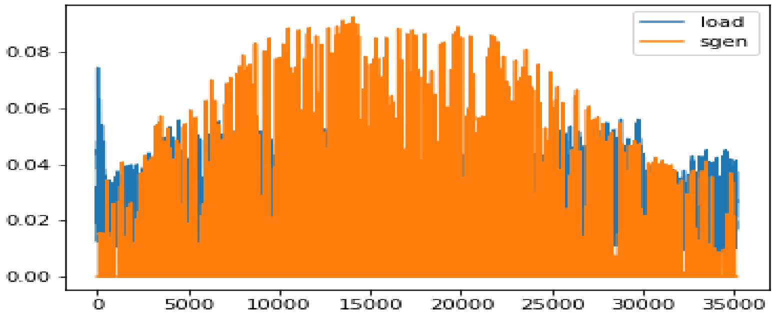

Figure 4.1: Low voltage network

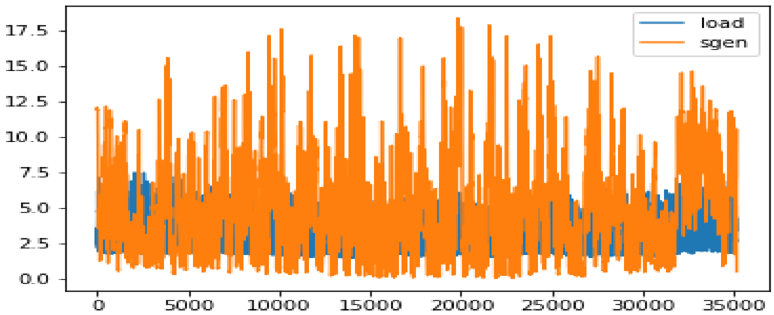

Figure 4.2: Medium voltage network

Figure 4.3: Static generator and load active power profiles

4.1.2 The PMG-ANN Algorithm Core

For the ANN algorithm, I used a multi-layer perceptron regressor from *sklearn*, which optimizes the squared-loss using a stochastic gradient descent based optimizer [42]. The MLP (Multi-Layer Perceptron) is a supervised learning algorithm which learns a function $f() : Z^m \rightarrow Y^n$ by training on a data set where m is the dimension of the input Z and n is the dimension of the output Y [42]. In Figure 4.4, we can see the structure of a multi-layer perceptron.

The *MLPRegressor* that I used implements a multi-layer perceptron which trains with backpropagation and uses the squared error as its loss function [44]. An example for an artificial neural network using backpropagation can be seen in Figure 4.5. Some of the advantages of multi-layer perceptrons are that they can learn on non-linear models and have a capability to learn models in real-time, but they require the tuning of a number of hyper parameters, like for example the number of hidden neurons and hidden layers [42].

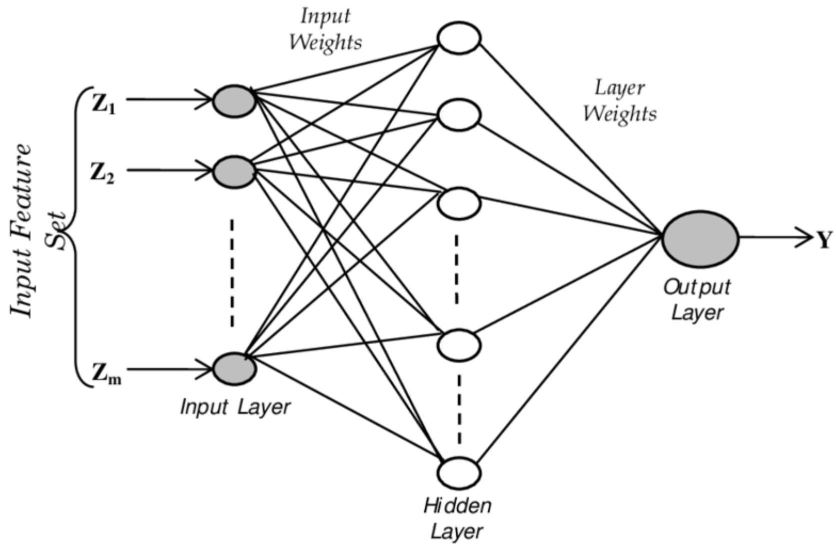

Figure 4.4: Multi-layer perceptron structure from [43]

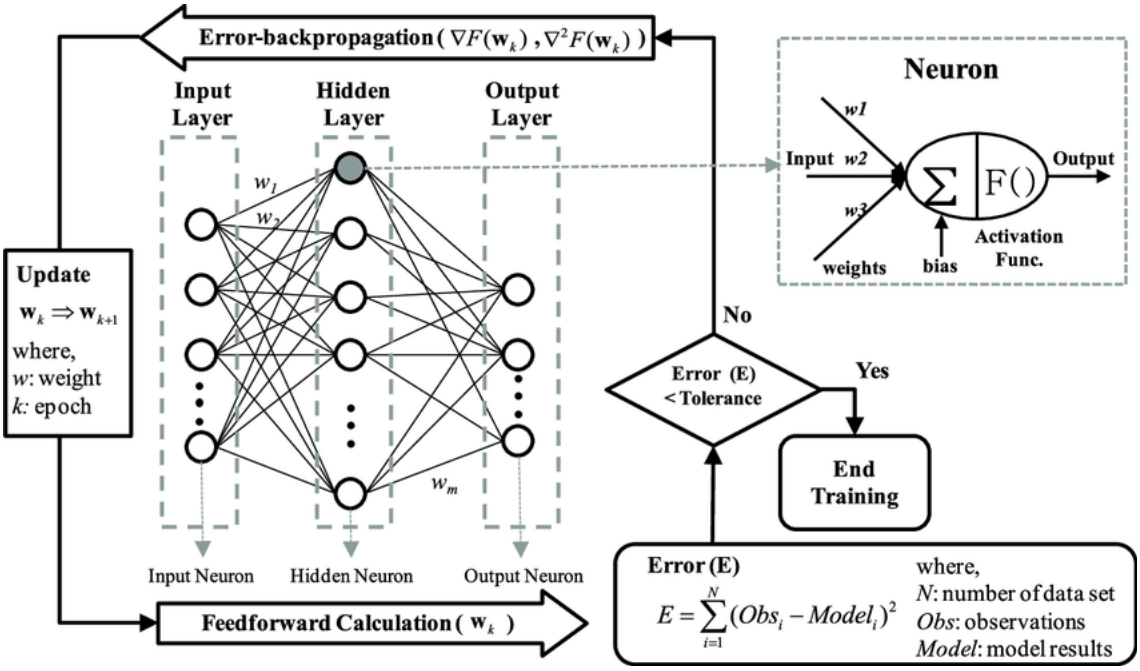

Figure 4.5: Example of a backpropagating training algorithm and a typical neuron model [45]

4.1.3 Scaling of the PMG-ANN Algorithm

While working on my algorithm, I found that scaling the data set brings significant improvements in the estimation. The *StandardScaler* from the *scikit-learn* preprocessing package proved to be the most effective in my case (with the *MinMaxScaler* for example, I could not achieve the same accuracy in results).

The *StandardScaler* standardizes the features by removing the mean and scaling to unit variance. Note that centering and scaling happen independently on each feature which is achieved by computing the relevant statistics on the samples in the training set. Mean and standard deviation are stored and used on later data [46] [44].

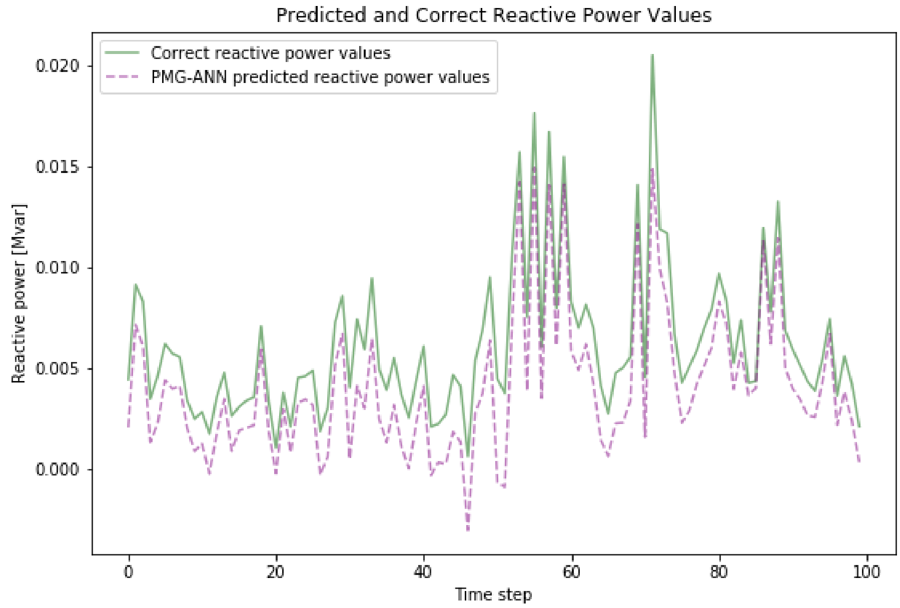

Figure 4.6: Unscaled PMG-ANN prediction for bus 35

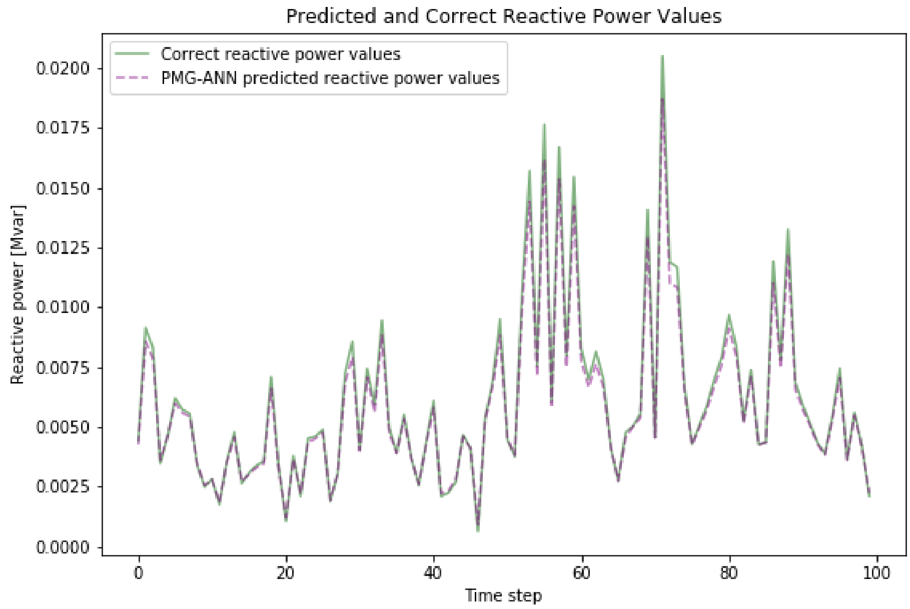

Figure 4.7: Scaled PMG-ANN prediction for bus 35

As an illustration, Figure 4.6 and Figure 4.7 contain the unscaled and scaled PMG-ANN predictions for a random bus (in the figures bus 35 is presented) in the medium voltage network.

It was interesting that in the medium voltage network the scaled PMG-ANN performed overall better (in the state estimation and the prediction on most of the busses), but the root mean square error on the testing data (the bus reactive power values prediction) was higher than that of the unscaled version. However, in the low voltage network, the scaled version performed better not just in the estimation, but also in the root mean square error of the testing set. Upon further inspection, I discovered that in the medium voltage network, the scaled PMG-ANN has a higher error on busses whose correct reactive power value is zero, what resulted in the higher root mean square error but still a better state estimation – thanks to the better accuracy on (most) of the other busses. A possible future research goal could be to improve the accuracy of the PMG-ANN's prediction for the zero reactive power valued busses.

4.1.4 Setting of the Hyper Parameters for the PMG-ANN Algorithm

The *MLPRegressor* has many hyper parameters which can be customized in order to achieve the best possible results with the algorithm [44].

One of the more important parameters is the activation function for the hidden layer. For the *MLPRegressor*, we can choose from 4 types of activation functions: identity, logistic, tanh and relu. For my problem of reactive power value prediction, the rectified linear unit function which returns $f(x) = max(0, x)$ has proven to be the best [44].

By setting the number of hidden layers and neurons in the algorithm, significant improvements can be achieved, although there is usually a trade-off between the computational speed and the accuracy of the result. I chose two hidden layers with 250 neurons each. In my case, the increase of computational time was not significant, but further increments in layer and neuron numbers yielded no notable improvements.

For my work I also changed some other parameters to force the algorithm to run longer, e.g. the tolerance of the optimization and the maximal number of iterations. This led to higher accuracy with a still feasible running time of the algorithm.

4.2 Distribution System State Estimation Using Pseudo Measurements

For the state estimation algorithm I used the weighted least squares (WLS) state estimation realized in *pandapower*. As mentioned in Section 2.2 this is a state estimation algorithm which has proven to be suitable for distribution system state estimation (more details about the WLS method can be found in Section 2.4).

To simulate the real time measurements, I used the active power data with added standard deviation for each bus and half of the bus voltage data (with added standard deviation) calculated for each time step. With this amount of data the network is unobservable for the state estimation, since the minimal number of the needed measurements is $m_{min} = 2n - k$, where n is the number of busses and k is the number of defined slack busses [38] [47]. When the created pseudo measurements (reactive power for busses) are added, the network becomes observable and the state estimation can be run without further problems.

To be able to compare the pseudo measurement generating ANN (PMG-ANN) algorithm, I created a reference algorithm (inspired by the algorithm in [4]). The implemented reference algorithm also creates reactive power measurement values, based on all available real reactive power values created from the time series (whereas the PMG-ANN had no access to the real values which are used in the examined state estimations and also had access to only 80% of the time series database while training). For the reference pseudo measurements, I drew random samples from a Gaussian (normal) distribution whose center was set to be the mean value of the real bus reactive power data set and had a standard deviation of 0.1.

4.2.1 Distribution System State State Estimation Evaluation

In Figure 4.8 and Figure 4.9, we can see a comparison of 20 separate distribution system state estimations with the created PMG-ANN and the reference algorithm for the medium and low voltage networks respectively. Note that all state estimations were performed on the data set which was not used for the PMG-ANN training.

In both figures (4.8 and 4.9) the root mean square error of the bus voltage state estimation is compared for several separate state estimations (the number of the here presented estimations was chosen to be 20 for a better overview). The root mean square error (see equation 4.1) is a verification measure which is defined as the square root of the mean of the squared differences between the corresponding elements of the forecast (z_{fi}) and the observation (z_{oi}) – in this case the difference between the distribution system state estimation attained bus voltage data and the real bus voltage data [48].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(z_{fi} - z_{oi})^2}{N}} \tag{4.1}$$

We can observe not only that in most of the cases the PMG-ANN (black colored bars) attains an estimation of higher overall accuracy, but also that the fluctuation of the estimation accuracy is significantly lower. This is a desirable trait, since we can estimate in which range the error will be. The RMSE of the PMG-ANN varies between approximately 0.0018 and 0.002, while the reference algorithm achieved values between 0.0011 and 0.00275 on the medium voltage network.

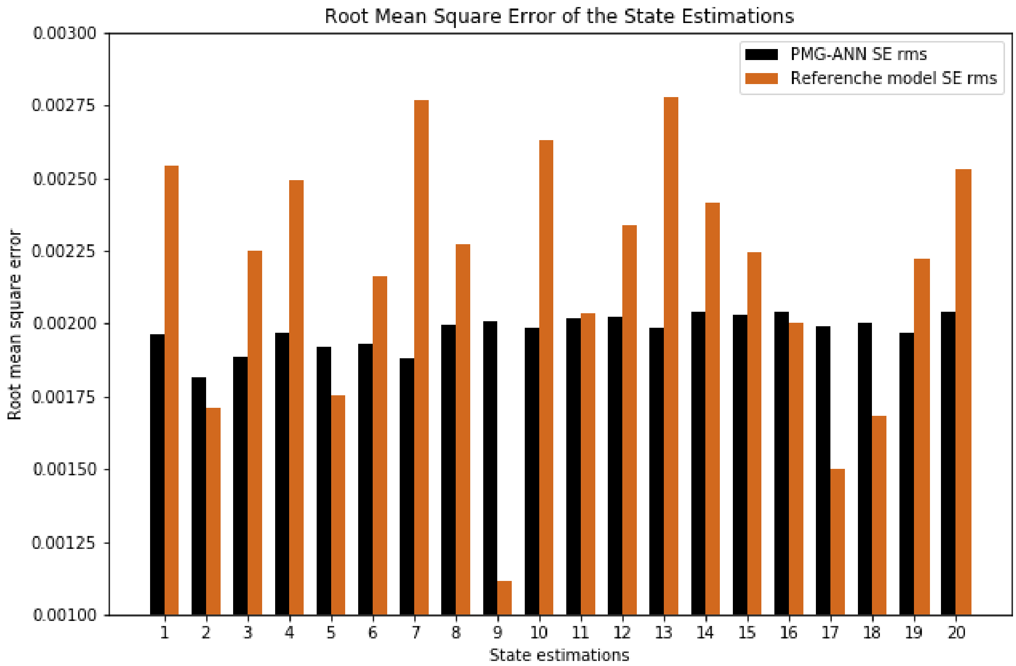

Figure 4.8: Root mean square error for 20 state estimations on the MV network

We can also observe that the PMG-ANN has noticeably better results in the low voltage network. Its score varies between 0.0005 and 0.001 (while the reference algorithm's error rises as far as 0.014). This is most probably because of the difference in network size. Of course, better results could be achieved for large and complex networks too, if there was a larger training data set.

4.2.2 Result for All Busses Separately

After the analysis of the overall performance of the DSSE with the created pseudo measurements, I examined how the state estimation performs on each bus. Since the system's static state can be fully described if we know the voltage phasors on all of the system's busses at a given point in time, I separately analyzed the bus voltage magnitudes and bus voltage angles for all busses in the low and medium voltage networks [7].

4.2.2.1 Bus Voltage Magnitude Estimation

In Figure 4.12 and Figure 4.15, we can see the differences between the bus voltage magnitudes estimated with pseudo measurements and the real voltage magnitudes. In blue we can see the differences achieved with the state estimation using the pseudo measurement generating artificial neural network (PMG-ANN) and in red the result achieved by the pseudo measurement generating reference algorithm.

In the medium voltage (MV) network, I observed that while the PMG-ANN algorithm usually achieves a lower error for the bus voltage magnitude [p.u.] the "shape" of the error curve is similar to the one achieved with the reference algorithm. Meaning that while the magnitude of the error is variable, most of the busses have a similar type of error (negative/positive) for both pseudo measurement generating algorithms. I concluded

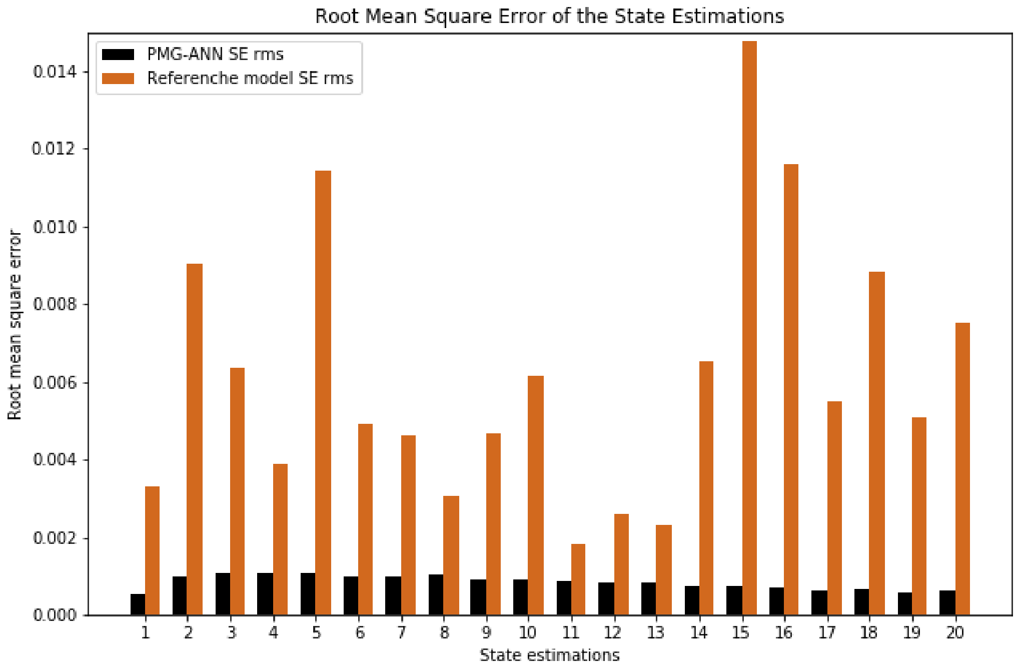

Figure 4.9: Root mean square error for 20 state estimations on the LV network

that this is connected to the measurement type, number and placement. In my work I used a very low redundancy (very low number) of measurements to simulate the lack of measurements in distribution systems. As stated in Section 4.2, I used half of the bus voltage magnitude measurements in the DSSE, and these voltage measurements were placed on the first 50% of busses. This can be very well observed in the Figure 4.12, since the first half of the busses (except the slack bus 0) have a much lower error rate. This also shows that with a higher measurement redundancy – more pseudo measurements – much better results can be achieved in the future.

In the low voltage network (Figure 4.15), we can observe that the PMG-ANN yields a much lower error rate. Since the diagrams 4.13 and 4.14 are scaled to the same values, the error of the PMG-ANN estimator almost seems to be null (except for the slack bus) and the fluctuation of the error is hard to discern. It is interesting that slack busses have a significantly larger error for both network types and both pseudo measurement generating algorithms. This is why in further research special attention should be given to the generation of accurate pseudo measurements for the slack bus in order to improve the accuracy of the overall state estimation.

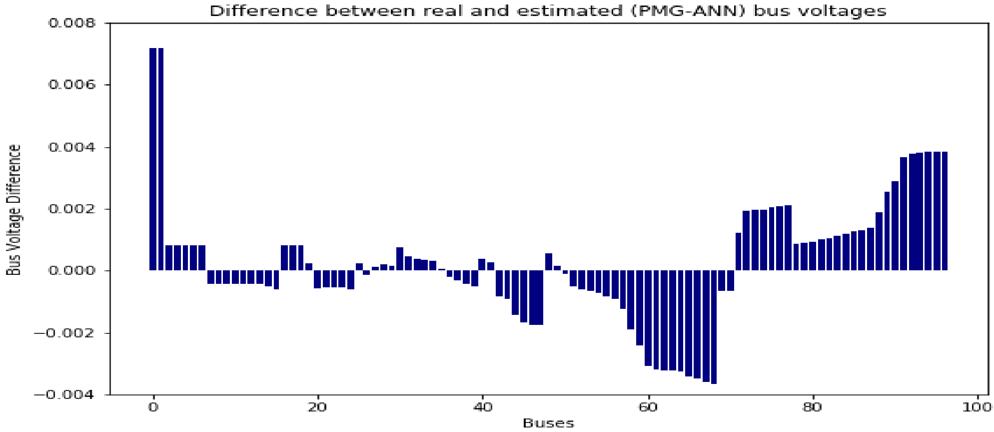

Figure 4.10: PMG-ANN bus voltage differences

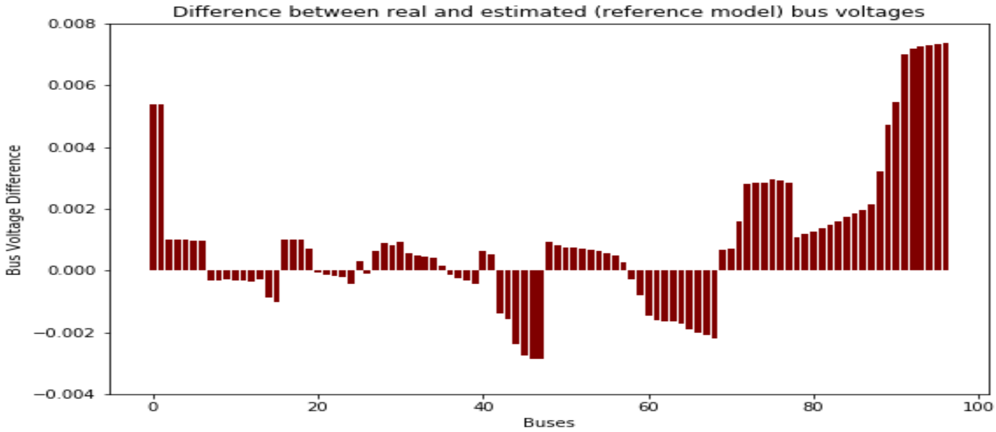

Figure 4.11: Reference model bus voltage differences

Figure 4.12: Bus voltage comparison in the MV network

4.2.2.2 Bus Voltage Angle Estimation

To compare the bus voltage angles [degrees], I ran a DSSE with the real measurements and compared the bus voltage angle results with the pseudo measurement generating algorithm estimated voltage angles.

In Figure 4.18, we can see the result for the medium voltage network. We can observe that the PMG-ANN has a better accuracy than the reference algorithm and that all PMG-ANN estimated and most of the reference algorithm estimated voltage angles have a negative error, meaning that in most cases a lower angle was estimated compared to when real measurements were used.

For the low voltage network 4.21, we can once again observe that the PMG-ANN estimator's errors are significantly smaller compared to the errors obtained with the reference algorithm.

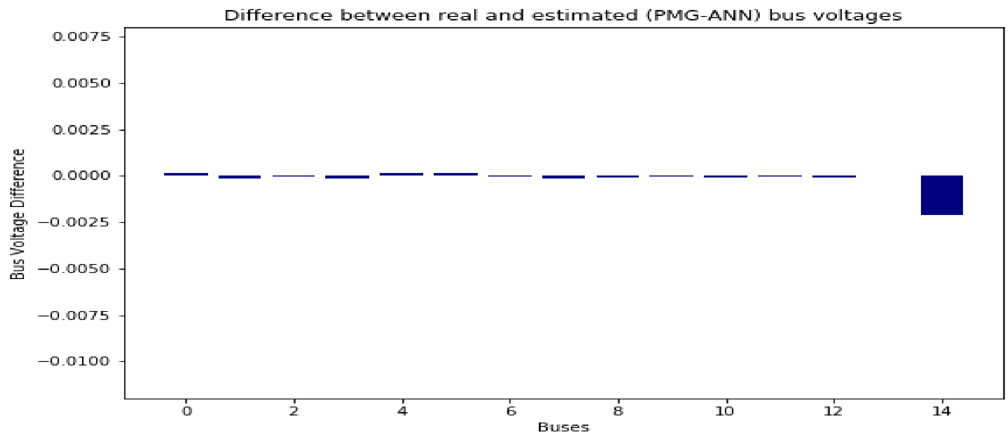

Figure 4.13: PMG-ANN bus voltage differences

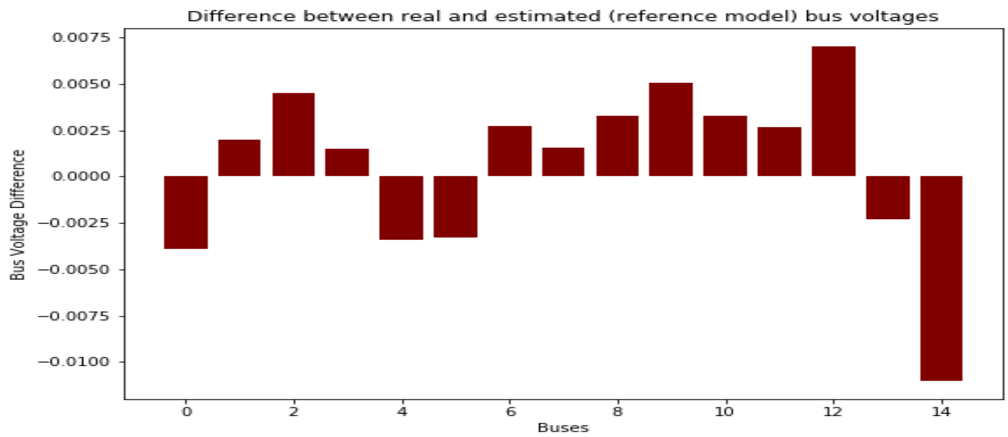

Figure 4.14: Reference model bus voltage differences

Figure 4.15: Bus voltage comparison in the LV network

4.2.3 Conclusions

After the analysis of the results of the distribution system state estimations with the artificial neural network based pseudo measurement generator and the reference model, it can be said that the PMG-ANN has successfully made the distribution network observable and achieved a high accuracy in the examined predictions. It outperformed the statistical reference model and made the static state estimation more stable.

I also identified some points which could further improve the PMG-ANN based distribution system state estimation in new works. One of these is the identification of key measurement points and the implementation of additional ANN algorithms for key and underperforming busses (slack bus, zero reactive power bus). Also, a larger training data set could significantly contribute to the betterment of results on large distribution systems.

It is also important to note that in this report only an illustration (a small fraction) of the performed DSSEs was presented, to support the description of the achieved results and the conclusions presented in Section 4.2.

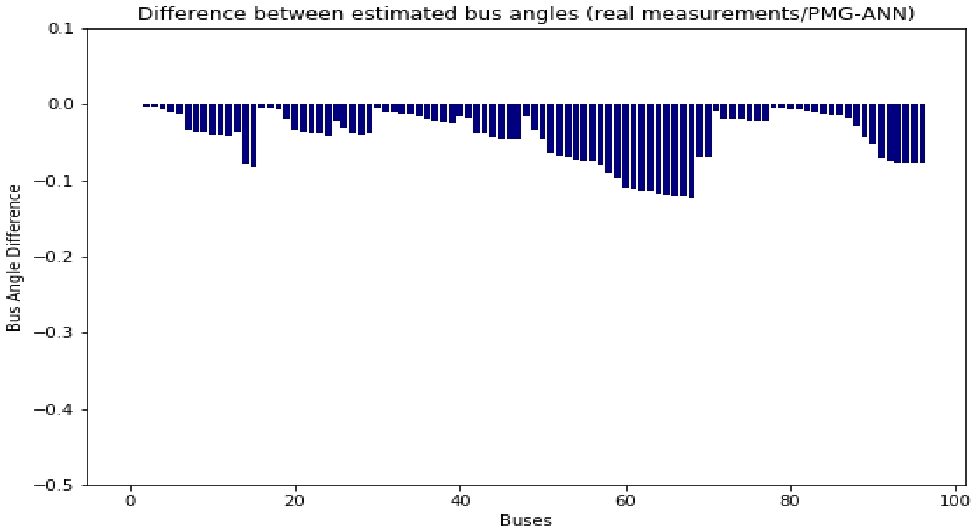

Figure 4.16: PMG-ANN voltage angle estimation differences

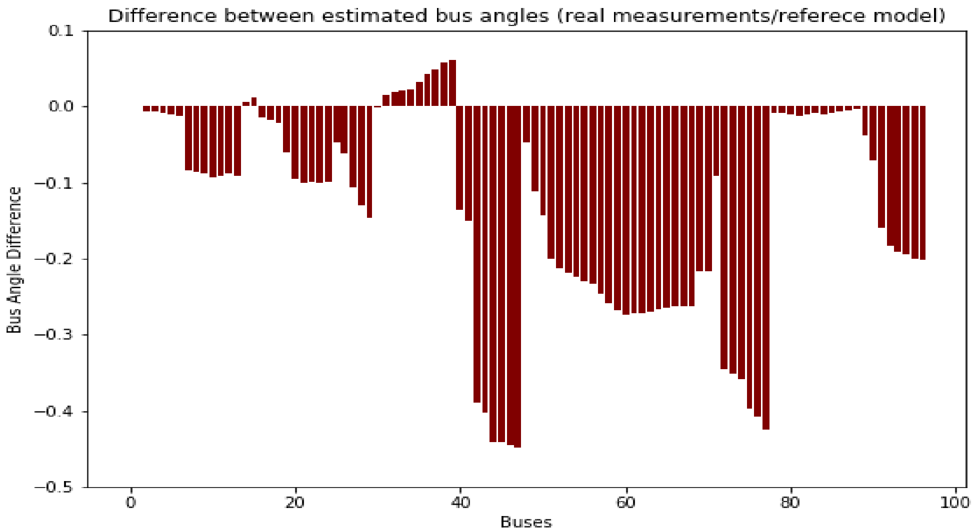

Figure 4.17: Reference model voltage angle estimation differences

Figure 4.18: Comparison of bus voltage estimation in the medium voltage network

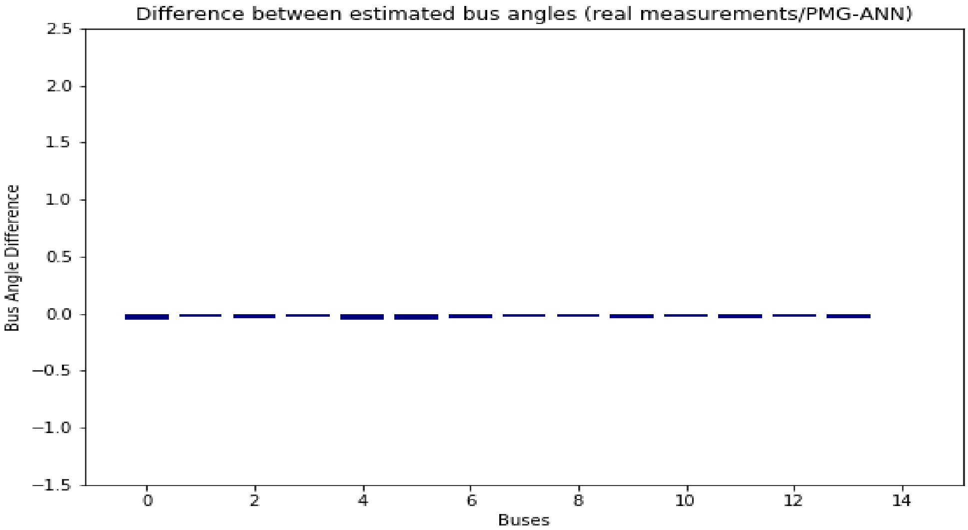

Figure 4.19: PMG-ANN voltage angle estimation differences

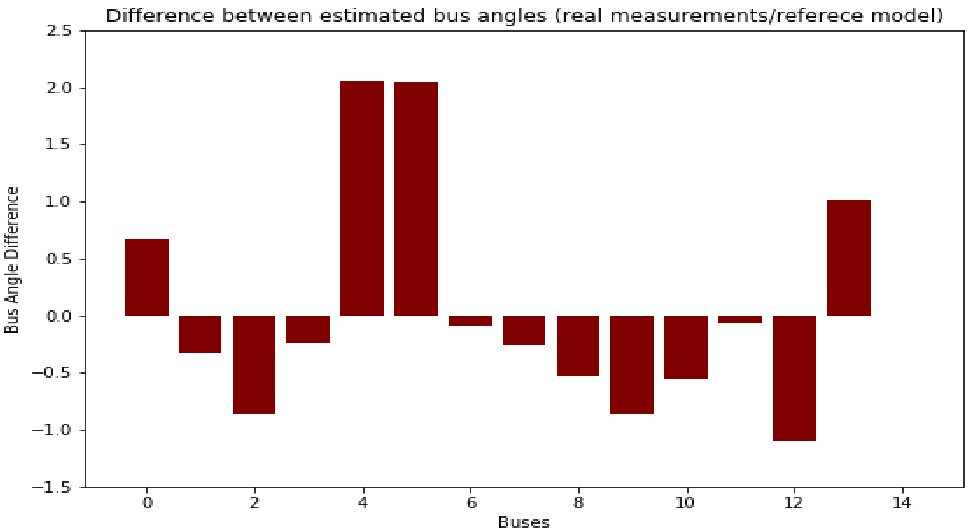

Figure 4.20: Reference model voltage angle estimation differences

Figure 4.21: Comparison of bus voltage estimation in the low voltage network

Chapter 5

Summary

In my work I studied how state estimation can be realized for distribution systems with the application of pseudo measurements. Because of the low number of real time measurements in distribution networks, pseudo measurements must be used to make the network observable and the state estimation feasible. Besides their necessity, accurate pseudo measurements can also help improve the state estimation and offer economic benefits.

I applied Artificial Neural Networks to pseudo measurement modelling in distribution networks, using the open source *SimBench* time series data and the python based power system package *pandapower*. For the modelling of the bus reactive power measurements, I implemented a tuned pseudo measurement generating artificial neural network (PMG-ANN) algorithm. I tested my algorithm on a simple low voltage and a more complex medium voltage network with a weighted least squares method based state estimation algorithm and compared it to a statistical reference pseudo measurement modelling algorithm.

The application of the PMG-ANN has demonstrated significant improvement to the accuracy of the distribution system state estimation. During the analysis of the results, some important observations could be made which can be used to further improve the PMG-ANN algorithm. In my future work, I plan to focus on finding measurement types and placements which have the most impact on the state estimation accuracy and focus on creating and/or improving their PMG-ANN generated pseudo measurement accuracy separately.

Bibliography

[1] John D Kueck and Brendan J Kirby. The distribution system of the future. *The Electricity Journal*, 16(5):78–87, 2003.

[2] Yih-Fang Huang, Stefan Werner, Jing Huang, Neelabh Kashyap, and Vijay Gupta. State estimation in electric power grids: Meeting new challenges presented by the requirements of the future grid. *IEEE Signal Processing Magazine*, 29(5):33–43, 2012.

[3] Anggoro Primadianto and Chan-Nan Lu. A review on distribution system state estimation. *IEEE Transactions on Power Systems*, 32(5):3875–3883, 2016.

[4] Ahmad Abdel-Majeed, Christoph Kattmann, Stefan Tenbohlen, and Roland Saur. Usage of artificial neural networks for pseudo measurement modeling in low voltage distribution systems. In *2014 IEEE PES General Meeting| Conference & Exposition*, pages 1–5. IEEE, 2014.

[5] Andrea Bernieri, Giovanni Betta, Consolatina Liguori, and Arturo Losi. Neural networks and pseudo-measurements for real-time monitoring of distribution systems. *IEEE transactions on instrumentation and measurement*, 45(2):645–650, 1996.

[6] Carlo Muscas, Marco Pau, Paolo Attilio Pegoraro, and Sara Sulis. Effects of measurements and pseudomeasurements correlation in distribution system state estimation. *IEEE Transactions on Instrumentation and Measurement*, 63(12):2813–2823, 2014.

[7] Ali Abur and Antonio Gomez Exposito. *Power system state estimation: theory and implementation*. CRC press, 2004.

[8] FI Izuegbunam, CB Ubah, and IO Akwukwaegbu. Dynamic security assessment of 330kv nigeria power system. *Academic Research International*, 3(1):456, 2012.

[9] Asma Meddeb, Hajer Jmii, and Souad Chebbi. Operation state classification of power system using fuzzy logic techniques. *International Journal of Process Systems Engineering*, 5(1):53–66, 2019.

[10] Samson Raja Simson, Sundar Ravichandran, Amudha Alagarsamy, and Nithiyananthan Kannan. Virtual state estimation calculator model for three phase power system network. *Journal of Energy and Power Engineering*, 10:497–503, 2016.

[11] Arpit Khandelwal, Ankush Tandon, and Akash Saxena. Power system state estimation by novel approach of kalman filter. *Indonesian Journal of Electrical Engineering and Computer Science*, 6(2):241–253, 2017.

[12] Fred C Schweppe and Edmund J Handschin. Static state estimation in electric power systems. *Proceedings of the IEEE*, 62(7):972–982, 1974.

[13] Carlos Hernández and Paul Maya-Ortiz. Comparison between wls and kalman filter method for power system static state estimation. In *2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST)*, pages 47–52. IEEE, 2015.

[14] Fred C Schweppe and J Wildes. Power system static-state estimation, part i: Exact model. *IEEE Transactions on Power Apparatus and systems*, (1):120–125, 1970.

[15] Milton Brown Do Coutto Filho and Julio Cesar Stacchini de Souza. Forecasting-aided state estimation—part i: Panorama. *IEEE Transactions on Power Systems*, 24(4):1667–1677, 2009.

[16] Antonio Gómez-Expósito, Antonio de la Villa Jaén, Catalina Gómez-Quiles, Patricia Rousseaux, and Thierry Van Cutsem. A taxonomy of multi-area state estimation methods. *Electric Power Systems Research*, 81(4):1060–1069, 2011.

[17] Gang Wang, Georgios B Giannakis, Jie Chen, and Jian Sun. Distribution system state estimation: An overview of recent developments. *Frontiers of Information Technology & Electronic Engineering*, 20(1):4–17, 2019.

[18] Roy Hoffman. Practical state estimation for electric distribution networks. In *2006 IEEE PES Power Systems Conference and Exposition*, pages 510–517. IEEE, 2006.

[19] Wikipedia. Electric power distribution — Wikipedia, the free encyclopedia. `http://en.wikipedia.org/w/index.php?title=Electric%20power%20distribution&oldid=982805153`, 2020. [Online; accessed 12-October-2020].

[20] I Dzafic, S Henselmeyer, and HT Neisius. High performance state estimation for smart grid distribution network operation. In *ISGT 2011*, pages 1–6. IEEE, 2011.

[21] R Singh, BC Pal, and RA Jabr. Choice of estimator for distribution system state estimation. *IET generation, transmission & distribution*, 3(7):666–678, 2009.

[22] Abhishek Sharma and Sachin Kumar Jain. A review and performance comparison of power system state estimation techniques. In *2018 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia)*, pages 770–775. IEEE, 2018.

[23] Efthymios Manitsas, Ravindra Singh, Bikash Pal, and Goran Strbac. Modelling of pseudo-measurements for distribution system state estimation. 2008.

[24] Kaveh Dehghanpour, Yuxuan Yuan, Zhaoyu Wang, and Fankun Bu. A game-theoretic data-driven approach for pseudo-measurement generation in distribution system state estimation. *IEEE Transactions on Smart Grid*, 10(6):5942–5951, 2019.

[25] David Gerbec, Ferdinand Gubina, and Z Toros. Actual load profiles of consumers without real time metering. In *IEEE Power Engineering Society General Meeting, 2005*, pages 2578–2582. IEEE, 2005.

[26] Vladimiro Miranda, Jorge Pereira, and João Tomé Saraiva. Load allocation in dms with a fuzzy state estimator. *IEEE Transactions on Power Systems*, 15(2):529–534, 2000.

[27] David Gerbec, Samo Gasperic, Ivan Smon, and Ferdinand Gubina. Allocation of the load profiles to consumers using probabilistic neural networks. *IEEE Transactions on Power Systems*, 20(2):548–555, 2005.

[28] Vladimiro Miranda, Jakov Krstulovic, Hrvoje Keko, Cristiano Moreira, and Jorge Pereira. Reconstructing missing data in state estimation with autoencoders. *IEEE Transactions on power systems*, 27(2):604–611, 2011.

[29] Amamihe Onwuachumba, Yunhui Wu, and Mohamad Musavi. Reduced model for power system state estimation using artificial neural networks. In *2013 IEEE Green Technologies Conference (GreenTech)*, pages 407–413. IEEE, 2013.

[30] Stuart J Russell and Peter Norvig. *Artificial intelligence: a modern approach.* Malaysia; Pearson Education Limited,, 2016.

[31] Anil K Jain, Jianchang Mao, and K Moidin Mohiuddin. Artificial neural networks: A tutorial. *Computer*, 29(3):31–44, 1996.

[32] Jure Zupan. Introduction to artificial neural network (ann) methods: what they are and how to use them. *Acta Chimica Slovenica*, 41:327–327, 1994.

[33] Imad A Basheer and Maha Hajmeer. Artificial neural networks: fundamentals, computing, design, and application. *Journal of microbiological methods*, 43(1):3–31, 2000.

[34] Mariana Landin and Raymond C Rowe. Artificial neural networks technology to model, understand, and optimize drug formulations. In *Formulation Tools for Pharmaceutical Development*, pages 7–37. Elsevier, 2013.

[35] Sanchit Tanwar . Introduction to machine learning and deep learning (2020. 10. 20.). `https://medium.com/@sanchittanwar75/introduction-to-machine-learning-and-deep-learning-bd25b792e488`.

[36] Rafael E Bourguet and Panos J Antsaklis. Artificial neural networks in electric power industry. *ISIS*, 94:007, 1994.

[37] M Tarafdar Haque and AM Kashtiban. Application of neural networks in power systems; a review. *International Journal of Energy and Power Engineering*, 1(6):897–901, 2007.

[38] Leon Thurner, Alexander Scheidler, Florian Schäfer, Jan-Hendrik Menke, Julian Dollichon, Friederike Meier, Steffen Meinecke, and Martin Braun. pandapower—an open-source python tool for convenient modeling, analysis, and optimization of electric power systems. *IEEE Transactions on Power Systems*, 33(6):6510–6521, 2018.

[39] pandapower. Timeseries module overview (2020. 10. 20.). `https://pandapower.readthedocs.io/en/v2.2.2/timeseries/timeseries_loop.html#timeseriesloop`.

[40] Steffen Meinecke, Džanan Sarajlić, Simon Ruben Drauz, Annika Klettke, Lars-Peter Lauven, Christian Rehtanz, Albert Moser, and Martin Braun. Simbench—a benchmark dataset of electric power systems to compare innovative solutions based on power flow analysis. *Energies*, 13(12):3290, June 2020.

[41] Christian Spalthoff, Dzanan Sarajlic, Chris Kittl, Simon Drauz, Tanja Kneiske, Christian Rehtanz, and Martin Braun. Simbench: Open source time series of power load, storage and generation for the simulation of electrical distribution grids. In *International ETG-Congress 2019; ETG Symposium*, pages 1–6. VDE, 2019.

[42] scikit-learn. Neural network models (supervised) (2020. 10. 18.). `https://scikit-learn.org/stable/modules/neural_networks_supervised.html`.

[43] S Kalyani and K Shanti Swarup. Study of neural network models for security assessment in power systems. *International Journal of Research and Reviews in Applied Sciences*, 1(2):104–117, 2009.

[44] Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, 12:2825–2830, 2011.

[45] Sung Eun Kim and Il Won Seo. Artificial neural network ensemble modeling with conjunctive data clustering for water quality prediction in rivers. *Journal of Hydro-Environment Research*, 9(3):325–339, 2015.

[46] scikit-learn. Standardscaler (2020. 10. 18.). `https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html`.

[47] pandapower. State estimation (2020. 10. 19.). `https://pandapower.readthedocs.io/en/v2.2.1/estimation.html`.

[48] Anthony G Barnston. Correspondence among the correlation, rmse, and heidke forecast verification measures; refinement of the heidke score. *Weather and Forecasting*, 7(4):699–709, 1992.