Improving the data-driven transient stability assessment of power systems

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Abstract

Power systems are undergoing major transformations due to the fast-paced grid connection of renewable sources such as wind and solar, replacing fossil fuel and nuclear power plants. This diversifies the range of load scenarios and generation schedules. Moreover, the characteristic of these resources is different from traditional plants which subsequently changes the dynamics of the power systems. For instance, the rotating part of synchronous generators in the traditional plants inherently provide inertia that instantaneously decelerates and damps a disturbance while this is not the case for the majority of wind and solar farms. Consequently, excessive integration of renewable resources can lead to reduction of inertia, which brings new stability challenges. Power system operators traditionally perform different types of security assessments through performing time-domain simulations for a number of critical disturbances to determine whether the system would become unstable, or returns to a new, stable equilibrium state. However, the computation intensity hinders the time-domain simulations from being employed for a large number of operational and contingency scenarios in future grids with high penetration of renewables.

Recently, the application of machine learning approaches have shown promising capability to augment the situational awareness regarding anticipated but not yet occurred contingencies through accelerating transient stability assessments (TSA). These approaches enable accurate TSAs over a wide range of operational instances and contingency scenarios by providing fast and reliable solutions. They predict the stability of power systems in milliseconds, at least a thousand times faster than time-domain simulations.

In this thesis, we introduce novel ideas to include the understanding of power system dynamics in the data collection process to improve the reliability, versatility, and robustness of the machine learning models to predict the transient stability of the power systems. We leverage the domain knowledge on how the disturbance effect will propagate from the fault location to the rest of the network, which provides crucial information regarding the unstable region of operation. Consequently, a novel data collection strategy is introduced that enables the use of conventional machine learning models in an instance transfer learning framework. Therefore, the proposed method does not solely rely on the collected data but uses insights from the system as well. Our studies show that this trained model can accurately predict the stability of the operational scenarios while reducing the risk of false prediction of unstable instances, compared to standard machine learning models.

Moreover, the general assumption of the data-driven TSA models in the literature is that the topology of the network invariably remains the same. In practice, however, the topology of power systems frequently changes, e.g. when new transmission lines are connected or an outage of an existing line occurs. This effectively compromises the performance of the trained classification models. To improve the robustness of trained the models under topology changes, a novel neural network-based transfer learning framework is introduced. We take advantage of a deep residual neural network structure which is pre-trained to predict the stability of a contingency in a module and re-train a second module to predict the stability of the system for the same contingency while the topology of the system changes. Our experiments demonstrate a significant improvement of performance in terms of computational effort and accuracy, compared to the standard deep learning framework.

Declaration

This thesis is an original work of my research and contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

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Publications during enrolment

Significant parts of this thesis are based on the following publications:

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Journal articles

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Abbreviations

ACOPF	**AC** **O**ptimal **P**ower **F**low
AEMO	**A**ustralian **E**nergy **M**arket **O**perator
AI	**A**rtificial **I**ntelligence
ANN	**A**rtificial **N**eural **N**etwork
CNN	**C**onvolutional **N**eural **N**etwork
CSIRO	**C**ommonwealth **S**cience and **I**ndustrial **R**esearch **O**rganisation
CCT	**C**ritical **C**learing **T**ime
DAE	**Differential**-**A**lgebraic **E**quation
DCOPF	**DC** **O**ptimal **P**ower **F**low
DER	**D**istributed **E**nergy **R**esources
DL	**D**eep **L**earning
EMT	**E**lectro**M**agnetic **T**ransient
ESS	**E**nergy **S**torage **S**ystem
FAA	**F**ault **A**ffected **A**rea
GFL	**G**rid **F**ollowing **I**nverter
GFM	**G**rid **F**orming **I**nverter
GTEP	**G**eneration **T**ransmission **E**xpansion **P**lanning
IBR	**I**nverter **B**ased **R**esource
NLP	**N**atural **L**anguage **P**rocessing
NN	**N**eural **N**etwork
OPF	**O**ptimal **P**ower **F**low
PLL	**P**hase **L**ocked **L**oop
PMU	**P**hase **M**easurement **U**nit
PV	**P**hoto**V**oltaics
RMS	**R**oot-**M**ean **S**quare

ROCOF	**R**ate **O**f **C**hange **O**f **F**requency
RRA	**R**elative **R**otor **A**ngle
SCR	**S**hort **C**ircuit **R**atio
SIME	**SI**ngle **M**achine **E**quivalent
TSA	**T**ransient **S**tability **A**ssessment

Chapter 1

Introduction

Electric power systems are networks of electrical components that supply, transfer, and distribute electricity. Traditionally, enormous fossil fuel or nuclear power plants were universally driven by synchronous generators and located at some distance from consumers. This power was transferred to transmission lines through step-up transformers and then delivered to residential, commercial, as well as industrial consumers through step-down transformers and distribution feeders. Fig. 1.1 visualises the high-level structure of the traditional power systems. The electricity industry, from generators to the distribution feeders, were mainly owned and solely controlled and operated by government organisations with the purpose of maximising benefits through minimising the operational loss. Moreover, the electric industry followed a consistent set of trends. Almost every year, the industry installed large power plants with increased efficiency. As a result production costs gradually fell, and the price of electricity declined. The utility companies would leave cost savings to customers where the price of electricity was fixed for 24 hours of the day, and every day of every month of each year. The only element of trivial uncertainty was the demand for electricity which had a well-predictable pattern with well-approximated minimums and maximums that were usually a function of seasons.

Modern power systems, however, have undergone a major transformation driven by the increasing penetration of inverter based resources (IBR) such as wind and solar farms, the decentralization and relocation of power generation from transmission to distribution such as rooftop photovoltaic (PV), and the use of energy storage systems.

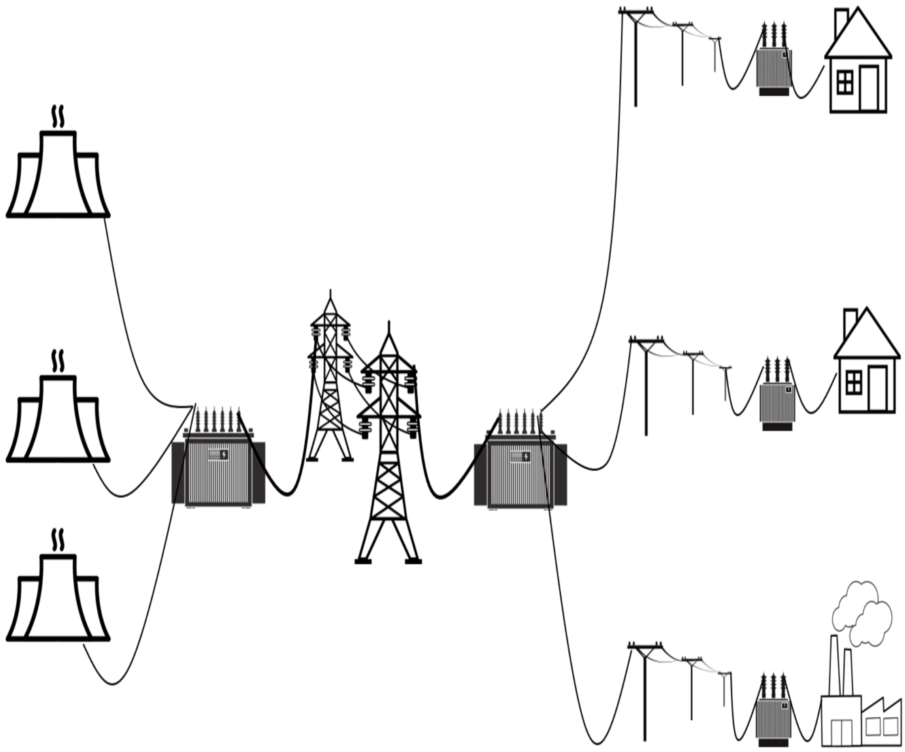

Figure 1.1: The structure of traditional power systems.

These major changes are shaping the power networks around the globe more or less in the same way, although the pace of changes could be different among countries. Fig. 1.2 visualises a high-level structure of modern power systems. It highlights the role of inverter based resources as well as storage systems in the modern power systems, compared to traditional power systems. Although these transformations are necessary for a sustainable and green future, they have significantly altered the characteristics of power systems and brought many new engineering challenges.

One challenge is the intermittent output of renewable sources, which is determined by meteorological conditions, while in contrast fossil fuel power plants can adjust their power output. The fluctuations in the output of the renewable generators leads to uncertainty in generation capacity and meeting the demand.

A further challenge comes from the extensive installation of inverter based resources (and particularly solar panels). These resources have drastically diversified the daily load patterns. In the middle of the day, when the residential load is minimum, the PV output is maximal. This consequently causes a rapid and extensive declining of minimum demand in the middle of the day. This phenomenon is referred to as the duck

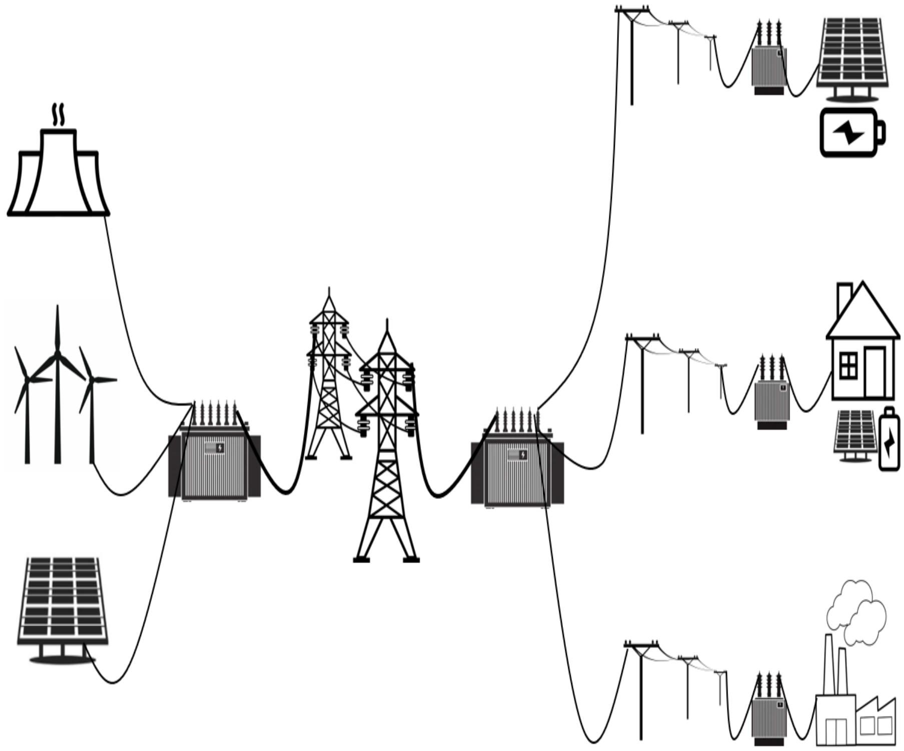

FIGURE 1.2: The structure of modern power systems.

curve [5] and leads to a wider range of load and generation scenarios during the day and introduces planning and supply challenges.

To summarise, the increasing share of inverter based resources in the generation portfolio of modern power systems along with the evolution of electricity markets are the major contributors to fundamental changes in generation patterns and power transfers. These changes significantly alter the statics and dynamics of power systems. Improving the statics and dynamics of power systems is the core theme of this research project. We will further discuss the consequence of these changes in Section 2.2.2 of Chapter 2.

1.1 Motivation

The evolution from a traditional to a modern power system includes a wide range of changes. The following examples will shed light on the changes that alter the statics and dynamics of power systems. These alterations can endanger the stability of power systems, that is the continuance of intact operation of the systems. This study highlights some of the corresponding challenges and the shortcomings of the current tools and techniques to manage them. In this section, we investigate whether the existing tools are still considered suitable for transition to a clean future power system. The need for this direction of enquiry is also acknowledged by power system operators across the world, such as Australian Energy Market Operator (AEMO) [6].

1.1.1 Stability assessment

To ensure the unimpaired operation of a power system, its performance under a particular set of conditions is studied using a time-domain simulation [7]. These studies are referred to as stability assessments, in which simulation software checks stability indices of interest (such as relative rotor angle of generators, voltage, frequency) and signal when they exceed a certain limit. In short, stability assessment includes monitoring and early detection of instability. For more information on stability assessment please refer to Chapter 2.

Traditionally, these analyses are carried out on a set of preselected $N-1$ contingencies, e.g. a lightning strikes one phase of a transmission line, and a limited number of $N-2$ contingencies, e.g. two conductors of a transmission line make contact with each other. Moreover, the hazardous effect of $N-3$ contingencies (and above) are ignored as they have a very low probability of occurrence [8].

The traditional methods of stability management will soon reach their limits in modern power systems for the following reasons: Firstly, renewable sources are naturally intermittent and the combinations of load, weather, and electricity market conditions are unlimited. This will affect the steady-state parameters, such as the dispatch of different types of generators (generation portfolio), power flows, and voltage profiles, as well as dynamic parameters of power systems, such as rotor angle of synchronous generators. Hence, base case and contingency case scenarios significantly vary on a minute-to-minute basis, and the number of required stability assessment scenarios significantly increases [9].

Moreover, modern power systems are pushed to operate closer to their stability limits more than ever. The main factors contributing to this fragility are listed as follows[1] according to [10].

[1]The issues arising from different inverter based resources (IBR) are further discussed in Section 2.4 of Chapter 2.

- **Low inertia:** Inertia results from governors' rotating mass of synchronous generators. Inertia levels can be reduced with high renewable penetration levels. This can challenge maintaining the synchronism of generators after a disturbance and cause transient stability concerns. In a power system, inertia and frequency are closely related and lower levels of inertia increase the susceptibility of the power system to rapid changes in frequency. More details on frequency stability can be found in Chapter 2 [11].

  Immediately after a contingency event that leads to a supply-demand mismatch, power system frequency changes. For a very short time following a contingency event, the rate of change of frequency (RoCoF) largely depends on the power system conditions prior to the contingency event [11], and is derived from the swing equation[2], during contingencies.

- **Low system strength level:** System strength is the ability of the power system to maintain the voltage magnitude within the specific range, both during steady state and following a disturbance. Synchronous machines have traditionally provided system strength in transmission networks. Hence, system strength level can be reduced with higher renewable penetration level.

The ever increasing fragility and tighter stability limits of modern power systems magnify the importance of real time or close-to-real time monitoring and evaluations to adequately support the operational security of power systems [9].

On the other hand, the $N - k$ ($k \geq 1$) analyses, which are required for close-to-real time monitoring and evaluations of power systems, are prohibitively computationally intensive [6, 12].

This means a drastic increase in the range of possible operating conditions (including power flow patterns) which has led to a significant increase in the computational burden of the computationally expensive time-domain simulations [12]. Hence, the traditional analyses are deemed insufficient and the operators of modern power systems currently run a large number of stability studies to compensate.

[2]More details on swing equation can be found in Appendix A.

Another challenge regarding dynamic stability management is the contingency inclusion and classification for modern power systems. Power system operators, such as the Australian Energy Market Operator (AEMO), only evaluate the stability of a system for reasonably likely events with the potential for significant impact on the power system (also known as credible events) due to computation time constraints [13]. This means if such an event occurs, the system is able to return to normal operating conditions after triggering remedial actions, such as activating reserves.

Moreover, non-credible contingencies can only be reclassified as a credible event under a set of special circumstances, e.g. if the system operator receives an abnormal conditions report (such as severe weather conditions) and it is determined that the non-credible event is likely to occur [13]. Then, the stability of the power system is analysed online through performing simulations using real-time or near-real time measurements [10]. However, if the event is not considered reasonably possible, no reclassification is done. Overall, this process is not only prone to error, but also computationally expensive and indicates that the existing tools may no longer be suitable for modern power systems.

1.1.2 Power system planing

The very low marginal cost of renewable sources has led to the displacement of more expensive conventional fossil fuel or nuclear synchronous generators. To reliably adapt to the changing generation mix, power system operators rely on their energy market, ancillary services, and near-real time operations [14]. These changes challenge the planning of modern power systems, namely short-term and long-term planning.

- **Short-term planning:**

  Short-term planning (also known as optimal generation schedule) is an optimisation problem that aims to schedule the generation of generators to meet the demand in the most cost effective manner with the time frame of interest of seconds to minutes.

  Operational constraints have been in place in the optimal generation schedule of generators to manage the system stability following contingencies to reassure meeting the demand instantaneously. These constraints include a set of linearised equations to adjust the output of generation units, reducing the effect of security criterion of a multi-machine system to a two-machine model [15]. More details on this optimisation problem can be found in Appendix B.

The fast-paced grid connection of new renewable generators has led to inertia reduction. Since modern power systems operate close to their stability limits, the constraint development processes has become more computationally expensive and complex. For instance, to reassure the stability in networks with high density of IBRs an increasing number of simulations need to be performed to confidently generate constraint equations [12]. These constraints are based on offline studies that generally include conservative assumptions to account for various potential real-time system conditions [14]. This puts the the efficiency of the created constraints into question.

Moreover, accounting for contingencies beyond the traditional $N-1$, that is $N-k$ ($k \geq 2$), is becoming more important and needs to be addressed through fast real power injection as per fast frequency response (FFR) criterion [12, 16].

- **Long-term planning:**

  Long-term planning, also known as optimum generation and transmission expansion plan (GTEP), is the process of determining the most cost-effective set of generation and transmission investments for connecting the fleet of new generators and transmission lines with the time frame of interest of years to decades.

  The GTEP problems are traditionally formulated with the goal of either minimising total cost or maximising social welfare, while co-optimising both generation and transmission expansion plans [17]. These studies are solely conducted through steady-state analysis (such as power flow and fault level analysis) [12], rather than detailed dynamic stability assessments. The recent studies have included some stability assessments methods in the GTEP problem [18]. Although this is a step forward towards a secure GTEP, it leads to inefficient use of the network since the constraints are overly conservative due to the simplifications techniques [19, 20].

  Hence, it puts the reliability of found solutions into question and calls for new tools to manage the changing system complexity and provide accurate stability assessment within the planning processes.

To summarise, the real-time workload for operators to keep the system secure is a critical and rising challenge. This indicates that conventional tools and techniques are reaching their limits to support a reliable transition to a clean future and new tools are desired that converge in real-time to ensure the secure operation of the power system [6].

This thesis focuses on techniques to accelerate transient stability assessment of power systems, which will potentially augment the traditional approaches and address their shortcomings.

1.2 Problem statement

The extensive changes in power networks such as the connection of IBRs will affect the steady-state parameters of power systems, such as the dispatch of different types generators (generation portfolio), power flows, and voltage profiles. It will also affect the dynamic parameters of power systems, such as rotor angle stability of synchronous generators. For instance, the latest studies show that the synchronising torque that is required to maintain the transient stability (also known as rotor angle stability) of power systems is improved by up to 40% penetration of renewables due to the increase head-room in generation capacity of synchronous generators [9]. However, the synchronising torque decreases after that level (after 40%) and quickly deteriorates with 80% renewable penetration and above. Therefore, monitoring the remaining synchronous generators' stability in real time will be critical with higher levels of renewable penetration [9].

The most accurate approach for analysing stability is to run time-domain simulations, namely root-mean square (RMS) or electromagnetic transient (EMT), for any contingency, i.e. fault scenario, to determine whether the system would go into an unstable state (and potentially resulting in a blackout), or returns to a new, stable equilibrium.

However, the diversified operation conditions and contingencies in modern grids as well as the computationally insensitive nature of time-domain simulations hinders the application of time-domain simulation for comprehensive TSA assessment. This crucially challenges the conventional tools and makes it impossible to assess power system stability for every possible operating point in real-word systems [21]. To address this challenge, several approaches have been proposed in the literature and some of them have been applied in real-world systems. Among those approaches, machine learning models have shown a great potential in achieving higher accuracy and reliability compared to other methods. This thesis introduces new techniques to improve the computational efficiency as well as prediction performance for transient stability assessment, compared to the standard machine learning models in the literature, without increasing the size of the required training dataset or using complex deep learning algorithms and structures.

1.3 Research questions

In the following, we discuss the three research questions of this work. These three questions are answered in details in the following chapters.

- RQ1:

How to implement a fast and reliable data-driven solution for transient stability assessment (TSA) that also provides an index regarding the severity of the contingency?

- RQ2:

Can we improve the performance of data models using a new data collection strategy based on the understanding of power systems dynamics?

- Does it improve the performance regardless of the applied model, i.e. conventional ML and deep learning?

- Can we use conventional ML models to improve explainability while reaching higher reliability, compared to deep learning models?

- Does it improve the versatility and robustness of data models?

- RQ3:

Is it possible to reduce the training effort of data models for operational scenarios with topology change?

- Can we use pre-trained models to accelerate the training process?

- Is it possible to add network augmentation and reduction later in the training process?

- How does it affect the performance of trained models compared to standard approaches?

1.4 Related work

The computation intensive nature of a time-domain simulation hinders its application for real-time transient stability assessment. Hence, new TSA methods have been developed over the years to accelerate the process, namely **direct methods** developed since 1981 [22] and **data-driven methods** developed since 2001 [23] which are presented below. These algorithms are exploited for online security monitoring (also known as pre-fault or preventive transient stability assessment) to provide situational awareness regarding an anticipated but not yet occurred contingency.

It is important to highlight that this section is not an exhaustive literature review on the techniques to accelerate transient stability assessment of power systems; however, it presents a summary of the most related literature and covers a selection of selection of the most prominent papers in this domain. Individual technical chapters contain more in-depth sections that detail the related work.

1.4.1 Direct Methods

Direct methods aim to accelerate the assessment process by simplifying the complex model of a multi-machine power system. They include transfer energy function based methods, the (extended) equal area criterion (EEAC) [24] and Lyapanov direct criterion [22], as well as the single machine equivalent (SIME) paradigm [25].

SIME drives a time domain program, for during fault and post fault configurations, to identify critical and non-critical machines by learning rotor angle deviations. It then aggregates the generators into critical and non-critical machines to form a One Machine Infinite Bus (OMIB) equivalent system. As a system enters a post fault phase, SIME considers candidate decomposition patterns, until one of them reaches the instability condition. It then uses Equal Area Criterion (EAC) to approximate contingency critical clearing time (CCT) [26]. It then ranks contingencies into dangerous, potentially dangerous, and harmless. This can be used for SIME preventive studies to reinforce stability. Moreover, it can be used for generation rescheduling, and as a constraint within the optimal power flow problem called transient stability constrained OPF (TSC-OPF) [15]. The main drawback of these approaches is that they fail to evaluate the full dynamic model of the system. Moreover, OMIB candidate decomposition is reached as soon as a decomposition pattern becomes unstable, which is not an accurate representation of the system state.

To summarise, although the simplifications were justifiable when the methods were introduced by satisfying the online and real-time stability assessment needs and ranking contingencies [27], they are not very suitable for today's systems as they underestimate the security of the system. Consequently, they may lead to more expensive operation scenarios.

1.4.2 Data-driven methods

Data-driven solutions are algorithms that can represent, reason about, and interpret data. They learn about the structure of the data and analyze it to extract patterns and meaning. By doing so, they can derive new information, and identify strategies and behaviors to act on the results of its analysis. In contrast to direct methods that aim to construct mathematical relationships between system state and the system stability status, data-driven solutions aim to map system state to stability status when properly trained on suitable datasets[3].

Data-driven methods can be divided into supervised, unsupervised, and semi-supervised methods.

In **supervised learning**, the aim is to develop models to obtain mapping relations between inputs (system variables) and outputs (stability status). The core idea is that a comprehensive set of simulations for transient stability analysis provides useful information regarding power system behaviour and data patterns during different operation

[3]This usually requires data preparation, selection of input and output, significant features, etc. [28].

scenarios. This information can be used to train data-models which can be used to reassure the stability of the system for any future generation schedule [29].

Since running the time-domain simulations to generate the outputs (stability status) is computationally expensive, alternative methods are introduced in the literature. These methods use unsupervised and semi-supervised learning to reduce the computational cost.

- In the application of **unsupervised learning**, the focus is on fast stability scanning of datasets by learning the underlying structure or distribution in datasets using the Relief feature selection algorithm [30]. The aim of the method is to capture intra-seasonal variation in RES output using time series analysis, rather than using time domain simulations to create labels for supervised learning. Although it accelerates the process, the reported accuracy is generally lower than supervised classification. Hence, this approach is not yet suitable for real-world applications.

- In the application of **semi-supervised learning**, the aim is to combine labeled and unlabeled data to train the model. In [31] a new data collection strategy is introduced where a tri-training algorithm is used to produce labels for unlabeled samples which will later be combined with some labeled samples in a semi-supervised learning framework.

  The major drawback of applying this multi-step and complex method for TSA is that this approach is only 12% faster than the actual time-domain simulation, while not improving the accuracy compared to standard supervised classification.

Due to the complex algorithms used in unsupervised and semi-supervised machine learning methods to compensate for the lack of sufficient labelled data, supervised machine learning algorithms dominate the stat-of-the-art literature. In supervised learning algorithms, data is collected from time-domain simulations (RMS or EMT), sampled from a fraction of the space of expected system states, and used off-line to train a data model. This can then be used to rapidly predict the stability of other system states. An important aspect of data-driven TSA is the difference between a single contingency and a multi-contingency model. Since the complexity of a multi-contingency model is highly dependent on contingency scenarios, its performance could be significantly lower than its overall performance for one of the contingencies. This is due to the averaging effect across all contingencies which reduces the reliability of the model for an individual contingency [32].

Both deep learning [29, 33] and conventional methods [28, 34, 35] have shown promising results in predicting the stability of power systems in milliseconds, at least a thousand times faster than time domain simulations.

For instance in [36], a TSA scheme is proposed for large-scale interconnected power systems using phasor measurements and decision trees. The scheme builds and periodically updates decision trees offline to decide critical attributes as security indicators. It uses a new classification method involving each whole path of a decision tree instead of only classification results at terminal nodes to provide more reliable security assessment results for changes in system conditions. Although the reported accuracy was fine at the time, it is significantly lower than currently used algorithms.

In [37], the authors present an approach to perform TSA by using a support vector machine. The model is trained based on the current system topology and the loading conditions. It is shown that the classifier can be trained using a small set of data using the Transient Energy Function (TEF) as input features. Not only the reported accuracy needs improvement, but also the generalisation of the trained model on large test sets is not studied.

The current state-of-the-art literature mainly focuses on different deep learning algorithms and deep network structures to predict the stability status of power systems, proving higher prediction accuracy compared to previously used algorithms [29]. These algorithms are specifically more efficient when dealing with a large amount of data and do not require in depth understanding of the feature space.

For instance, in [38], 200 single Extreme Learning Machines that generalizes the randomness of single ELMs during the training are used. They train the model to predict the stability of a limited number of load-generation patterns, with narrow ranges for load variations. The proposed model achieves a classification accuracy of up to 95%, while for other locations it can drop as low as 89%. Therefore, it would be beneficial to develop approaches that improve versatility, i.e., which can be used for different fault locations.

Recent works also aim to improve the accuracy of predictions. For instance, assuming that state variables, such as rotor speed or acceleration rate, are accessible has recently obtained attention [39]. Although it leads to higher accuracy due to the access to the most fundamental features determining the stability of the system, this assumption may not be a real-world practice.

Convolutional neural networks (CNN) are widely used in many energy related field, such as wind power forecasting [40], electricity demand and price forecasting [41] due to its acceptable training convergence and GPU acceleration. This deep learning algorithm has recently been exploited for pre-fault transient stability assessment [21, 42, 43], while using a moderate yet different deep neural network structure (i.e. the number of hidden layers and the neurons at each layer) for the same test cases. This is because in practice, the performance of CNN is greatly influenced by the parameter construction. Therefore, for a given dataset the best model with appropriate deep network structure can only be determined by running numerous trials [44].

The proposed deep learning algorithms typically use customised deep neural network structures tailored for specific systems, to extract features and map the inputs to the stability status. This potentially leads to poor performance when applying the same method to other systems, due to the inherent change in system dynamics and patterns in the collected datasets. Consequently, it is difficult to ensure that the selected classifier can always perform the best for any test case [44]. As an example, in [32], a wide range of average accuracy level is reported for TSA of one contingency scenario, varying from 92% to 99%, using six different deep network structures and methods from the literature. This reduces the scalability and generalisation of these methods. Furthermore, the lack of interpretability of the deep learning models would be formidable and reduce its application in the sensitive industries. This indicates the trade-off between the performance of models and its interpretability. This subject is further discussed in details in Section 2.3.1. Moreover, the larger size of required data could impose significant computational burden, specially as generating stability status data requires running time-domain simulations.

Concisely, the main deficiency of the applied deep learning algorithms applied to TSA in the literature is that they consider no prior understanding of power system operation and the foundations of transient stability assessment. Therefore, they rely solely on large-sized collected data and use of complex algorithms to extract features and map the inputs to stability status which reduces interpretability as well as versatility of these approaches.

Furthermore, the assumption of all the aforementioned methods is that the topology of the network invariably remains the same. In practice, however, the topology of power systems can change, e.g. when new transmission lines are connected or an outage of an existing line occurs. This is especially relevant as the grid evolves to connect new renewable energy zones. The topology changes alter the dynamics of the system. This means the data patterns inside the training datasets change. As a result, topology changes compromise the performance of the trained classification model for $N-1$ scenarios. Thus, the trained models have to be frequently updated using new datasets generated for each newly anticipated topology change instance, which in turn imposes a high computational cost [31]. Moreover, data-driven transient stability assessment in the presence of topology change in the literature is only studied in an $N-2$ framework, where either two transmission lines are out of service at the same time [8, 31], or a transmission line along with another line that is overloaded are removed which has a severe impact on the security of power systems [45]. Furthermore, the $N-2$ and $N-1$ transient stability assessments are always treated independently and irrespective of the other, where for each contingency category the same number of samples are fed to the machine learning model [32]. This leads to exceedingly large datasets with hundreds of thousands or millions of instances.

We will later explore limitations and extensions of data-driven methods further in much more details in the following chapters. For more details on the application of AI for stability analysis we refer the reader to references [29] and [42].

1.5 Significance of research

Data-driven machine learning approaches aim to address these issues by providing fast and reliable solutions. In supervised machine learning algorithms, data is collected from time-domain simulations, sampled from a fraction of the space of expected system states, and used offline to train a data model. This can then be used to rapidly predict the stability of other previously unseen system states. This is known as preventive/ pre-fault transient stability assessment.

This research aims to achieve higher computational efficiency as well as better prediction performance for the data-driven transient stability assessment problem using both conventional and deep learning models, compared to the standard machine learning approaches. We achieve this without increasing the size of the required training dataset, and additionally reduce the training effort given a fixed size of dataset.

Moreover, this work provides clear guidelines and proposes new ideas to facilitate the application of machine learning models (conventional as well as deep learning) to predict the transient stability of the power systems using fast, reliable, and generalisable methods. The understanding of power system dynamics is applied in the fundamental theory of the methods as well as implementation, such as in the data collection and training machine learning models. As a result, the proposed methods do not solely rely on the collected data and the Data Science theories, but also use insights from the understanding of power system dynamics.

In this thesis we introduce the following novel contributions to knowledge in the research field:

- A hybrid machine learning solution for transient stability assessment(TSA) is introduced that predicts transient status as well as time to instability as an index indicating the severity of disturbance. A significant part of this is adapted from my published work [33].

- A novel data collection strategy, leveraging the expert knowledge of power system dynamics, is introduced to improve the reliability as well as accuracy of transient stability assessment (TSA). A significant part of this is adapted from my published work [28].

- A novel training strategy in a deep transfer learning framework is introduced for the first time to maintain the performance of the trained machine learning models in case of topology changes. The significant part of this is adapted from my final work that is currently under review [46].

1.6 Thesis outline

This thesis includes six chapters and is organized as follows:

Chapter 2 presents the required background in Electrical Engineering as well as Data Science and Machine Learning, designed to better understand the context of this thesis. It includes a spectrum of fundamental to advanced information to better understand the concepts discussed in the remaining sections of the thesis.

Chapter 3 explains Transient Stability Assessment with standard ML approaches. It introduces a new hybrid machine learning framework to facilitate the use of machine learning models to predict the transient stability of a power system as well as time to instability as a fault severity index. The simple algorithm with simple data models only works for small systems with simpler data patterns and is not generalisable to bigger systems and larger variations in load scenarios. Our work in this area was published in [33].

Chapter 4 introduces a new data collection method in a data-driven algorithm incorporating the knowledge of power system dynamics. The expert knowledge on how the disturbance effect will propagate from the fault location to the rest of the network is leveraged to recognise the dominant conditions that determine the stability of a system.

Accordingly, we introduce a new concept called Fault-Affected Area (FFA), which provides crucial information regarding the unstable region of operation. This information is embedded in an augmented dataset to train an ensemble model using an instance transfer learning framework. Our case study shows that this trained model can accurately predict the stability of the operational scenarios while reducing the risk of false prediction of unstable instances (also known as *False Positives*), compared to standard machine learning models. Moreover, it provides a transparent baseline for using conventional supervised models in a transfer learning scheme to assess the transient stability of the system. Our work in this area was published in [28].

The general assumption of the data-driven TSA models in the literature is that the topology of the network invariably remains the same. In practice, however, the topology of power systems can change, e.g. when new transmission lines are connected or an outage of an existing line occurs. When the topology of power networks changes, the performance of the trained models will be compromised. Hence, the trained models require frequent updates for newly anticipated topology change scenarios. This is especially relevant as the grid evolves to connect new renewable energy zones. Chapter 5 introduces a deep neural network-based transfer learning framework to improve the robustness of trained models to topology changes. This deep neural network-based transfer learning approach is conventionally used in other domains such as image recognition and natural language processing. We take advantage of a deep residual neural network structure which is pre-trained to predict the stability of a three-phase fault (i.e. $N-1$ transient stability assessment) in one module and re-train another module to predict the stability of the system for the same fault location while the topology of the system changes.

In other words, in the first module we take advantage of a CNN structure which is pre-trained to predict the stability of a three-phase fault (i.e. $N-1$ transient stability assessment) by extracting the dominant features. Then, the second module is trained to predict the stability of the system for the same fault location while the topology of the system changes.

We show that this method will significantly reduce the training effort (in GPU hours) while increasing accuracy compared to standard deep learning approaches. This work is currently under review [46].

Finally, Chapter 6 contains an overall conclusion of this thesis summarising the contributions of this work. It also includes a future work section that provides guidelines for expanding this work and contributing to the future domain knowledge.

1.7 Conclusion

Data-driven machine learning approaches aim to enhance situational awareness by providing accurate and reliable transient stability assessment in real-time. This research aims to achieve higher computational efficiency as well as better prediction performance for the data-driven transient stability assessment problem using both conventional and deep learning models, compared to the standard machine learning approaches. We reach this without increasing the size of the required training dataset and additionally reduce the training effort for a fixed size of dataset through leveraging the understanding of power system dynamics and incorporating novel insights from Machine Learning and Transfer Learning.

Chapter 2

Background

2.1 Introduction

The focus of this research is to use machine learning techniques to improve the confidence in continued intact operation of power systems. Hence, this chapter brings the required information to read this thesis from two different fields, namely Electrical Engineering and Data Science. We first will detail the Engineering background and then will explain the required Data Science background in detail. In the final section, we briefly explain the assumptions of the test cases used to validate our hypotheses.

2.2 Electrical Engineering Background

A power system includes components such as generators, transmission and distribution lines, and transformers. Generators are the heart and the driving force of power systems and are of special importance. Moreover, they are one of the main elements of distinction between modern and traditional power systems, as discussed in Chapter 1. Here, we briefly introduce the two main categories of generators, namely synchronous generators and inverter based resources (previously referred to as asynchronous generators).

- **Synchronous machines:**

  Synchronous machines have traditionally been the main source of generating electricity. They include many mechanical and electrical components that work together to deliver the desired output. We explain the sub-systems of a fossil-fueled power plant in sequence as follows:

  1. The fuel is burnt in a furnace so that a boiler can generate steam (controlled by a speed governor, and hydraulic servomotors). This steam rotates the blades of turbine and prime mover that generate mechanical torque and creates inertia. This concludes the mechanical aspects of synchronous generators.
  2. The torque generated by the turbine will rotate the rotor of a generator that will generate electromagnetic torque that leads to production of electricity (controlled by stabiliser and exciter). This concludes the electrical aspects of synchronous generators.

- **Inverter based resources:**

  Most renewable generators, such as wind and solar farms, are coupled to the grid using power electronic components, rather than the mechanical coupling in synchronous generators. We refer to these generators as Inverter Based Resources (IBR).

  The overall performance of inverter based resources are dominated by the exploited control systems and strategy for very fast control of the inverter output. Consequently, there are two categories of IBRs, namely grid forming (GFM) and grid following (GFL), with two different control algorithms.

  The fundamental difference of the two inverter categories are as follows, as indicated in [1]:

  – Grid-following inverters mimic current sources at their output terminals while controlling the magnitude of active and reactive power output.
  – Grid-forming inverters act like voltage sources while controlling the magnitude and angle of voltage at their output terminals according to droop laws.

  Moreover, GFLs rely on synchronous generators for their stable operation while GFMs do not rely on synchronous generators for their stable operation. Therefore, GFLs cannot solely operate at 100% power electronics penetration, while GFMs theoretically can [47].

Fig. 2.1 shows the high-level control block diagram of the two IBR categories and contrasts their different control strategy.

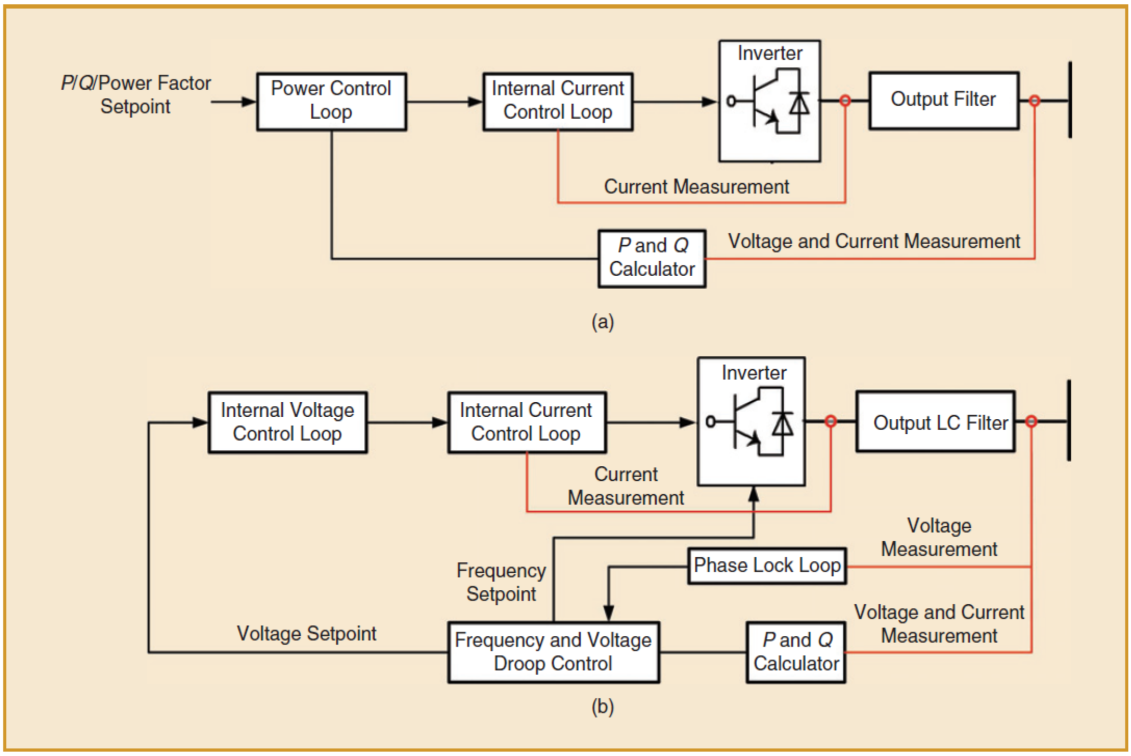

FIGURE 2.1: IBR control diagrams: (a) GFL and (b) GFM (Image source: [1]).

Overall, the performance of inverter based resources is dominated by the control strategy and they are primarily distinguished by their response at shorter control timescales, compared to synchronous generators [47].

2.2.1 Reliability, Security and Stability

To design and maintain a reliable power system is of prominent importance as societies, industry, and economy are heavily relying on a continuous power supply. Power system reliability is therefore the overall objective in power system planning and operation. The conceptual definition and relationship of reliability, security and stability are crucial and are introduced below, as outlined in [25].

- **Stability** of a power system refers to the continuance of intact operation following a disturbance. Traditionally, power systems only included synchronous generators and the system stability considered different and at the same time interrelated scopes, namely transient stability, frequency stability, and voltage stability. These are briefly explained below as detailed in [25]:

- **Transient stability:**
  The ability of synchronous generators in the system to remain in synchronism after large disturbances. This is also known as rotor angle stability.
- **Voltage stability:**
  The ability of power systems to maintain or recover voltage magnitude within acceptable levels. Voltage instability stems from the inability of a power system to meet demand for reactive power.
- **Frequency stability:**
  The ability of power systems to maintain steady frequency after a large system contingency by invoking control actions that are not modelled in conventional transient stability or voltage stability studies. Typically, that contingency event causes an unbalance between generation and load.

Reference [2] presents the revised definition of power system stability and includes additional considerations regarding the extended connection of Inverter Based Resources (IBRs) into the bulk power systems. Fig. 2.2 depicts the components of the revised definition of stability. It is of prominent importance to highlight that the presented classification is only based on intrinsic system dynamics (time constants associated with actual physical phenomena) and not on the scenario or disturbance initiating the instability. This suggests that further studies are required in these areas and implies the unknown characteristics of IBRs during disturbances.

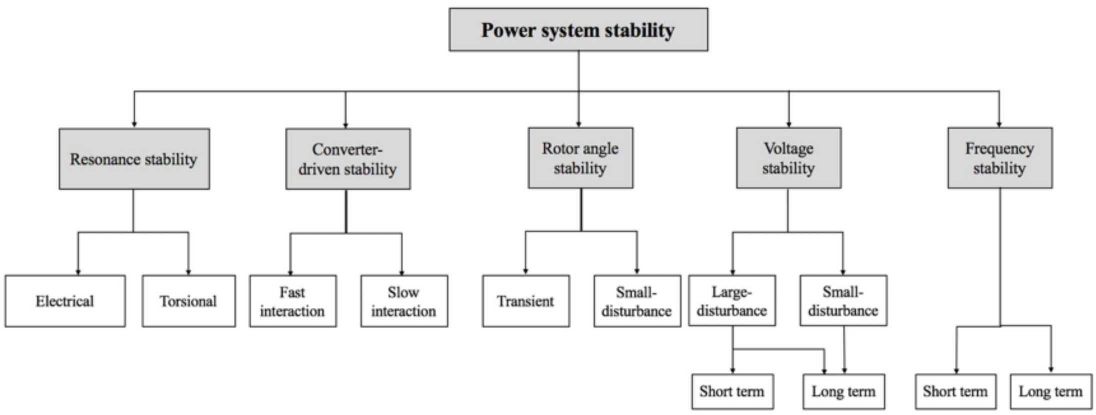

FIGURE 2.2: Revised classification of power system stability (Image source: [2]).

The importance of reference [2] is in introducing two new stability classes, namely **Converter-driven** and **Resonance** stability.

- Resonance stability encompasses sub-synchronous resonance (SSR), which can either be associated with an electromechanical resonance or an entirely electrical resonance.
- Converter-driven stability is caused by the different dynamic behaviour of IBRs compared to that of the conventional synchronous generators. The instability stems from the wide time scale related to the control of IBRs that can result in coupling with both electromechanical dynamics of machines and electromagnetic transients of the network [2]. It further categorises converter-driven stability into fast-interaction and slow-interaction stability.

- **Reliability** of a power system refers to the probability of its satisfactory operation over the long run. It denotes the ability to supply adequate electric service on a nearly continuous basis, with few interruptions over an extended time period.
- **Security** of a power system refers to the degree of risk in its ability to survive imminent disturbances (contingencies) without interruption of customer service.

2.2.2 Security assessment

Security assessment is monitoring and early detection of instability and includes two important components, namely static and dynamic security analysis, detailed below according to [7].

2.2.2.1 Static security analysis

The management of static (also known as steady-state) stability involves steady-state analysis to ensure thermal, voltage, and frequency bounds are not violated, usually by performing power flow studies [7]. This has become a challenging task in modern power systems. The increasingly large generation source of rooftop PV is resulting in voltage management issues in the distribution level. The low demand leads to voltage rise in the middle of the day and congestion at distribution feeders. This can also lead to voltage drops during the evening load peak [6]. Moreover, the changes in generation patterns (hourly, daily, and seasonal) and power transfers lead to complications in maintaining the thermal constraints of power system elements [12].

2.2.2.2 Dynamic security analysis

It is essential to continue the reliable operation of power systems as our societies and economy are dependent on continuous and uninterrupted power supply. Dynamic security analyses refer to the ability of the system to cope with disturbances. These analyses require performing time-domain simulations, in which power system components are represented by a system of differential-algebraic equations (DAE) that are solved in iterations using numerical integration, providing essential information about the system's dynamic evolution (e.g. generator swing curves, bus voltage trajectories, system frequency trajectory) following a disturbance. These analyses are performed in the time interval of several minutes and are computationally intensive [6].

On the other hand, these analyses are crucial for both systems planning and systems operation and can be further divided into two categories: pre-contingency and post-contingency [38].

- Pre-contingency analysis aims to find operational scenarios that are secure with respect to a set of anticipated contingencies. This improves situational awareness and facilitates decision making.
- Post-contingency analysis aims to trigger emergency control actions to impede propagation of instability, considering the post-disturbance dynamic transition process. This improves control actions and requires dynamic measurements such as rotor angle and voltage trajectories.

In this thesis, we focus on techniques to accelerate pre-contingency (also known as preventive) dynamic security assessment of power systems.

2.2.3 Transient stability assessment

Stability assessment is the monitoring and early detection of instability and plays an important role in the stability of power systems. Transient stability, also known as large signal or rotor angle stability, refers to the stability of synchronous machines to remain in synchronism after being subjected to a fault, e.g. when one or more conductors of transmission lines make contact with each other or ground [25]. This can upset the equilibrium between the input mechanical torque and the balancing electromagnetic torque of a synchronous generator which results in either acceleration or deceleration of the rotor.

The transient stability is dependent on both the initial operating condition of the system and the severity of the disturbance in the system, while the instability is caused mainly due to insufficient synchronizing torque (controlled by the excitation system) resulting in angular separation of synchronous generators.

As an example, let's assume a three-phase fault occurred in a three generator system. Fig 2.3 shows a scenario where the system remains stable (class 1). This means the relative rotor angles (RRA) of synchronous generators, that is the difference of rotor angle of each generator compared to the swing generator[1](the plot on the left-hand side of the figure), are smaller than 180 degrees. However, the rotor angles of all three generators steadily increase (the plot on the right-hand side of the figure).

On the other hand, Fig 2.4 shows a scenario where the system loses stability (class 0) and the RRA of synchronous generators are greater than 180 degrees. In this case, the rotor angles of two generators steadily increase while the rotor angle of the third generator stops increasing, which causes the increase in the RRA. It is of prominent importance to ensure that power systems withstand reasonably likely events with the potential for significant impact on the power system (also known as credible events). This is becoming more vital as replacing big synchronous generators with distributed, asynchronous solar and wind generators not only diversifies the range of operational scenarios (i.e. load and generation dispatch of generators), but also reduces the available inertia in the system and causes the system to operate closer to its stability limits, which increases the chance of black-outs. The impact of inverter based resources (IBRs) on the transient stability of the system will be further discussed in Section 2.4.

[1]It is the biggest synchronous power plant in the system that will supply the balance of the real power required to cover for line losses and sets the angular reference for all the other buses [48].

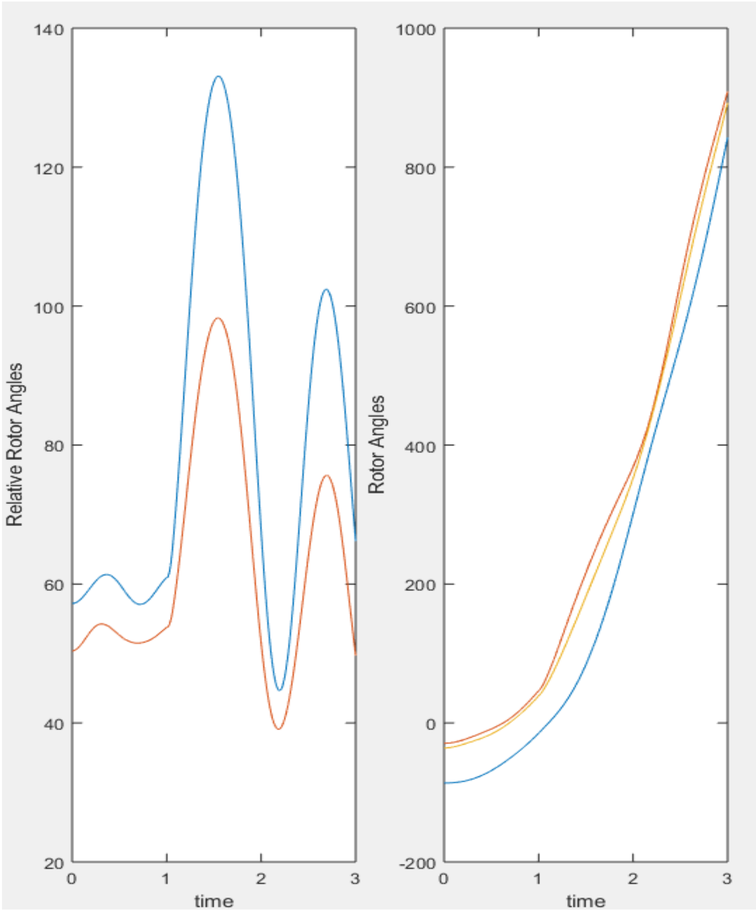

FIGURE 2.3: A stable operational scenario (class 1).

In order to analyse transient stability, time-domain simulations are performed, namely root-mean square (RMS) or electromagnetic transient (EMT), for any disturbance scenario to determine how the system evolves during as well as after clearing a fault. This will establish whether the system would go into an unstable state (resulting in a blackout), or returns to a new, stable equilibrium. These simulations require solving a system of differential-algebraic equations (DAE) using iterative numerical integration approaches to determine the system's dynamic state following the disturbance.

However, the computation insensitive nature of time-domain simulations hinders their application for comprehensive TSA assessment and makes it infeasible to run them for every potential grid design and fault scenario in future grids. Hence, data-driven methods have been used to accelerate the process. The most common practice is to train a classifier and learn the mapping between features representing operational scenarios and stability status [33].

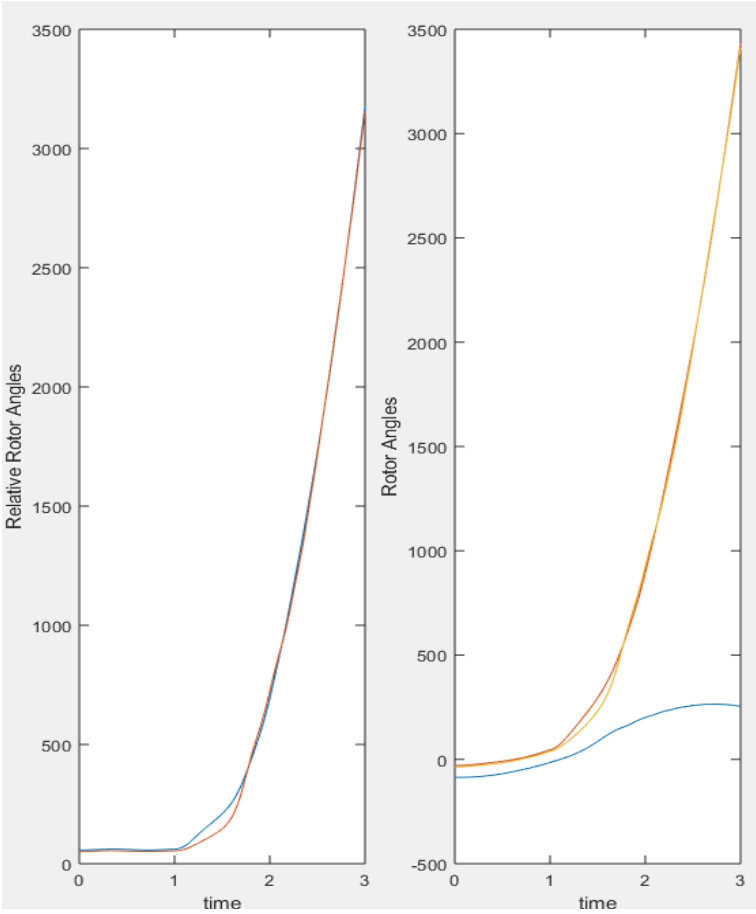

FIGURE 2.4: An unstable operational scenario (class 0).

As discussed in Chapter 1, data-driven methods can perform transient stability assessment significantly faster than traditional time-domain simulations. These methods use different machine learning concepts to reach this goal. Now that the Electrical Engineering background is discussed, in the following sections we cover the data science background of these methods.

2.3 Machine Learning Background

Machine learning is an important branch of Artificial Intelligence (AI) and aims to find patterns in a dataset. It can be categorised mainly into supervised, unsupervised, semi-supervised, and reinforcement learning [49].

- **Supervised learning:**

  The aim is to develop models to obtain mapping relations between inputs (also known as features) and outputs (also known as labels). The supervised learning algorithms are further divided into two categories, namely classification and regression. In classification the model takes a feature vector as input and predicts its category amongst some discrete options, while in regression the prediction is done amongst a continuous range of values [50].

- **Unsupervised learning:**
  The focus is on learning the underlying structure or distribution in datasets without an explicit output label as in the supervised learning case, using feature selection algorithms.

- **Semi-supervised learning:**
  The aim is to build models in the absence of labels in the majority of the observations. Semi-supervised learning is based on cluster and manifold assumptions. The cluster assumption indicates that there is a high chance that all samples in the same cluster have the same system response. Manifold assumption indicates that samples within close proximity have a similar response.

- **Reinforcement learning:**
  The aim is to use observations gathered from the interaction with the environment to take actions that would maximize the reward or minimize the risk.

In summary, supervised learning techniques require a full access to ground-truth labels for a big training dataset. Hence, weakly supervised learning, where noisy, limited, or imprecise labeling is used for a large amount of training data, is an umbrella term covering a variety of studies that attempt to construct predictive models by learning with weak supervision [51].

It is also discussed in Chapter 1, that the accuracy and reliability of unsupervised and semi-supervised algorithms for transient stability assessment are comparatively lower than supervised algorithms, with binary stability index as labels. Moreover, although acquiring labels is relatively computationally expensive, its process is simple and performed off-line. Hence, in this thesis we focus on supervised classification algorithms.

2.3.1 Classification algorithms

Classification algorithms aim to train a model relating its inputs and parameters to its outputs by minimising an objective function (i.e. a loss function). In the following we introduce some of the most common methods, namely decision trees, support vector machines, artificial neural networks, and ensembling.

- **Decision tree:**
  Decision trees split data based on the value of "best" attributes (i.e. significant features). They are easy to interpret, instantly trained, and consume very low memory. However, they can have low predictive accuracy.

- **Support Vector Machine (SVM):**
  An SVM finds the best separator (hyperplane) to separate data points of one class from other classes. This hyperplane provides the largest margin between classes.

- **Artificial neural network:**
  Artificial neural networks are data models inspired by biological neural networks, used to approximate functions that are generally unknown and incorporate a non-linear function from a set of input variables to a set of outputs controlled by a vector of adjustable parameters [3]. For many applications, the resulting model can be relatively more compact and faster to train (with access to GPUs) and evaluate as well [3]. A neural network structure includes neurons in several layers that are connected to the neurons in other layers. The layers include input, hidden and output layers, as shown in Fig. 2.5.

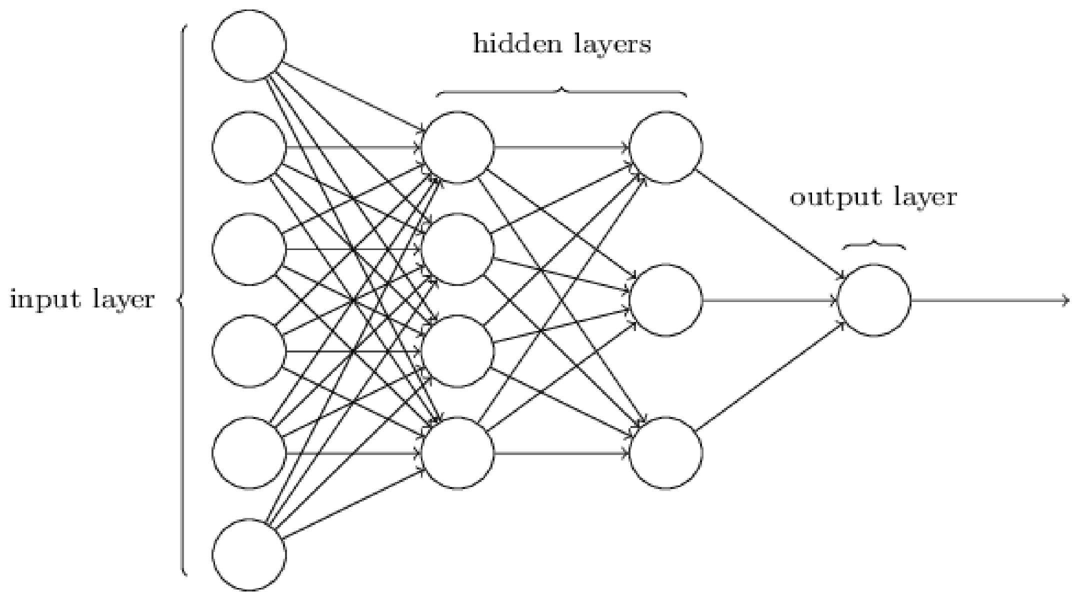

FIGURE 2.5: A simple Artificial Neural Network structure [3].

This algorithm encompasses many categories. Here we only introduce the two main neural network categories based on their structure, namely shallow neural network and deep neural networks.

  - **Shallow Neural Network:**
    In a shallow neural network there are a limited number of hidden layers connecting the inputs to outputs.
  - **Deep Learning:**
    In deep learning algorithms an unbounded number of layers (at least in theory) can be used to extract more information from data compared to shallow neural networks.

- **Ensemble:** Ensemble classifiers combine predictions from a variable number of learners into one high-quality ensemble model. It leads to enhancing the performance of single, and usually weak, learners. The learners could include boosted trees and bagged trees.

2.3.1.1 Comparison of classification algorithms

Model interpretability is the process of giving explanations to humans. Our need for interpretability arises from our need to know what the machine learning model has learned from the data, expressed in a way that humans can understand, to produce the final decision, and whether it can help us discover some potential associations [4]. This has always been the limiting factor of the application of many machine learning approaches for real-world problems. In general, the performance and the interpretability are two trade-off factors [50]. Fig. 2.6 is taken from [4] and depicts the typical spectrum of accuracy versus interpretability in different machine learning algorithms and visualises the trade-off.

Later in Chapter 4 we further discuss this in terms of the common practice to reach high overall accuracy in the data-driven transient stability assessment literature, that is to collect a large dataset and fine tune a complex deep neural network structure for a particular collected dataset.

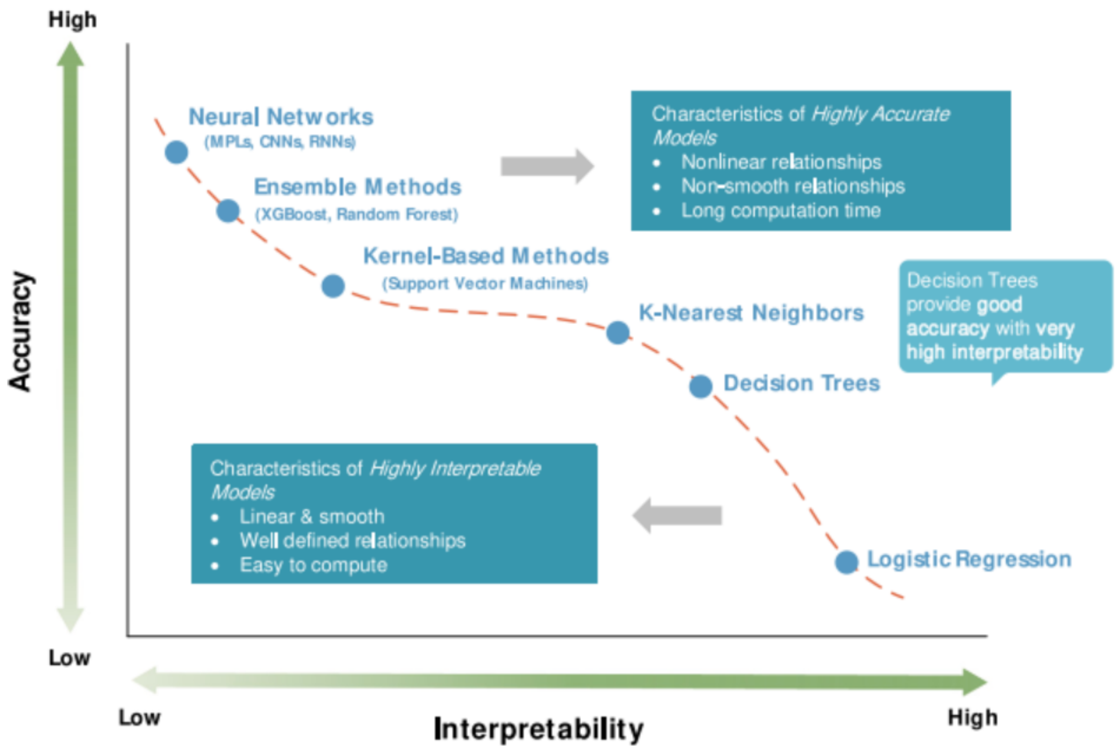

FIGURE 2.6: Interpretability versus accuracy of data-models (Image source: [4]).

However, concerns about the convergence, versatility and robustness of deep network structures for different datasets have recently been raised [52–55]. Therefore, the algorithm should be chosen wisely depending on many factors such as the application of classification algorithm, the dataset in hand, etc.

2.3.2 Transfer Learning

Transfer learning enables us to use existing datasets (the so-called source domain) that are related but not exactly the same as a target domain of interest. It aims to improve a learner from one domain by transferring information from a related domain.

In other words, it focuses on the gained knowledge from different datasets. More specifically, when training data is expensive or difficult to collect, learners can be trained with more easily obtained data from different domains [56]. Moreover, a major assumption in many machine learning algorithms is that either training and future data have the same feature space or they have the same underlying distribution, which may not be valid in real-world applications [57].

There are many different categorizations of transfer learning in the literature, with numerous differences in terminology including availability of labeled and unlabeled data and implementation strategies for solving a transfer learning problem [56]. We use categories based on the transferred knowledge according to [58], namely instance-based, feature-based, relation-based, and model-based. The two categories used in this thesis are instance-based (referred to as instance transfer learning) and model-based (referred to as network-based transfer learning), as detailed below.

2.3.2.1 Instance transfer learning

For a successful classification in classical ML approaches, the two datasets have to have similar underlying distributions. However, in instance transfer learning, this is not the case when looking at the training set (source domain, X_S) and test set (target domain, X_T). It is categorized in two cases where either the feature space between source and target domains are the same but the marginal probability distributions of the input data are different while they both perform the same task ($P(X_S) \neq P(X_T)$) or the feature space between source and target domains are different ($X_S \neq X_T$) [56].

In [59], transfer adaptive boost learning (*TrAdaBoost*) is introduced specifically for datasets with different underlying distribution in training instances. This would result in low classification accuracy of traditional machine learning algorithms. However, in *TrAdaBoost* if instances are wrongly predicted due to distribution changes by a learnt model, a mechanism is introduced to decrease the weight of these instances in order to weaken their impacts. As a result, it improves the accuracy of predictions. This concept is used in Chapter 3.

2.3.2.2 Neural network-based transfer learning

Neural network-based transfer learning refers to pre-training a neural network on the source domain and then transferring its network structure as well as connection parameters to be a part of a deep neural network used in the target domain [58]. In the current literature, this is also known as supervised domain adaptation for the new task [60].

This concept is conventionally used in image recognition and computer vision [61, 62] as well as natural language processing (NLP) [63] domains, and is based on the idea that the knowledge from previously learned tasks can be applied to newer, related ones [58]. For instance, in [61] they propose to transfer learnt image representations on large datasets to other visual recognition tasks with limited training data.

This is also traditionally known as inductive learning [57] where the objective is to infer a mapping from a set of training examples for other examples. As a result, transferring information from previously learned tasks for the learning of new tasks remarkably improves the sample efficiency as well as training effort. This concept is used and further discussed in Chapter 4.

2.4 Used test cases

Now that we have covered all the required Electrical Engineering and Data Science background, we can detail the assumptions of the test cases used to validate the performance of the novel machine learning methods proposed in this thesis.

We use the RMS model of IEEE 9 and 39 bus test cases to demonstrate the performance of the proposed TSA approach for a number of contingency scenarios throughout this thesis. In our test cases, a synchronous generator is modeled using numerous differential and algebraic equations representing the behaviour of the generator as well as its embedded components and control mechanisms such as governor, exciter, and power system stabiliser.

In Section 2.2.3 we detailed the definition and evaluation method of transient stability. It is important to highlight that the integration of IBRs does not change the fundamental definition of rotor angle stability [2]. However, the displacement of synchronous generators by IBRs affects the stability of power systems. Here we briefly highlight their impact on steady-state and dynamic stability.

- The steady-state performance of inverter based resources is dominated by the control systems and the strategy used to control the power electronic converter interface between the energy source and the electric grid. There are numerous examples of newly arising steady-state stability problems caused by fast converter interactions, density of IBRs, coupling between IBRs and grid, synthetic inertia controllers, etc [2]. Hence, the impact of the interaction of IBRs in steady state operation of power systems is not fully discovered yet.

- In terms of dynamic stability, especially transient stability, the impact of IBRs on the remaining synchronous generators is not fully understood. For instance, when studying the transient stability of the system, the concern is whether the control system is able to keep these sources connected to the system, known as fault ride-through capability. As another example, the influence of IBRs on damping torque of nearby synchronous generators calls for design of supplement controls mitigating power oscillations. Moreover, there is no consensus regarding the effects of increased penetration of IBRs on electromechanical modes and rotor angle stability [2]. Moreover, due to the proprietary nature of inverter controls, simulations are currently performed using the vendor-specific, confidential models of IBRs. Accordingly, the impact of IBRs on transient stability is an open research question and is not fully discovered yet.

The focus of this study, however, is on the application of Machine Learning algorithms for fast and accurate transient stability assessment while leveraging the knowledge of power system dynamics, rather than the steady-state and dynamic impact of IBRs on the transient stability of power systems. Therefore, we approximate the impact of renewable sources with negative loads. This results in larger load variation ranges in training and test sets.

The prediction error of renewable output (e.g. solar radiance and wind speed) will be more critical for systems with high penetration of renewables; however, the nature of this issue is different from modelling the dynamics of IBRs and should not be considered as an element affecting the performance of trained machine learning models to predict TSA, which is the focus of this thesis.

2.5 Conclusion

In this chapter we introduced the concepts related to data-driven transient stability assessment as follows:

- Firstly, we briefly covered the major Electrical Engineering background. We aimed to paint the big picture while bringing enough guidance and references for enthusiastic readers for more details.
- Secondly, we detailed the required Data Science background covering a range of basic to advanced topics necessary for better understanding of following chapters.

In the rest of this thesis we bring these two concepts together to address the research questions.

In the next chapter we introduce a novel hybrid machine learning algorithm including a binary classifier to predict the transient stability status as well as a non-binary classifier to predict the time to instability as a contingency severity index. This will count as a relatively simple implementation of a data-driven solution for transient stability assessment.

In the following chapters; however, we will discuss more complex problems, from both the Data Science as well as the Electrical Engineering aspects of the TSA, that require more complex solutions.

In general, we are interested in techniques that enable leveraging the knowledge of power system dynamics in the data collection process, while improving the reliability, accuracy, and training effort of data models. The latter is especially important as the trained models need to be updated due to the evolutionary nature of power system topology. This means training a model is a continuous offline process, rather than a sole event. Hence, it is important to develop efficient algorithms in terms of training speed.

Chapter 3

Transient Stability Assessment With Standard Machine Learning

3.1 Introduction

This chapter introduces a new two-stage classification algorithm following previous data-driven approaches, i.e., machine learning-based frameworks, such as neural networks (NN) [64], support vector machines (SVM) [65], or decision trees (DT) [36] that have been exploited to perform transient stability assessment by predicting stability status of operational scenarios. The highly nonlinear, computationally expensive, and time-constrained nature of transient stability analysis makes ML approaches well suited for this application.

Recent studies have used deep learning (DL) approaches, exploiting the effective automatic feature selection capability of DL algorithms. For instance, authors in [7] use Extreme Learning Machine (ELM), a DL based framework where large datasets are required, to increase the accuracy of classification. ELM has also been used to accelerate stability scanning using an improved feature selection and self-adaptive PSO-k-means clustering algorithm [30], amongst other methods.

The authors in [38] suggest pattern discovery (PD) for knowledge extraction since these classifiers tend to be sensitive to small changes in the data. It exploits a distance-based feature estimation algorithm called RELIEF to statically identify critical generator features. The credibility of the algorithms, an index of trust in the classification outputs, is not reported as sufficiently high. They introduce new classes for inputs, especially where little data is available, while the reported credibility of the results varies between 89.25% and 94.48% depending on the fault location. Therefore, not only the calculation burden and the complexity of the proposed algorithms is significant, but also the lack of engineering insight escalates its low interpretability.

It should also be highlighted that the data models that only use the steady-state variables that are related to the steady-state stability, e.g. voltage magnitude and angle at different buses and real and reactive power flow at transmission lines, have a higher chance of being adopted in the real world. It would not be practical if the algorithm required pre-fault dynamic state variables, such as rotor angle and speed of synchronous generators, or post-fault variables as inputs, since they impose significant pre-processing calculations [66–69].

The algorithm proposed in this chapter highlights weak lines, i.e. the lines with a high number of unstable instances. These are the contingencies with a very short time to instability, that is the time it takes for the system to become unstable after fault occurrence for any given generation scenario.

Moreover, by introducing the time to instability as a fault severity index, it not only accurately avoids the most dangerous scenarios, which are the operational scenarios where the system is at its lowest security level with a short time to instability, but also it will potentially reduce the operating cost of the power system as it enables choosing scenarios with fewer online fossil fuel power plants.

Moreover, our new algorithm potentially enables taking the contribution of energy storage systems (ESS) to system stability during the frequency response sequence, specifically the primary frequency response (PFR), into account as well.
To demonstrate the mechanism of this idea, assume ζ is the time to instability of a given contingency and τ is the time constant representing the time required for detection of a contingency and the activation of an ESS system to damp the disturbance. Therefore, the algorithm can allow the operation of scenarios where time to instability (ζ) is larger than τ ($\zeta \geq \tau$). This increases the feasible search space of the generation schedule problem and may lead to cheaper dispatch scenarios.

3.2 Contributions

We introduce a novel intelligent transient stability assessment framework. A hybrid machine learning tool is used where a binary classifier predicts the transient stability status of operational scenarios (zero indicates an unstable and one indicates a stable scenario) and a non-binary classifier predicts the time to instability, which is used as an index of the severity of the disturbance.

- **Critical line method:**

  A novel method, called **critical line** is proposed in this chapter, enabling the use of straightforward machine learning techniques. It will avoid the use of complex mathematical calculations finding critical machines in other algorithms by breaking the very large stability assessment problem into a number of smaller sub-problems. This is based on the fact that the disturbance effect will spread from the trip location to the rest of the network according to the network impedances and generator inertias [70]; therefore, the interactions of the dynamics of synchronous generators are more significant among adjacent generators.

  Therefore, the stability of generators in each area of the power network, which effectively groups generators in close proximity to each other, will be studied separately.

  Critical lines are defined as the lines with a large number of unstable instances for a comprehensive set of generation scenarios based on the average power transfer and the topology of the system. Within each area, the critical lines will characterize and determine the response of the group of generators in an area to disturbances. Therefore, it can clearly describe how the instability manifests in each area.

  Note that inter-area oscillations have a time scale in the range of tens of seconds and have not been considered in this study.

  We identified the following characteristics within unstable instances and propose a solution accordingly:

  - The relation between line loading and the proportion of generation scenarios that make the system unstable after the occurrence of a fault on the line, on each line for any given generation scenarios (unstable operational scenarios) is very significant.

  - Unstable operational scenarios in lines with fewer unstable instances (strong lines) are subclasses of the line with the highest number of unstable instances (weak lines). This means the same generation scenario that leads to an unstable operation in strong lines also makes the system unstable after fault occurrence at the weakest line.
  - Time to instability is greater in strong lines compared to weak lines. This means those operational instances are less dangerous at strong lines.

  Although this method could be applied to all the lines in the system, the data gathered from strong lines would not be statistically significant. Therefore, we hypothesise that once the weak lines are detected, assessing the stability at strong lines does not add notable information about the behaviour of the sub-systems. Moreover, it improves the scalability of the algorithm when applied to larger systems as the supervised learning process is only executed for the critical lines in each area, where the group of generators are located in close proximity of each other. Therefore, it enhances the use of machine learning algorithms to enable faster and more reliable decision-making during planning.

- **Two stage classification algorithm:**

  The algorithm we propose exploits a hybrid (or two-stage) classification procedure for all of the critical lines in the system. It predicts the stability index as well as the time to instability. This machine learning tool could potentially be added to the optimal unit commitment problem (aka. short-term planning). The ML model will provide the stability status of any calculated feasible operation scenario, augmenting the computationally expensive time-domain simulations. It is composed of a binary and a non-binary classifier.

  The binary classifier is used to detect the stability index, i.e., distinguish stable cases from unstable ones with a very high level of precision. The non-binary classifier predicts the time to instability which is used as a severity index for the three-phase faults.

3.3 Intelligent transient stability assessment

An intelligent system can provide a high level of ability to uncover salient but previously unknown characteristics of a system. It is used to map operation conditions to the security status when it is properly trained. Fig. 3.1 depicts the overall process to prepare a transient stability assessment (TSA) model. The core of a TSA is the classifier which immediately distinguishes the transient stability of a power system, once an operating condition is fed.

A key feature of a classifier is its generalization ability, referring to its ability to give reliable and accurate predictions using previously unseen operating conditions. In supervised learning, a training set consists of a group of operating conditions and their corresponding stability labels obtained using time domain simulations.

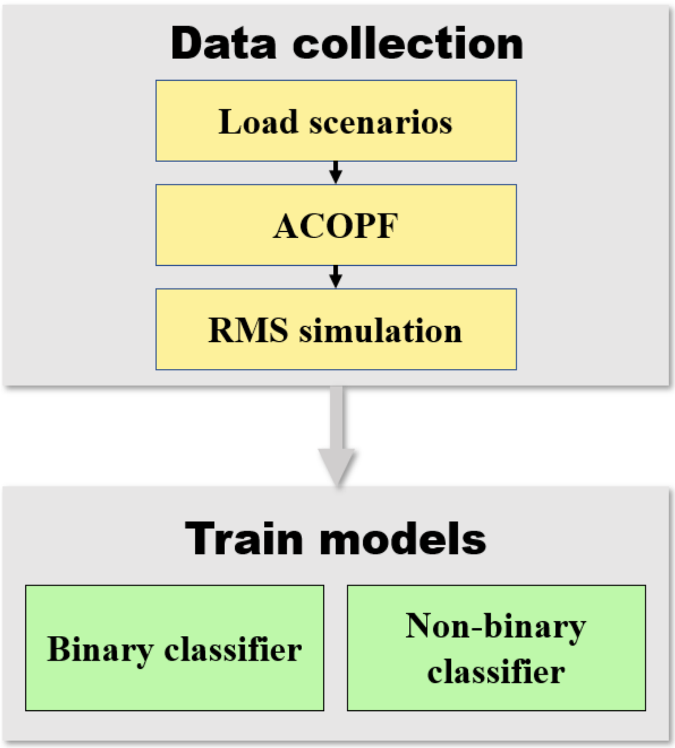

FIGURE 3.1: Block diagram of the proposed machine learning solution

The main steps to generate the training and validation datasets and train models are detailed in the following sections.

3.4 Data collection steps

3.4.1 Load scenarios

Postulated load scenarios are constructed using a broad range of values centered around the benchmark load values of the test case. These not only should reflect the possible operating region, but also should be able to push the system to its stability margins. Consequently, there should be enough unstable instances, enabling generators and transmission lines to operate close to their thermal limits in the presence of the power system controllers, such as exciter and governor that are further detailed in Section 3.6.

3.4.2 AC Optimal Power Flow

AC optimal power flow (ACOPF) is used to create optimal generation dispatch for postulated load scenarios. ACOPF is a non-linear optimisation problem that minimises the cost function while ensuring the operation of the system within its allowed limits. MATPOWER, an open-source software, is used in this study to solve the AC-OPF problem [71]. More details on the ACOPF algorithm can be found in Appendix B.

3.4.3 Transient stability assessment

A detailed simulation including all system components is created and three-phase to ground faults are applied and cleared after 100ms. The training dataset is prepared to be used for supervised learning in the next step. Real and reactive power of loads and generators as well as the angle and magnitude of bus voltages, extracted from the ACOPF study, are supplied to the root-mean-square (RMS) simulation model. More details on the RMS simulation model can be found in Section 3.6.

3.5 Model training

3.5.1 Feature selection

Transient stability in the presence of all of the system regulators is the outcome of numerous iterative numerical integration calculations. Therefore, mapping the measured pre-fault steady-state parameters to stability status and time to instability at the same time is difficult. For a successful supervised classification, firstly, standardization of the collected data is crucial to establish clear and consistently defined elements and attributes. Secondly, it is vital to find an appropriate feature set that minimizes the difference between the source and target domains and the error of classification[1]. Hence, different approaches to feature selection have been introduced in the literature to reduce the number of input features [30, 72, 73]. It is important to emphasize that well-known feature selection approaches including Relieff and Lasso usually do not agree on a specific set of features. This is due to the fact that they merely rely on the statistical aspects of the dataset and perform feature ranking without taking the labels into account. Here, we select the common features indicated by correlation analysis as indicated in [30].

The proposed approach uses the following parameters as inputs to the machine learning tool: real and reactive power of each load, real and reactive power of each generator, voltage angle and voltage magnitude at each bus, and real and reactive power flow in transmission lines.

3.5.2 Two-stage classifier

A two-stage classifier is trained to predict the transient stability of a contingency at critical lines. It will predict both the stability status and the time to instability. Each classifier predicts the dynamic behaviour of a contingency. Then, all classifiers will be put in parallel to depict the big picture by representing the behaviour of the large system.

Hyperparameters are the variables that determine the structure of the data model and the variables which determine how the network is trained. For instance, the number of hidden neurons (as shown in Section 2.3.1) and the learning rate are some of the available hyperparameters in ANN. In a decision tree, the number of splits, minimum leaf size, and split criterion are considered as hyperparameters. These variables need to be selected in advance as the model will not update them following the optimisation strategy. To fine tune these hyperparameters, a Bayesian optimisation method is used, that is a sequential design strategy used for global optimization of different functions [74], to iteratively develop a global statistical model of the unknown objective function, achieving maximal effectiveness in a fixed time [75].

[1]These two steps are consistently taken in the following chapters as well.

3.6 Application to an IEEE test case

In this section, the proposed intelligent system is created, tested, and then results are reported. The Western Electric Coordinating Council (WECC) nine-bus benchmark is used to conduct the experiments (Fig. 3.2). This system, while small, is large enough to be nontrivial in terms of stability status after disturbances and data patterns. Thus, it permits the illustration of a number of stability concepts and results. We will consider this system as one group of generators.

The simulation of the benchmark system includes fourth order model of generators, DC1A model of exciters, IEEE type one governor for steam and hydro turbines (IEEEG1 and HYGOV respectively), and IEEE type one power system stabilizer (PSS). The time step of calculations should be small enough so that each numerical integration step would produce accurate results and so 5e-05 seconds is chosen. This simulation model is verified through comparison with the same system built-in the DigSilent Power Factory software.

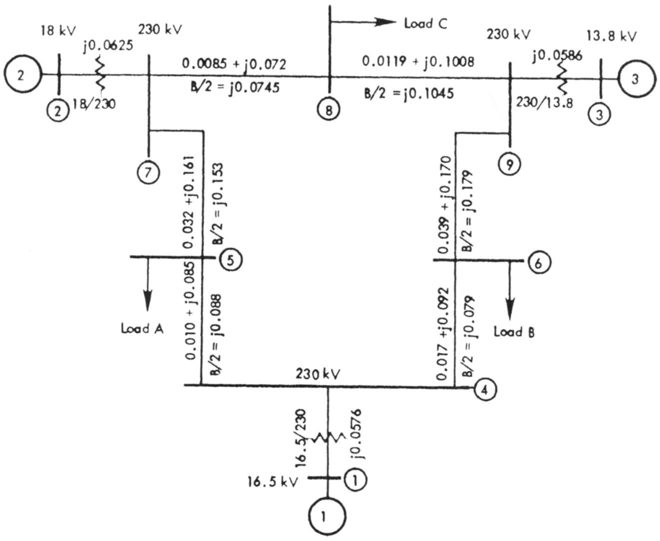

FIGURE 3.2: One line diagram of WECC system

To provide an unbiased evaluation of the trained model, two different data sets are required to train and test the classifiers. A supervised learning approach will be conducted on the training dataset, and the performance of the trained algorithm will be examined on a previously unseen test set. This will enhance the generalisability of the trained model for any future test set.

For the training dataset, loads can randomly take a value within 0.3 and 1.7 of the benchmark values subject to the following constraint: the summation of all coefficients must be within a bandwidth (upper and lower) ensuring both high and low loading scenarios are covered.

Fig. 3.3 shows the scenarios produced for training purposes (455 scenarios). The x-axis shows the generation scenario sequence number and the y-axis depicts load value in MW. Each load in the validation data set can take a coefficient from 0.25 to 1.85, where the summation of all coefficients must be within the same limit as in the training dataset. The performance of the classifiers is guaranteed while they interpolate. However, comparing load coefficients of training and validation datasets indicates that the validation dataset is designed to cautiously test the inter- and extrapolation capability of the trained classifiers.

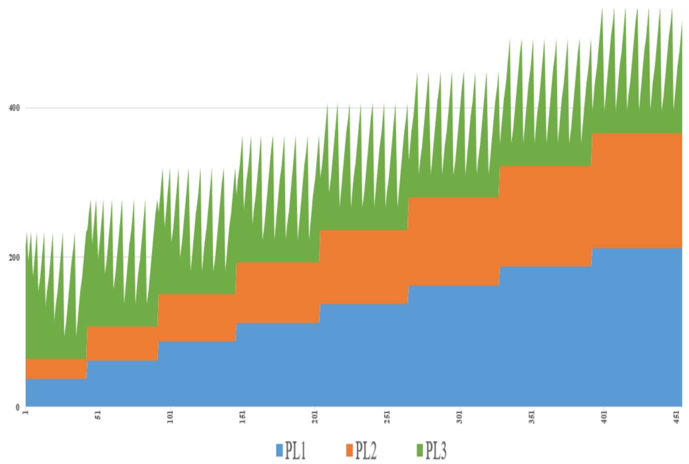

FIGURE 3.3: Proposed load variation for the training dataset (in MW)

Fig. 3.4 shows 699 produced validation scenarios. Then, for each scenario, real (P) and reactive power (Q) of each load along with all generators' real and reactive power, voltage magnitude and voltage angle of both ends of the line, and the cost of the generated power (dispatched scenarios) calculated by the ACOPF algorithm, are extracted.

Fig. 3.5 indicates ACOPF solution values regarding active power output of each generator for postulated load variations of the training dataset. It was observed that the number of instabilities for the most critical line of the test system, line 5-7, are 104 out of 455 scenarios (23%) for the training dataset and 198 out of 699 scenarios (28%) for the validation dataset. Subsection 3.6.1 and 3.6.2 explain the training process of the two classifiers on training scenarios.

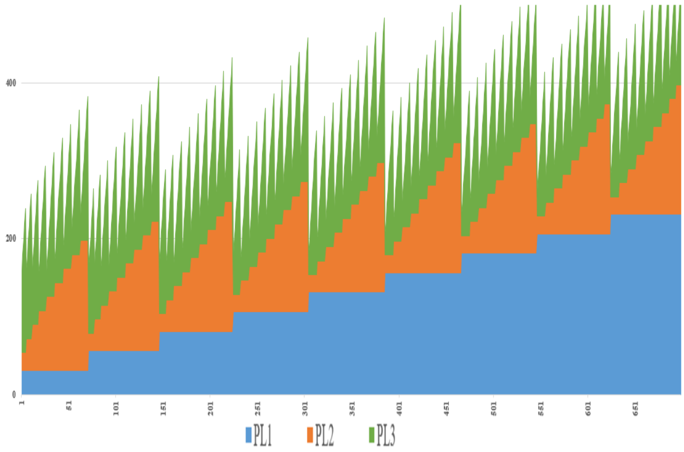

FIGURE 3.4: Postulated load variation for validation dataset (in MW)

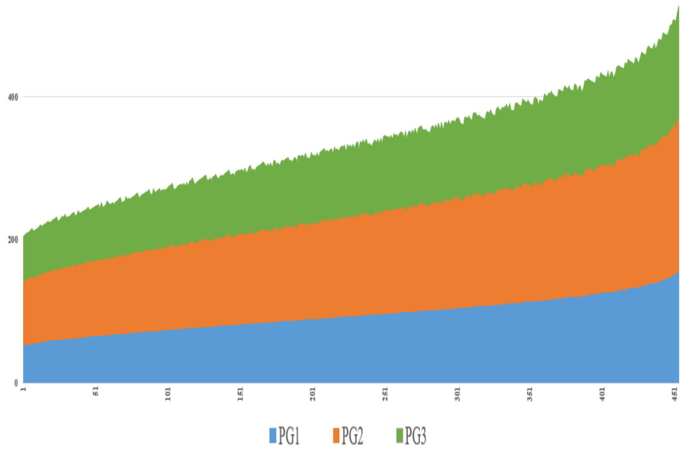

FIGURE 3.5: Generation values of ACOPF (in MW)

3.6.1 Binary classification

A shallow neural network with one hidden layer of 10 hidden neurons is trained using a scaled conjugate gradient backpropagation algorithm to capture the highly nonlinear relations between the inputs and binary output, indicating a negative class (unstable scenario) or positive class (stable scenario) respectively.

If the output of the NN falls between zero and one, the stability should be determined based on the confidence of the NN output. The distance of the values between zero and one to each end of the range can be used as a measure of confidence of the neural network's performance and will be used during further development of the algorithm.

Fig. 3.6 shows the confusion matrices of the proposed binary classifier on the training scenarios, and proves a high accuracy level, where each cell value is shown in percentage.

It is important to highlight that due to the high performance of the trained neural network, there was no need to use deep network structures with multiple hidden layers.

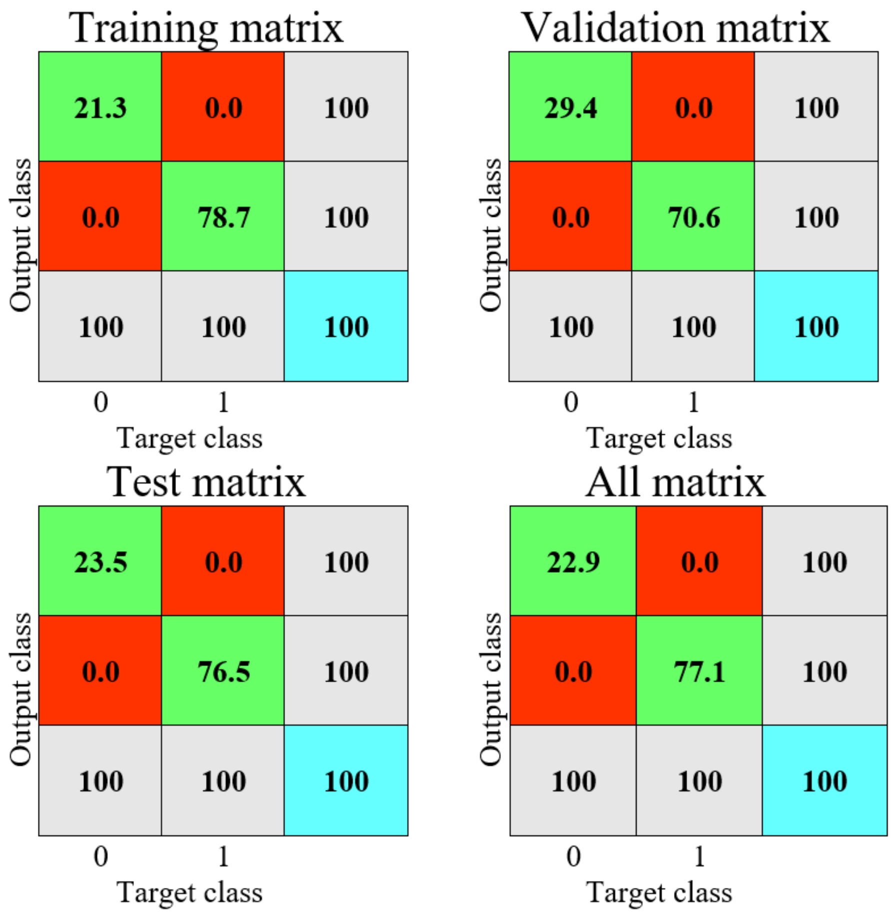

FIGURE 3.6: Confusion matrices of the trained NN binary classifier

3.6.2 Non-binary classification

For the unstable instances in the training process, the multiclass classifier needs to predict the time to instability with a very low level of error, even though it can only be trained on a small number of unstable instances. Therefore, estimating the time to instability is a difficult task. A multi-class regression with 20-fold cross-validation was selected for this study.

The data are standardized and the Kernel scale is chosen using a heuristic procedure. Then, the predictive accuracy of various fitted models was tested. Afterwards, fine tuning of the most accurate algorithms was performed to improve their efficiencies leading to find the best fit. It is important to acknowledge that these tunings are conducted both manually, such as cost of misclassification, and automatically using Bayesian optimisation, such as kernel scale and box constraint value.

Fig. 3.7 depicts the multi-class confusion matrix of the regression, showing an acceptable accuracy. It can be seen that most mis-classifications were due to the trade-off between the size of the collected data set and accuracy. For instance, a true class of 2 is miss-classified as 1.7 since only 2 data points where provided.

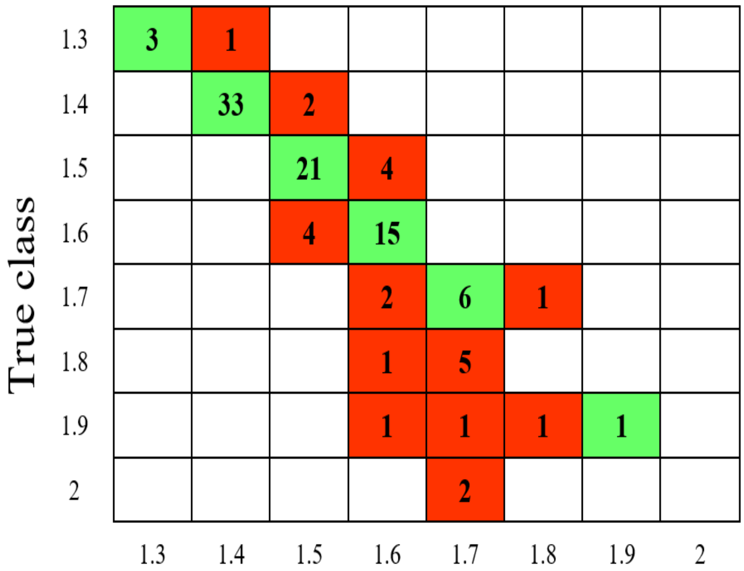

FIGURE 3.7: Multi-class non-binary classifier confusion matrix

After the two classifiers are trained, postulated load scenarios for the validation dataset are used and the same process is conducted to generate the dataset. Then, the output of the proposed algorithm using the trained classifiers is compared to the actual response of the system, obtained from time domain simulations.

3.7 Results and discussion

Regarding machine learning implementation and accuracy, for the 455 instances of the training data set, the algorithms achieve 100% accuracy for binary classification and 76% accuracy for the non-binary classification on the training data set.

To test the performance of the proposed algorithm, a validation dataset with 699 scenarios (different from training) was fed into the two-stage classification algorithm. It was observed that the binary classifier could distinguish stable and unstable cases accurately, with only 0.57% error.

The non-binary classifier also performed a remarkable prediction in detecting the time to instability, where the predicted time to instability had 6.8% labelling error. It provided 100% credibility, e.g. it did not introduce a new class as a response to inputs, which is one of the drawbacks of deep learning methods especially where little data is provided. To better understand the performance of the non-binary classifier, the mean absolute error (MAE) is calculated using equation 3.1.

$$MAE = \sum_{i=1}^{N} |y_i^{predicted} - y_i^{actual}| \tag{3.1}$$

The MAE of the proposed approach is as small as 0.0145, showing the accurate performance of the non-binary classifier. Moreover, the mean value of actual versus predicted time to instability are 1.61 and 1.57 respectively. Also, the variance of actual versus predicted time to instability within misclassified instances (i.e. FP and FN) are 0.03 and 0.02. These incidents are very similar.

Fig. 3.8 shows a scatter plot indicating the error of prediction for all 48 misclassified incidents. A small difference between the predicted time to instability (in orange) and the actual ground truth (in blue) is evident, where the error value is plotted in green.

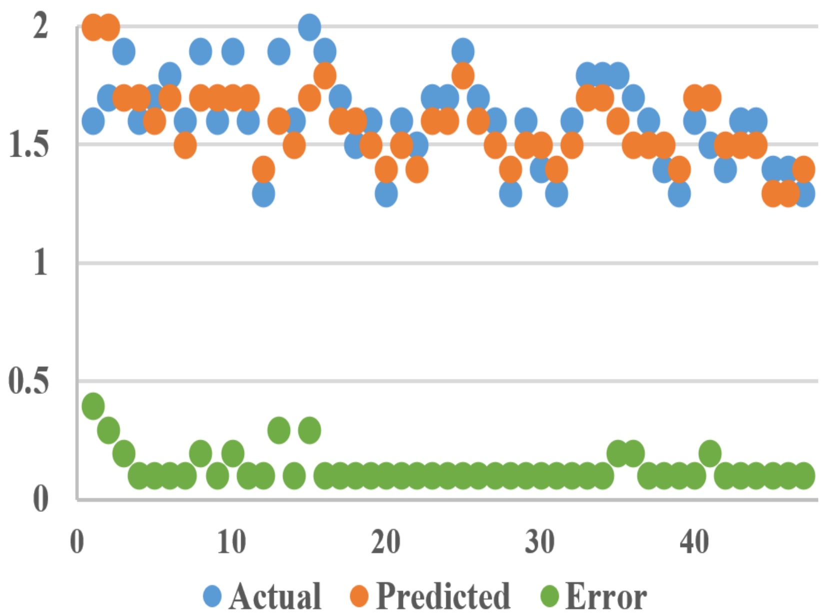

FIGURE 3.8: Scatter plot of the time to instability predictions.

There is a trade-off between the accuracy of the predicted time to instability and the size of the gathered dataset. For instance, introducing previously learnt mislabelling will increase the accuracy; however, the aim of the author was to keep the size of the required dataset as small as possible and to minimise the manual interference while still maintaining justifiable accuracy.

3.8 Conclusion

The highly nonlinear, computationally expensive, and time constrained nature of transient stability assessment makes data-driven classification techniques well-suited for this application. This study addressed the bottleneck of using fast stability prediction approaches in the presence of control devices – a step forward compared to some data-driven methods as well as all the direct methods introduced in Section 1.4.1 which incorporate simplified versions of the system with minimum available control units[2], resulting in lower level of non-linearity in data patterns.

We introduced a two-stage classification algorithm to not only predict the stability status, but also predict the time to instability as in indication of the severity of the disturbance.

This new approach will help not to underestimate the security of the system and can potentially help decrease electricity costs for costumers, as it increases the available search space for the optimal power flow (OPF) problem.

In this chapter we followed the instructions available in the literature. Specifically, we did not use any insight from the power system dynamics to learn more about the highly nonlinear function that governs the transient stability of the system. This not only makes the process more understandable for power system operators, but also could lead to higher level of accuracy.

In the next chapter, we further explore methods to include the power system dynamics insights in the data collection process. At the same time, we aim to reach higher accuracy as well as higher reliability of prediction. High reliability of prediction means minimising unsafe misclassification (*False Positives*) that endanger the security of power

[2]Including the governor, exciter, and power system stabiliser.

systems. We aim to find an acceptable compromise between accuracy and unsafe misclassifications (FP), which is a bi-objective problem.

Chapter 4

Transient Stability Assessment With An Instance Transfer Learning Scheme Based On Power System Dynamics

4.1 Introduction

Power systems are facing a range of unprecedented challenges in a new technological and economic landscape, including the uptake of rooftop PV and expanded adoption of renewable resources and storage systems. The resulting changes in grid behaviour require new grid capabilities and modelling approaches, including better assessment of the ability of the system to withstand faults.

As discussed in Chapter 1 and 3, conventional machine learning and deep learning solutions have been introduced to augment transient stability assessment and provide real-time situational awareness. In addition to deep learning and conventional machine learning models, Transfer Learning, a collection of methods for improving the performance of data models on data with different distributions or feature spaces, has recently gained attention in power system contexts. For instance, transfer learning for on-line TSA is proposed in [76], where after training a model on one fault location, the learning is transferred to assess faults at different locations. This has the advantage of requiring fewer trained models while improving accuracy.

In Chapter 3, we used a simple shallow neural network with one hidden layer of 10 hidden neurons to predict the transient stability for a small power network and a small number of operational scenarios with a small variation range. Our experiments show that the performance of that simple model for larger power networks and larger variations in load scenarios does not meet the expected accuracy level (above 90% accuracy). This means in order to capture the patterns in the dataset with higher degree of non-linearity (as a result of more DAEs governing the classification label), a more complex model is required.

This chapter introduces a novel framework for data-driven TSA based on the understanding of a power system's dynamics. The benefit is to produce a method with versatile, and robust outcomes for single contingency pre-fault TSA, in particular improving reliability. The reliability of prediction is improved by minimising unsafe misclassification (*False Positives*) that endanger the security of power systems. We achieve this by combining two datasets in an instance transfer learning framework: in addition to the standard dataset that captures the behaviour of the entire system, we use an auxiliary dataset that integrates the knowledge of rotor angle stability, by focusing on a small part of the network that is known to have a crucial impact on the stability for a given contingency. Moreover, we add a key element to previous approaches, emphasising the internal trade-offs in the model to minimise the cases where the model incorrectly predicts a scenario as stable.

The proposed method makes two significant improvements over the state of the art. Firstly, the new data collection strategy boosts the reliability of TSA predictions while maintaining a high accuracy level, regardless of the applied data model. Secondly, to avoid the low generalisation [52], convergence [55], and interpretability of DL methods, we exploit a transfer learning-based ensemble adaptive boost model, introduced in [59]. This also leads to high versatility (i.e. no parameter tuning is required for different contingencies) and robustness to outliers.

We show in an empirical evaluation that this new framework outperforms standard ML and DL approaches.

4.2 Contributions

- **A novel data collection strategy:**

  We introduce a new data collection strategy (the **augmented dataset**) employing the knowledge of power system dynamics in a transfer learning scheme. The augmented dataset has two components.

  The first is an **auxiliary dataset** prepared based on the dynamics of the synchronous generators that are in close proximity to the fault location, where a fraction of the loads in the system vary. We call this the **Fault-Affected Area** (FAA).

  The second dataset is a set of scenarios similar to the whole-system classical machine learning approach, where all the loads in the system vary. Since it has the same underlying distribution as the test set we call it the **same-distribution dataset**.

- **Application of instance transfer learning:**

  These two datasets (auxiliary and same-distribution datasets) have different distributions. In order to incorporate them in the training process, we use a transfer learning framework introduced in [59]. More details on the FAA concept and transfer learning scheme can be found in section 4.3.1 and section 4.3.3, respectively.

The proposed approach in this chapter uses a novel data collection strategy in a transfer learning framework and makes two significant improvements compared to the current literature:

1. Improved reliability: In our proposed approach we reduce the unsafe misclassifications by incorporating the auxiliary dataset in a transfer learning framework, compared to standard machine learning approaches.

2. Improved versatility and interpretability: The common practice to reach high overall accuracy in the literature is to collect a large dataset and fine tune a complex deep neural network structure for a particular collected dataset. However, concerns about the versatility and interpretability of deep network structures with a significant number of parameters have recently been raised [52–55]. Hence, we instead exploit the transfer learning ensemble adaptive boost model (TrAdaBoost)

as introduced in [59] to efficiently perform instance transfer in our proposed transfer learning framework. This leads to high versatility (no parameter tuning is required for different contingencies) and interpretability (it has a clear decision making process as it is composed of an ensemble of decision trees) of the model compared to deep learning models.

We show in an empirical evaluation that this new approach can achieve better performance compared to standard machine learning and deep learning approaches.

The remainder of this chapter is organised as follows. The detailed methodology of our approach follows in Section 4.3. Section 4.4 details the simulation platform and analysis. Section 4.5 presents results and discussions.

4.3 Methodology

We develop a novel method that increases the reliability of data-driven TSAs by incorporating the power systems engineer's intuition and knowledge of power systems dynamics and stability. The methodology is described below in three sections, covering the Electrical Engineering, Data Science, and Optimisation concepts used in this study.

4.3.1 Fault-Affected Area and the novel data collection method

The knowledge of power system dynamics we leverage has three core pillars. Firstly, according to the equation of motion, for a given unit commitment and network configuration, variations in load result in variations in initial rotor angle of synchronous generators. Secondly, after a fault, the disturbance effect will spread from the fault location to the rest of the network according to the network impedance and generator inertia [77]. Thirdly, power systems typically consist of distinct areas that are only loosely coupled.

Hence, for a given unit commitment, network configuration, and fault location, the interaction of synchronous generators in close proximity to the disturbance dominates the transient stability status, as depicted in a simplified form in Fig. 4.1. It is important to highlight that the beyond first-swing superposition of a slow inter-area and a local plant swing mode in larger time frames [78] is not considered.

We empirically confirmed through simulations that for a generator far from a fault location, transient instability only occurs if there is at least one unstable generator within the area where the fault occurred. An area is a part of a network that includes a number of interconnected generators and loads with small electrical distances, connected to the rest of the grid through boundary buses and tie transmission lines with high impedance or low capacity.

This highlights the significance of variables (features in an ML sense) in close proximity to a fault location. We refer to this concept as the Fault-Affected Area (FAA). It determines the variables that dominate transient stability, e.g. the output power of local synchronous generators, voltage magnitude and angle at local buses, and power flows in local transmission lines. Therefore, for any given operational scenario, the combination of these variables follows a specific pattern based on the dynamics of the FAA. While we could train a model using only FAA scenarios, the next step combines these with scenarios sampling features from the entire network. This improves the reliability of the TSA predictions by gaining a rich feature space from which the model can better learn the dynamic behaviour of the system.

4.3.2 Instance transfer learning

Transfer learning is a technique for improving the prediction power of a model on one dataset by transforming information from a related dataset [59]. Following this approach, we combine operational scenarios where only loads within a Fault-Affected Area

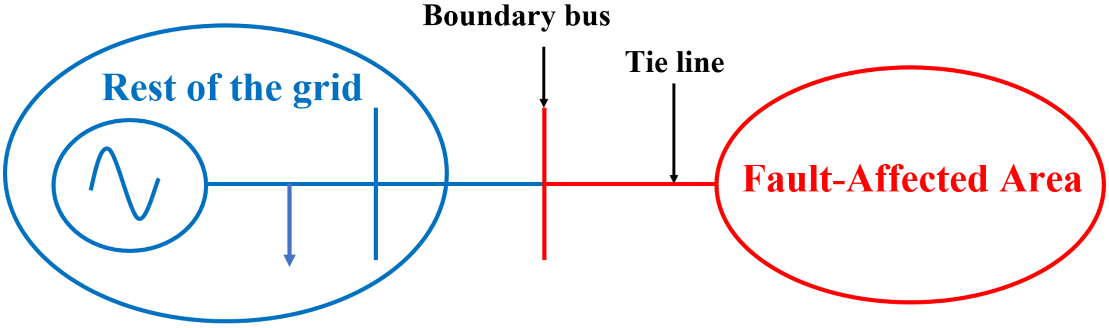

FIGURE 4.1: The rest of the grid from the Fault-Affected Area's point of view.

vary with operational scenarios where all the loads in the network vary. The set of scenarios based on the FAA is called the **auxiliary dataset**, and it incorporates the knowledge of power system dynamics. The set of scenarios where all loads vary is similar to the whole-system classical machine learning approach, and it is called the **same-distribution dataset**. The combination of auxiliary and same-distribution sets is called the **augmented dataset**, which is used as the training set for our models.

The trained model will be tested on a dataset that has the same underlying distribution as the same-distribution set, hence the naming. However, the probability distribution of the auxiliary set is typically different from the one of the test set and of the same-distribution set, which would prevent the successful use of classical ML approaches, where the probability distributions of the training and test sets have to be similar [56]. Therefore, instance transfer learning is applied, a technique that was developed for situations where the distributions of data in the training and test sets are different [57].

We use a transfer learning ensemble adaptive boost algorithm (TrAdaBoost) introduced in [59], where the instances are weighted so that the most useful ones have positive impact in learning the stable region of operation while the weights of the incorrectly classified samples with different distribution are adjusted to reduce their influence. The simplified schematic of the algorithm is shown in Fig. 4.2.

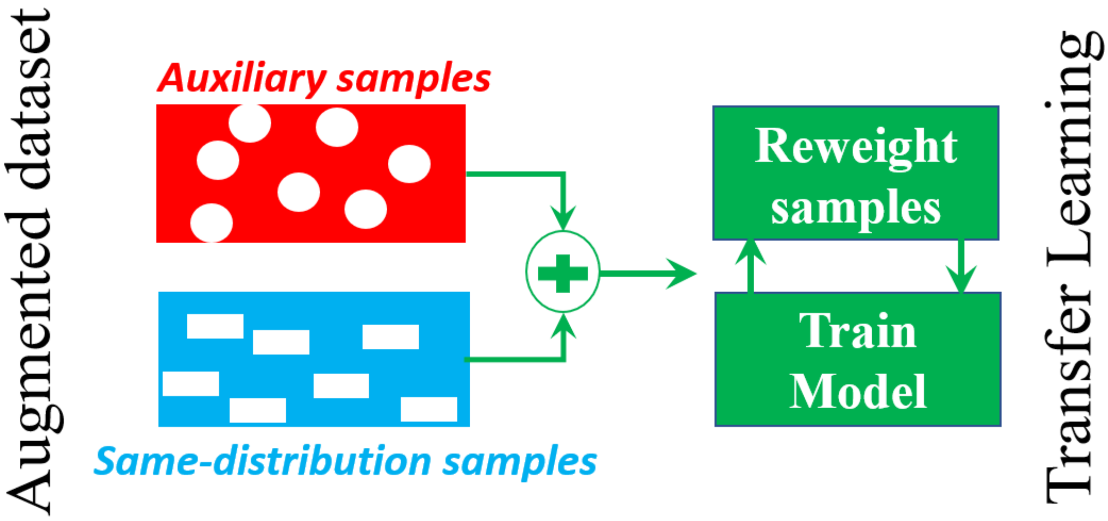

FIGURE 4.2: The overall training process of the proposed transfer learning framework.

4.3.3 Internal trade-off

The aim of this element of our framework is to reduce unsafe misclassifications to improve the reliability or safety of our method. Machine learning approaches often minimise overall misclassifications, i.e., both false positives (FP) and false negatives (FN). We are particularly concerned about FP, or unsafe misclassifications, which wrongly classify a scenario as stable when in reality it is unstable, since these endanger the security of the power system.

A secondary objective is to achieve low safe misclassifications (FN), where the model predicts a scenario as unstable but the ground truth label is stable, so that the model does not become unnecessarily conservative. Hence we use a cost-sensitive loss function to tune the trade-off between FP and FN.

4.4 Data preparation and training procedure

Our framework follows three major steps. The first is the new data collection approach, the *augmented dataset*, encompassing the *auxiliary* and the *same-distribution* datasets. The second is the transfer learning scheme based on the TrAdaBoost model. And finally, we optimise FP and FN while maintaining overall accuracy.

In order to demonstrate the performance of our new approach we use the IEEE 39-bus test system, in line with previous studies using the same experimental framework [31, 34, 35] to demonstrate the performance of the proposed TSA approach for a number of contingency scenarios. The network configuration along with its network areas are shown in Fig. 4.3. As discussed in Section 2.4, we approximate the impact of renewables with negative loads (i.e. large load variation ranges), while the impact of converter dynamics will be left for future work. To show that the performance of the model is independent of the fault location, we study two contingencies inside an area, line 21-22 and line 17-18, and another two on boundary lines, line 14-15 and line 3-4. Here we detail the steps to evaluate the stability for a contingency on line 21-22.

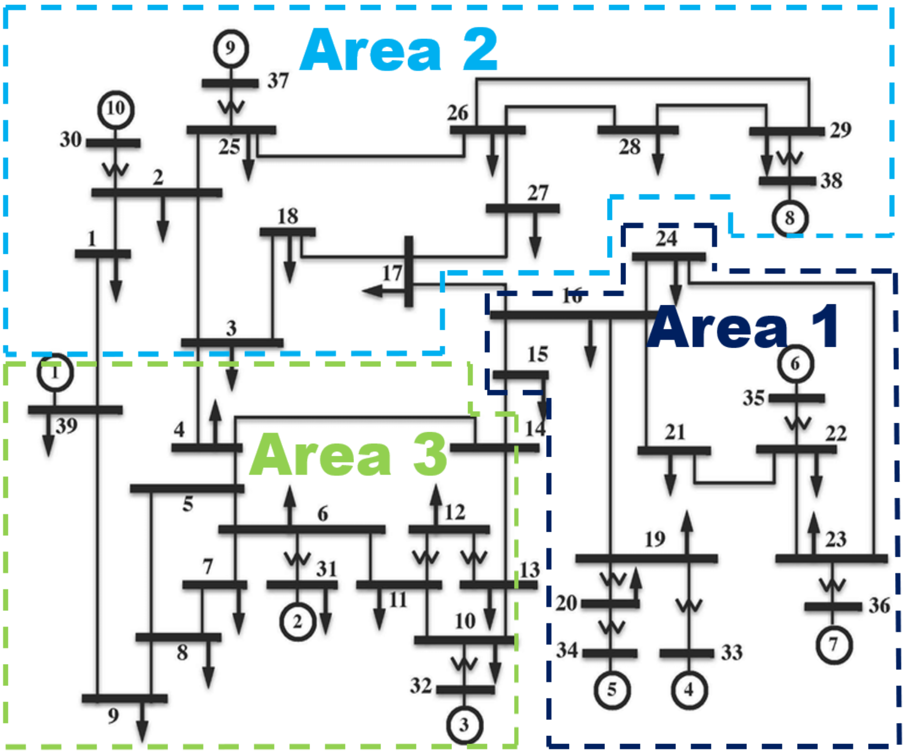

FIGURE 4.3: IEEE 39-bus system and its areas.

4.4.1 Used dataset

Our aim is to map the stability of the augmented dataset, composed of the auxiliary and the same-distribution sets, to the stability of the unlabelled instances in the test set. The augmented dataset includes a *same-distribution set* of 10,000 samples and an *auxiliary set* of 5,000 samples, with the same proportion of classes in the two datasets.[1]

To enable comparison with standard ML approaches, we also generate a set of labelled samples for training those data models. The training set includes 15,000 samples, where all loads in the system are randomly varied between 60% and 140% of their initial values. This large span is designed to resemble the impact of spatial and temporal uncertainties of future grids with high penetration of renewables. The trained models will be tested on a common test set of 15,000 samples with the same underlying distribution as in the training and the same-distribution sets.

[1]The Sobol sampling approach is utilised throughout this study.

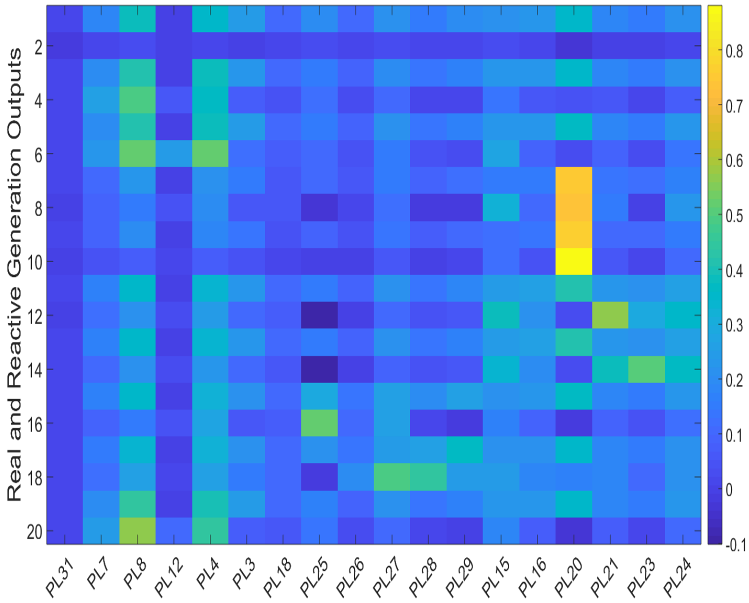

FIGURE 4.4: Sensitivity analysis: output power of generators vs. loads.

4.4.1.1 Design of operational scenarios in the augmented set

The same-distribution set is made by randomly varying all the loads in the system between 60% and 140% of initial values, which has the same underlying distribution as the test set. On the other hand, the auxiliary set is made by randomly varying a subset of loads, as per the FAA concept, determined using two **sensitivity analyses**.

The first analysis clarifies which loads in the system dominantly affect the output of local generators within the FAA. Fig. 4.4 depicts the correlation between standardized load values and generator output. The highest positive correlations are shown in yellow, while the highest negative correlations are shown in dark blue. This figure reveals the great impact of the load at bus 20 and the partial importance of the loads at buses 4 and 8 in determining the output of generators.

The second analysis defines which loads dominantly influence the power flow of local transmission lines. Fig. 4.5 shows the correlation between standardized load values and power flows in transmission lines, which confirms the great impact of the load at bus 20, and reveals the significance of the loads at buses 15, 16, 21, 23 and 24. In accordance with the conclusion of the two analyses, the loads at buses 4, 8, 15, 16, 20, 21, 23 and 24 are selected to produce the load scenarios of the auxiliary set.

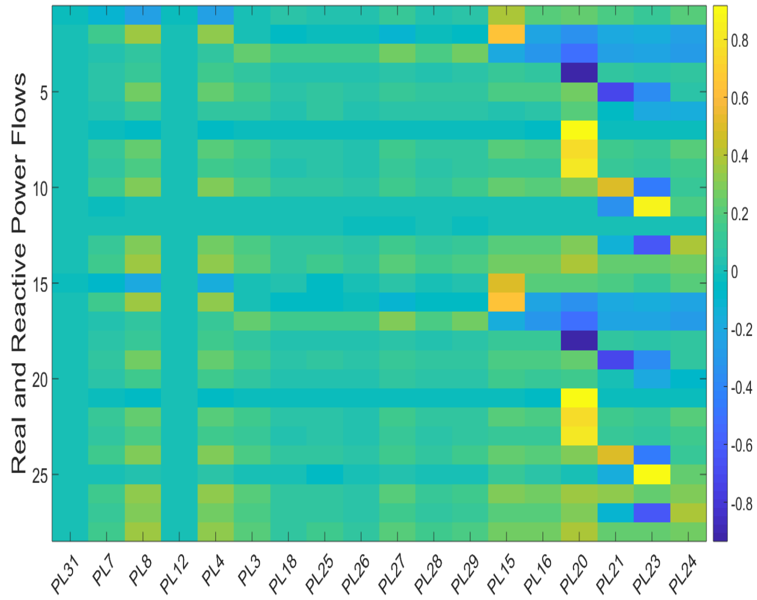

FIGURE 4.5: Sensitivity analysis: power flow of transmission lines vs. loads.

Moreover, since the auxiliary set and the same-distribution set include different sets of loads in their load scenarios, the distribution and range of features in the two sets are different. For instance, Fig. 4.6 shows the voltage magnitude at bus 19, where the distributions and the range of feature values in the two sets are different. To reduce the dissimilarity in the range of feature values, the loads in the selected subset are varied within a 40% to 160% range of the initial values. To summarise, the samples in the

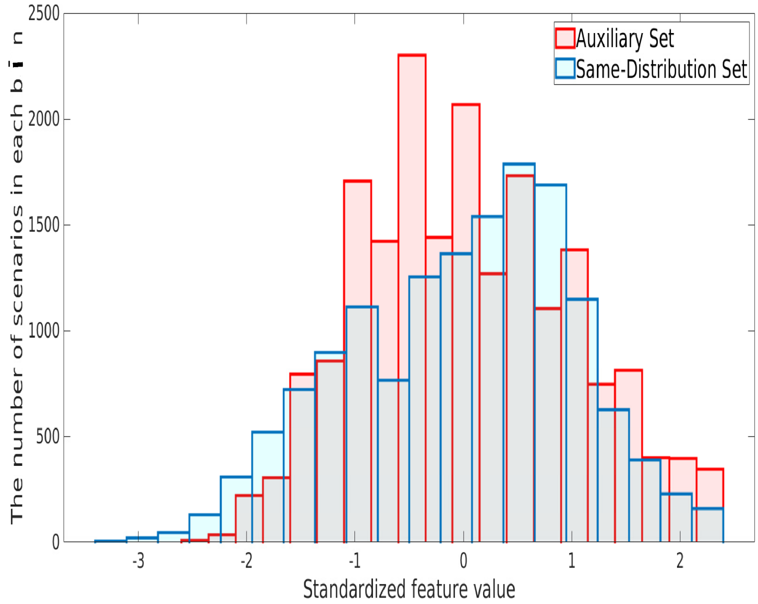

FIGURE 4.6: The range of auxiliary and same-distribution sets don't coincide for voltage at bus 19.

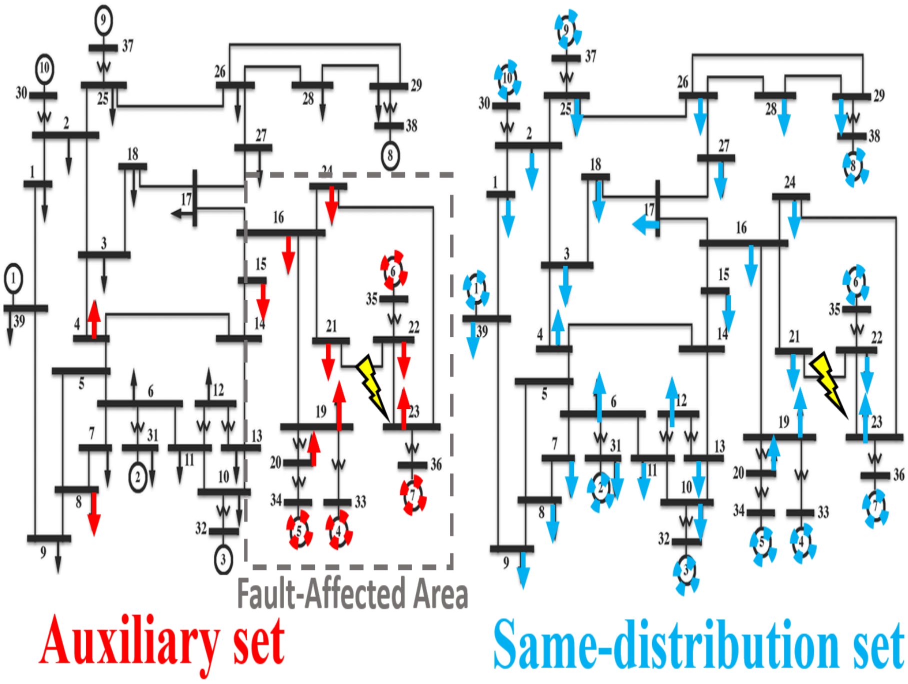

FIGURE 4.7: The schematic of the used dataset for fault on line 21-22.

same-distribution set are randomly varied between 60% and 140% of their initial values while the samples in the auxiliary set are randomly varied between 40% and 160% of their initial values to cover a similar minimum and maximum range of features as in the same-distribution set.

Fig. 4.7 shows the overall design of operational scenarios. The auxiliary set determines the stability of generators inside the FAA (red circles) as a function of the eight varying loads (red arrows). The same-distribution set, where all the loads (blue arrows) vary, determines the stability of all the generators (blue circles).

4.4.1.2 AC optimal power flow

For every load scenario produced, the most cost-effective generation schedule is computed using an ACOPF algorithm defined by an objective function and bounded by a set of engineering laws and physical constraints [71]. AC optimal power flow (ACOPF) is a non-linear optimisation problem that is used to create optimal generation dispatch for postulated load scenarios while ensuring the operation of the system within its allowed limits. More details on the ACOPF algorithm can be found in Appendix B.

4.4.1.3 Transient stability analysis

To determine whether each operational scenario (computed by ACOPF) remains stable after any of the contingency scenarios, a time-domain simulation is performed by simulating 5 seconds of system operation, where a three-phase fault is applied at 1s and then cleared by tripping the faulty line after 100ms. The resulting answer of either *stable* or *unstable* is used as the classification label.

4.4.2 Training the models

In addition to our proposed framework using the TrAdaBoost algorithm, we also experiment with a Convolutional Neural Network (CNN) consisting of three consecutive series of convolutional layers with decreasing filter sizes of 9, 7, and 5, while the number of filters is increased. Each convolution layer is followed by ReLu, max-pooling, and batch normalisation layers. Afterwards, a dropout layer is included followed by two fully connected layers. Finally a customised classification layer is used to measure the performance of the models, as introduced in [21], shown in Fig. 4.8.

The standardised augmented set is randomly divided into training (80%) and validation (20%) sets while maintaining the same proportion of classes, using a stratified sampling approach, prior to training the models. The trained model will then be tested on a dataset that has the same underlying distribution as the same-distribution set where all the loads in the network vary.

4.4.2.1 Cost-sensitive loss function

In order to measure the performance of the models we define the cost of misclassification as the cost of classifying a point into class X while its true class is Y. Unsafe misclassification (FP) must be minimised for the security of power system operation. Additionally, we are interested in keeping the safe misclassification cases (FN) as low as possible. To tune the trade-off between FP and FN, we apply the weights α and β to the misclassification costs. To replicate the cost array of the TrAdaBoost model objective, a cost-sensitive loss function (4.1) was implemented as a customised output layer of the CNN.

$$Loss = -\sum_{i=1}^{N}\sum_{j=1}^{2}(t_{ij}\log y_{ij} - \alpha \times FN - \beta \times FP) \tag{4.1}$$

Here, N is the number of samples, j ranges over the two classes (stable and unstable), t_{ij} are the targets, y_{ij} are the predicted values, and α and β are the varying weights applied to the misclassification costs.

4.4.2.2 Bi-objective optimisation

Based on the parameters α and β, a model that results in the desirable TSA predictions can be selected. We aim to find an acceptable compromise between accuracy and unsafe misclassifications (FP), which is a bi-objective problem. We followed a *grid search* approach by creating a 10×10 matrix of α and β coefficients for both models. From the resulting 100 options for each model, we selected the ones that minimise the FP while staying within 0.2 percentage points of the maximum accuracy. We refer to this

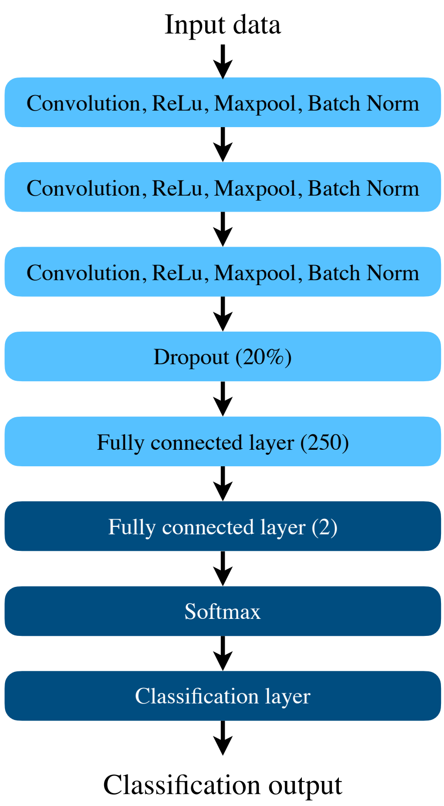

FIGURE 4.8: Convolutional neural network structure.

as the compromise strategy. Other trade-offs could also be achieved depending on the application, for instance minimum FP or maximum accuracy.

4.5 Results and Discussion

This section presents empirical results that demonstrate the comparative advantage of using the proposed data collection approach, i.e. the *augmented set*, over the existing one that uses a standard training set. We also compare the performance of TrAdaBoost with a CNN model using training and augmented sets. We first compare the grid search results of the two models for both datasets and the three contingency cases, which are prepared by varying the misclassification cost coefficients (α and β) and reported based on different trade-off strategies in section 4.5.1.

4.5.1 Trade-off strategy

Here, we report different trade-off strategies for the bi-objective optimisation problem of the grid search results, namely minimum FP, maximum accuracy, and our proposed compromise strategy, where we minimise the FP while staying within 0.2 percentage points of the maximum accuracy. To compare these strategies, we use the False Positives and the overall accuracy measures, reported in Table 4.1.

Firstly, it can be seen that minimising FP leads to a decrease in accuracy the same way that maximising accuracy leads to an increase in FP.

Secondly, the results confirm that the introduced compromise selection strategy consistently favours low FP over overall accuracy, compared to the maximum accuracy guideline, even though these two strategies occasionally provide the same option, e.g. CNN trained on training set for contingency on line 21-22 and 14-15.

Thirdly, and the most important result of this study, we can see that by compromising on up to 0.2 percentage points of accuracy, the strategy is always able to achieve a larger improvement in FP. For instance, for the fault on line 21-22, in the TrAdaBoost model trained on the augmented set the compromise strategy loses 0.02 percentage points of accuracy while achieving 0.05 percentage points lower FP compared to the maximum accuracy strategy.

TABLE 4.1: Comparison of trade-off strategies for the three contingency scenarios.

Contingency on line 21-22							
		Minimum FP		Maximum Accuracy		Compromise	
Algorithm	**Data-Set**	**FP**	**Accuracy**	**FP**	**Accuracy**	**FP**	**Accuracy**
TrAdaBoost	Augmented set	0.35%	91.60%	1.60%	95.46%	1.55%	95.44%
CNN	Augmented set	1.42%	94.72%	2.19%	95.15%	1.75%	95.14%
TrAdaBoost	Training Set	1.16%	93.16%	2.62%	95.45%	2.30%	95.35%
CNN	Training Set	1.89%	95.14%	2.11%	95.59%	2.11%	95.59%
Contingency on line 14-15							
		Minimum FP		Maximum Accuracy		Compromise	
Algorithm	**Data-Set**	**FP**	**Accuracy**	**FP**	**Accuracy**	**FP**	**Accuracy**
TrAdaBoost	Augmented set	0.41%	94.90%	0.78%	96.29%	0.72%	96.28%
CNN	Augmented set	0.62%	94.99%	0.74%	96.18%	0.74%	96.18%
TrAdaBoost	Training Set	0.42%	93.91%	1.06%	96.04%	0.92%	96.00%
CNN	Training Set	0.64%	94.92%	0.91%	96.04%	0.91%	96.04%
Contingency on line 17-18							
		Minimum FP		Maximum Accuracy		Compromise	
Algorithm	**Data-Set**	**FP**	**Accuracy**	**FP**	**Accuracy**	**FP**	**Accuracy**
TrAdaBoost	Augmented set	1.16%	92.74%	1.82%	95.01%	1.82%	95.01%
CNN	Augmented set	1.75%	94.30%	2.11%	94.60%	1.96%	94.52%
TrAdaBoost	Training Set	1.38%	94.13%	2.34%	94.56%	2.24%	94.38%
CNN	Training Set	1.81%	94.01%	2.13%	94.35%	2.06%	94.32%
Contingency on line 3-4							
		Minimum FP		Maximum Accuracy		Compromise	
Algorithm	**Data-Set**	**FP**	**Accuracy**	**FP**	**Accuracy**	**FP**	**Accuracy**
TrAdaBoost	Augmented set	0.50%	88.95%	1.55%	95.29%	1.55%	95.29%
CNN	Augmented set	1.42%	94.76%	1.65%	94.95%	1.65%	94.95%
TrAdaBoost	Training Set	0.84%	90.80%	2.03%	94.42%	2.03%	94.42%
CNN	Training Set	1.69%	94.22%	2.11%	94.62%	1.94%	94.61%

4.5.2 Comparative combination of models and datasets

Since the distribution of labels in the test set is a function of fault location, each contingency has a different label distribution. Therefore, to comprehensively evaluate and compare the performance of the two data models using training and augmented datasets for our proposed compromise trade-off strategy, we use the *Recall*, *Precision*, *Specificity*, and *Accuracy* measures formulated in (4.2), (4.3), (4.4) and (4.5), respectively, where *TP* and *TN* stand for True Positives and True Negatives respectively [79]. These measures are reflected in Table 4.2.

$$Recall = \frac{TP}{TP + FN} \tag{4.2}$$

$$Precision = \frac{TP}{TP + FP} \tag{4.3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4.4}$$

$$Accuracy = \frac{TP + TN}{100} \tag{4.5}$$

The best combination of each model and dataset not only has a very high accuracy, but also provides the lowest unsafe misclassifications (FP), compared to the safe misclassifications (FN). Table 4.2 shows the comparison of the performance of analogous models using the two datasets. The TrAdaBoost model using the augmented set performs best overall in terms of reliability (lowest FP) of the transfer learning framework, supported by providing the highest precision and specificity measures for all contingency scenarios.

Occasionally, there is a slight trade-off between reaching the lowest FP and the highest overall accuracy amongst the combinations of model and dataset. For instance, the contingency on line 21-22 shows 95.59% accuracy for CNN trained on training set compared to 95.44% for TrAdaBoost trained on augmented set. However, since the improvement in FP (0.51%) is much larger than the slight reduction of the overall accuracy (0.13%) the trade-off sounds reasonably justifiable. This fact is also confirmed with the consistently highest precision and specificity measures of the TrAdaBoost model trained on the augmented set for all the contingencies.

Regarding the training effort of the two models, the CNN was trained on two parallel GPUs (TESLA-V100-PCIE-16GB) while TrAdaBoost was trained on 16 parallel CPU cores (Intel-Xeon-E5-2680-v3). Although the CNN was trained 20% faster on average, it required additional engineering effort for adjusting to new datasets (i.e. different contingencies) as we faced different convergence and gradient explosion issues. On the other hand, the TrAdaBoost took more time to train but did not require any further attention for new datasets. This indicates the higher versatility of this model compared to CNN.

Moreover, according to our experiments, the CNN exhibits a larger number of outliers with high errors compared to TrAdaBoost. For instance, Fig. 4.9 shows the FP of the models and datasets for the contingency on line 21-22, proving the greater robustness of TrAdaBoost.

TABLE 4.2: Comparative combination of models and datasets.

Model	DataSet	FP	Recall	Precision	Specificity	Accuracy
Contingency on line 21-22						
TrAdaBoost	Augmented	1.55%	92.74%	96.13%	97.35%	95.44%
CNN	Augmented	1.75%	92.48%	95.63%	97.02%	95.14%
TrAdaBoost	Training	2.30%	94.13%	94.25%	96.16%	95.35%
CNN	Training	2.11%	94.28%	94.73%	96.47%	95.59%
Contingency on line 14-15						
TrAdaBoost	Augmented	0.72%	93.37%	98.33%	98.68%	96.28%
CNN	Augmented	0.74%	93.21%	98.28%	98.65%	96.18%
TrAdaBoost	Training	0.92%	93.18%	97.86%	98.32%	96.00%
CNN	Training	0.91%	93.24%	97.88%	98.34%	96.04%
Contingency on line 17-18						
TrAdaBoost	Augmented	1.82%	89.89%	93.93%	97.35%	95.01%
CNN	Augmented	1.96%	88.85%	93.47%	97.14%	94.52%
TrAdaBoost	Training	2.24%	89.15%	92.53%	96.75%	94.38%
CNN	Training	2.06%	88.53%	93.13%	96.99%	94.32%
Contingency on line 3-4						
TrAdaBoost	Augmented	1.55%	88.12%	93.80%	97.89%	95.30%
CNN	Augmented	1.65%	87.29%	93.40%	97.75%	94.95%
TrAdaBoost	Training	2.03%	86.61%	91.88%	97.24%	94.42%
CNN	Training	1.94%	86.99%	92.24%	97.36%	94.61%

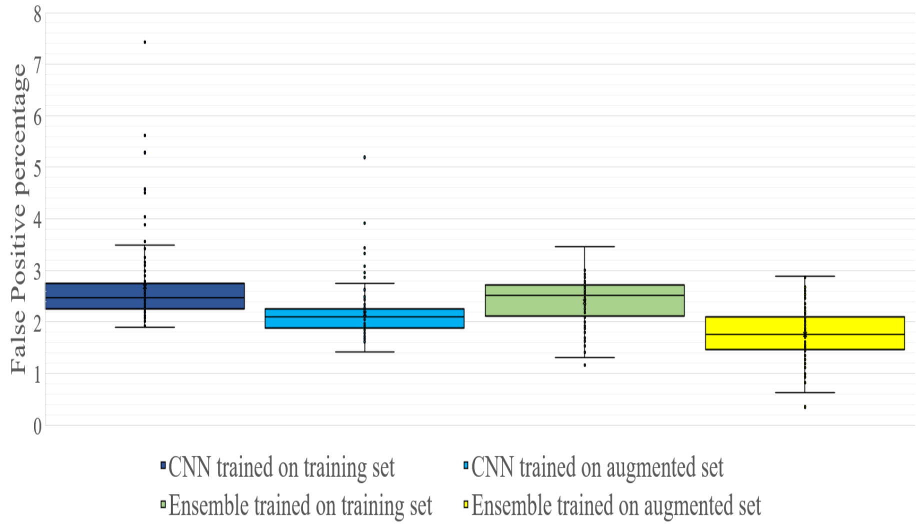

FIGURE 4.9: The False Positives of the two models and datasets.

4.6 Conclusions

In this chapter, we explored how to improve the pre-fault prediction of transient stability of power systems using a transfer learning scheme, introducing a novel data collection approach. We incorporate an auxiliary dataset into the training process that captures crucial information about the stability of operational scenarios, focusing on the Fault Affected Area of the network.

To the best of the authors' knowledge, this is the first attempt at incorporating the knowledge of power system dynamics to develop a transfer learning mechanism for transient stability assessment.

Using the IEEE 39-bus test case we empirically showed that the proposed data collection method achieves improved reliability compared to the standard approach, resulting in the lowest number of unsafe misclassifications on the augmented set for both models. The use of conventional machine learning algorithms also improves the interpretability of the approach compared to deep learning.

Furthermore, the high accuracy of the TrAdaBoost model yields a high degree of confidence in the security of the analysed operational scenarios.

Moreover, compared to the deep learning model (CNN), the proposed approach provides more versatility, due to the absence of convergence and gradient explosion issues, and robustness, with fewer high-error outliers. It therefore leads to a smooth training experience of the model.

In this chapter we used the insight from the power system dynamics to learn more about the highly nonlinear function that governs the transient stability of the system. However, we did not test the performance of the trained models in the presence of topology changes such as adding or removing transmission lines, reflecting the real-world practice in short term and long term operation of power systems. This will be further explored in the following chapter.

Chapter 5

Transient Stability Assessment Using Modular Deep Neural Networks For Power Network Topology Changes

5.1 Introduction

As discussed in Chapter 3 and 4 in details, data-driven approaches aim to provide situational awareness regarding anticipated but not yet occurred contingencies through accelerating stability assessments using fast and reliable solutions. Recent studies mainly collect data from time-domain simulations, sampled from a fraction of the space of all system states, and train a data model off-line. This model can then be used to predict the stability of any other system state without having to run the time-domain simulation, with promising results from both deep learning [29, 33] and conventional methods [34, 35]. Convolutional neural networks (CNN) have also recently been exploited for pre-fault transient stability assessment [21, 42, 43], using a moderate yet different deep neural network structure for the same test cases in the literature [44].

The trained models can generally predict the transient stability status of a system with high accuracy about 1000 times faster than performing actual RMS simulations[1]. As discussed in Chapter 2, the assumption of recent studies, as well as the methods introduced in Chapter 3 and Chapter 4 of this thesis, is that the topology of the power network (that is the connectivity among power system components such as generators, transmission lines, loads, etc.) invariably remains the same. In practice, however, the topology of power systems constantly evolves for various reasons, including when new transmission lines connect new wind or solar farms to the grid or an outage of an existing line occurs due to maintenance. These topology changes alter the dynamics of the system and therefore compromise the performance of the trained classification model for $N-1$ scenarios. We confirm this drop in classification accuracy experimentally in Section 5.6.

To accommodate the fast changing and evolutionary nature of power system topology, the trained models have to be frequently updated (i.e. retrained) using new training samples that cover a wide range of diverse operational scenarios for each topology change. Therefore, ensuring the robustness of trained models imposes a high computational cost and reduces the training speed of data-driven TSA approaches [31]. However, reducing the number of training samples is not a viable option as it would reduce the generalization ability of the classifier [3]. Further, although the training is conducted offline, it is a recurring process, rather than an isolated event. Hence, it is important to develop efficient algorithms in terms of training speed.

To increase the training speed of the updates, in [31], a semi-supervised algorithm is introduced that reduces the required number of labeled samples to predict stability in the presence of outages. This in turn speeds up the process of updating the trained models by reducing the overall data collection time. In particular, instead of performing time-domain simulations in a supervised learning framework, they introduced a tri-training approach that exploits three classifiers to generate labels (i.e. stability status) for unlabeled samples, combined with a multi-stage data editing (deputation) process to eliminate mislabeled samples. Although the accuracy of this method of generating labels is not discussed, it is claimed that the tri-training process achieved a reduction in training time of 12% compared to running time-domain simulations. Moreover, the number of labeled samples are varied from under 1000 to 15,000 (out of 29,698 operating

[1]For instance, using six CPUs in parallel, an RMS simulation of a 39-bus system for a period of 5 seconds takes about 10 seconds, while it takes only a few milliseconds for a trained machine learning model to output the TSA result.

points in the training set) to compare the performance of the semi-supervised method with a standard supervised method. A noticeable difference (about 2.5%) is reported between the classification accuracy of semi-supervised and supervised learning when the number of labeled samples are very low (with 1,509 labeled samples). However, as the number of labeled samples is increased (9,500 samples), the difference between the accuracy of the two algorithms becomes negligible (about 0.05%). Hence, whether the complexity of the proposed algorithm justifies the improvement in prediction accuracy or training time is unclear. Moreover, the connection of new lines is not considered in their topology change scenarios.

Although supervised learning algorithms may need more labeled data, the framework is less demanding (in terms of the complexity of data preparation and training procedures) compared to semi-supervised learning. In the literature, transient stability assessment using supervised learning algorithms in the presence of topology change is only studied in an $N-2$ framework, where either two transmission lines are out of service at the same time [8], or a transmission line along with another line that is overloaded are removed [45]. Moreover, the $N-2$ and $N-1$ transient stability assessments are always treated independently and irrespective of the other, where for each contingency category the same number of samples are fed to the machine learning model [32]. This leads to exceedingly large datasets with hundreds of thousands or millions of training instances, due to the recurring update requirement of trained models. However, existing research has not considered the frequent update requirement of the trained models in a supervised learning framework or the connection of new transmission lines to the power network. These topics are currently of crucial importance as the power network rapidly evolves to connect new renewable energy zones.

In this study we focus on a novel aspect of the robustness of $N-1$ security assessment when the system topology changes. We are interested in transient stability assessment where a three-phase fault occurs not only while there exists a line outage (e.g. out of service for maintenance), but also when a new transmission line is added to the grid according to transmission expansion plans. We refer to these topology changes as **Network Augmentations and Reductions (NAR)**. An example of such topology change scenarios in a test system is shown in Fig. 5.1 where a three-phase fault occurs on a transmission line (line 21-22) while either another transmission line is out of service (line 1-2) or a new transmission line is added to the system (line 14-17). We believe that this not only represents a set of more credible contingencies compared to the aforementioned $N-2$ studies in the literature, but it also has already challenged the operation and planning of power systems. Let us consider two examples of these challenges that share topology change as a common factor.

Firstly, the TSA of operational instances in the presence of **line outage** scenarios has traditionally been a risk-based process. Due to computation time constraints, power system operators, such as the Australian Energy Market Operator (AEMO), only evaluate the stability of a system for credible contingencies, i.e., reasonably likely events with the potential for significant impact on the power system [10]. Non-credible contingencies can only be reclassified as a credible event under a set of special circumstances, e.g. if the system operator receives an abnormal conditions report (such as severe weather conditions) and it is determined that the previously non-credible contingency event is now likely to occur [13]. Then, the TSA is analysed online in short time spans by running simulations using real-time or near-real time measurements [10]. However, if the event is not considered reasonably likely, no reclassification is done. This process is not only prone to error, but also computationally expensive.

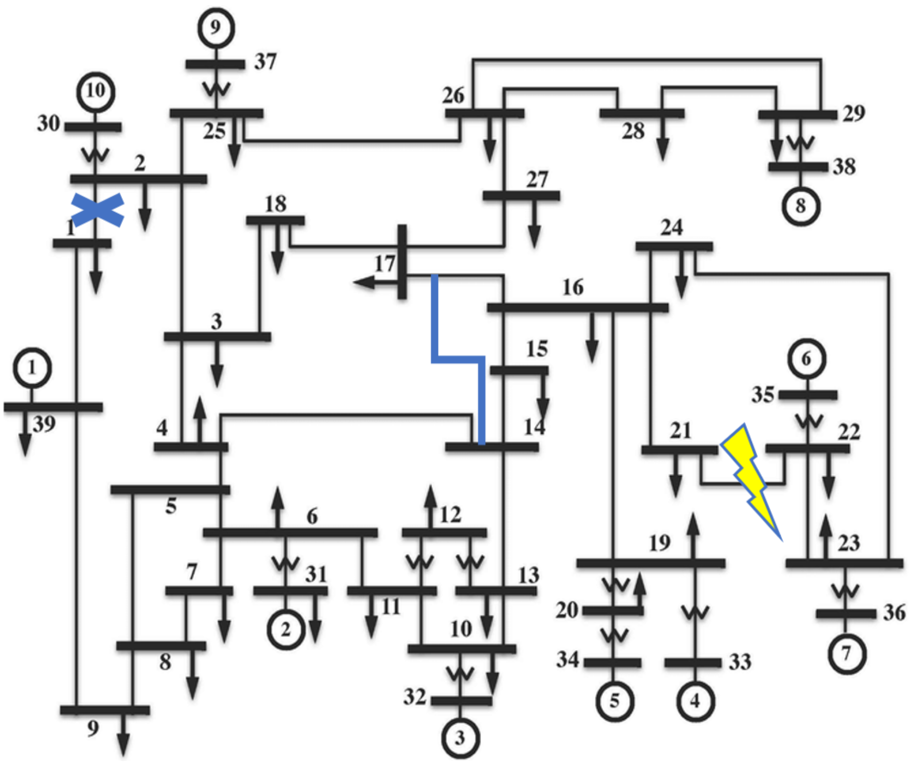

Figure 5.1: Network augmentation or reduction scenarios-IEEE 39-bus system.

Secondly, the security of **network augmentation** scenarios as the output of optimum generation and transmission expansion planning (GTEP) is weak. GTEP is traditionally formulated with the goal of either minimising total cost or maximising social welfare, while co-optimising both generation and transmission expansion plans [17]. These studies are solely conducted through steady-state analysis (such as power flow and fault level analysis) [12], rather than detailed dynamic stability assessments. Recent studies have included some stability assessments methods in the GTEP problem [18]. Although this is a step forward towards a secure GTEP, it not only leads to inefficient use of the network since the constraints are overly conservative due to the used simplification techniques [19, 20], but also the diversified range of load scenarios and generation schedules results in a dramatic increase in problem size.

To summarise, the need for new tools that converge in real-time to augment the current pre-fault TSA process is emphasised by the frequent topology change instances. They increase the real-time workload for power system operators to keep the system secure, even more than what already is known as a critical and rising challenge [6, 12].

5.2 Motivation

Data-driven approaches provide new tools that converge in real-time to augment the current pre-fault TSA process. Moreover, frequent topology changes and the subsequent trained model updates make efficient training algorithms indispensable. The requirement to frequently update trained models significantly increases the computation workload for power system operators to keep the system secure, even more than what is already known as a critical and rising challenge [6, 12]. Therefore, the application of data-driven approaches in the industry might face barriers.

This chapter aims to address this challenge by introducing a novel framework that is robust to topology changes and accelerates the training process. The hypothesis of this work is that network topology changes will alter the patterns in the steady-state variables as well as the dynamic behavior of the system, which would result in new patterns in the dataset. Therefore, although the previously trained model for $N-1$ TSA of a given contingency cannot precisely capture these new patterns, it can contribute to efficiently learn them through transfer learning. Transfer learning has proven to be a powerful technique that allows us to adapt a machine learning model from one domain to a related but different domain, which has been used very successfully in image classification and computer vision. For a survey on transfer learning approaches, see [58]. We adapt a transfer learning framework introduced in [61] that infers a mapping from a set of training examples (also known as the source dataset) for other examples (also known as the target dataset) with limited samples. In this framework, the layers of a classifier, pre-trained on the source dataset, are applied to the classification of the target dataset [61]. As a result, a comparatively small dataset and short additional training time is required for adaptation to topology changes, compared to the large initial cost of training the original deep neural network from scratch. This will result in less training time to update the trained models for the frequent topology changes of power networks.

5.3 Contributions

The theoretical and technical contributions of this chapter are as follows:

- We address the offline frequent update requirement of trained models that occur as a result of topology changes in network augmentations and reductions. We introduce a supervised learning framework using a novel modular deep neural network scheme with two modules that is more efficient in terms of training effort (i.e. the speed of training) as well as accuracy, compared to standard supervised learning approaches in the literature.

- To improve the speed of the training process, we propose an adaptation of a neural network-based transfer learning framework from the computer vision domain, detailed in [61]. Our work validates the use of this algorithm in the domain of data-driven transient stability assessment in the presence of topology change.

- We develop a test procedure to validate the hypothesis of this chapter and contrast the advantages of the proposed algorithm in comparison to a standard deep learning approach.

In other words, our framework uses **deep neural network-based transfer learning** for transient stability assessment in the presence of network augmentations and reductions. We first train a deep neural network model for $N-1$ security assessment for thee-phase faults on the original power network without topology changes. Then, we transfer that learned model to accommodate the $N-1$ security assessment for scenarios that contain network augmentations or reductions. From a data science point of view, the applied transfer learning framework infers a mapping from a set of training examples (also known as the source dataset) for other examples (also known as the target dataset) with limited data. This is done through re-using the layers of the pre-trained model along with new adaptation layers that are only trained on the target task. This also highlights the incompetence of the formerly introduced algorithms in the previous chapters which led to the use of deep learning in this chapter.

We empirically show that compared to standard deep learning approaches, our framework achieves a significant reduction in computational cost for training the neural networks, while improving the accuracy of predictions at the same time. This is particularly important as the offline training is a recurring process, rather than an isolated event, due to the evolutionary nature of power system topology that requires frequent updates for trained models.

5.4 Methodology

In this study, we use *transfer learning* to adapt a trained model (on $N-1$ contingency scenarios) to predict the stability of the same contingency while the topology of the network has changed.

Therefore, we propose a novel modular deep neural network scheme with two modules. The first module is trained to predict the transient stability for a particular fault location on the original dataset, that is similar to previously introduced datasets in this thesis, provides information regarding the TSA of original power network without any topology changes. The second module includes new adaptation layers that are only trained on the target task. This module is trained to predict the stability of the system for the same fault location while the topology of the system changes. We will show that combining the two models in a modular deep network structure will not only significantly reduce the computational effort, but also improve the overall accuracy compared to standard deep learning approaches, even though the topology changes may strengthen or weaken the ability of the system to maintain stability.

In order to show that our method is neither dependent on the location of the three-phase fault nor the topology change scenario, we study four contingency scenarios with one line outage (i.e. network reduction) in each area and one line addition (i.e. network augmentation) between each of the areas of a power network.

5.4.1 Backbone neural network

The backbone neural network takes advantage of a convolutional neural network structure which is pre-trained to predict the stability of a three-phase fault on the original power network (i.e. $N-1$ transient stability assessment without topology change) by extracting the dominant features. We refer to this as the **backbone neural network**. The trained model would therefore not be able to solely perform reliable predictions in the presence of network augmentations or reductions. This will be empirically studied in Section 5.6. The backbone could be trained using standard deep learning approaches; however, in this study we use the method introduced in Chapter 4 where a novel data collection strategy is presented that combines two datasets.

5.4.2 Deep Neural Network-Based Transfer Learning

When the network topology changes, the patterns in the steady-state variables that were used to train the backbone neural network model, such as voltage magnitude, angle at different buses and the power flow in transmission lines, will change and so will the dynamic behavior of the system. For instance, adding a new transmission line may reduce or lengthen the electrical distance between a fault location and a generator bus. This would result in different patterns in the training dataset. Therefore, the previously trained model cannot precisely capture these new patterns and will have to be updated for the new power network topology.

The proposed deep neural network-based transfer learning framework takes advantage of the pre-trained model for $N-1$ scenarios (the backbone neural network model) and uses this trained model in a modular deep neural network structure to better learn the dynamic behavior of the system for operational scenarios with power network augmentation or reduction (NAR). This is inspired by and adapted from transfer learning concepts that are commonly used in the image recognition and computer vision [61, 62] as well as the natural language processing (NLP) [63] domains, where the knowledge from previously learned tasks is transferred to other, related ones [58]. For example, in [61] a deep residual network structure composed of convolution layers is trained in a transfer learning framework to transfer learnt image representations on large datasets to other visual recognition tasks with limited training data. They argue that convolution layers enrich learning mid-level features, also known as mid-level descriptors that are intermediate representation between low-level descriptors derived from the signal and high-level descriptors conveying semantics associated to the image [80]. These features are transferable to a variety of tasks.

Hence, the initial convolutional neural network layers are usually described as capturing generic features and are used as fixed feature extractors, while the later layers fine-tune the deep neural network to learn features specific to the new task by learning high-level combinations of features learned by the earlier layers [58, 61]. We can freeze (fix weights) or use the learnt parameters to warm start the training at certain layers and retrain the deep network structure to suit our needs, while the knowledge in the pre-trained module is transferred to predict the transient stability of NAR instances.

5.5 Data preparation and training procedure

In order to demonstrate the performance of our new approach we use the same network and assumptions as in Chapter 4, the IEEE 39-bus test system for a number of contingency scenarios.

5.5.1 Data generation steps

To generate the training dataset we perform similar steps as in Chapter 4, summarised below.

- Generate random load scenarios.
- Generate the optimised generation schedule using the ACOPF algorithm.

- Perform transient stability assessment for each generation schedule running time-domain simulations. Moreover, in this study we analyse four contingencies, applying three-phase faults on line 21-22, 14-15, 3-4, and 25-26.

5.5.2 Training the backbone neural network

We use the method introduced in Chapter 4 to generate load scenarios. The augmented dataset includes a *same-distribution set* of 10,000 samples and an *auxiliary set* of 5,000 samples, with the same proportion of classes (stable and unstable) in the two datasets.

The convolutional neural network structure we use was presented in Chapter 4 and is shown in Fig. 5.2.

The cost of misclassification is the same as Chapter 4, defined in terms of unsafe misclassification (*FP*, for *False Positives*), and safe misclassification cases (*FN*, for *False Negatives*), the same as in Chapter 4.

This deep neural network structure is trained to predict the stability of N-1 contingency scenarios, and it will form the Backbone model that is the first module in our proposed modular deep residual network structure.

5.5.3 Topology change scenarios

The network augmentation scenarios add transmission lines between all areas, while the network reduction scenarios remove transmission lines from all the areas in the test case, covering one example from each possible topology change combination as indicated in Table 5.1. This is to determine whether the performance of the proposed approach is limited to specific NAR scenarios.

Table 5.1: Power network topology change scenarios and datasets

Topology change type	Affected transmission line
Network augmentation scenarios (add a transmission line)	24-27 16-4 4-17
Network reduction scenarios (remove a transmission line)	16-24 17-18 1-2

To collect data for topology change scenarios we follow the steps detailed in Section 5.5.1 above. The only difference is that the topology change (adding or removing a transmission line) is reflected in the ACOPF algorithm as well as the time-domain simulation model.

For each topology change scenario we gather 5,000 instances for training and 2,500 independent instances for validation, the distribution of the labels being equal in both sets. We also use 2,500 independent instances as a test set. As an example, for the contingency on line 21-22, we gathered 30,000 instances for training, 15,000 instances for validation and 15,000 instances for the test set. It is important to highlight that this dataset and the augmented dataset are standardized using the z-score method while using the same mean and standard deviation values.

5.5.4 Deep transfer learning and the modular structure

Our modular structure is composed of a deep Residual Network (ResNet) platform shown in Fig. 5.3 with two modules, where each module has a number of layers.

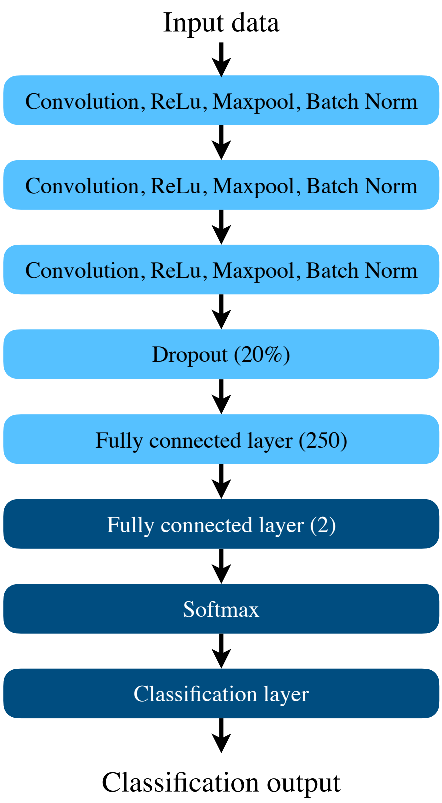

FIGURE 5.2: The backbone neural network structure.

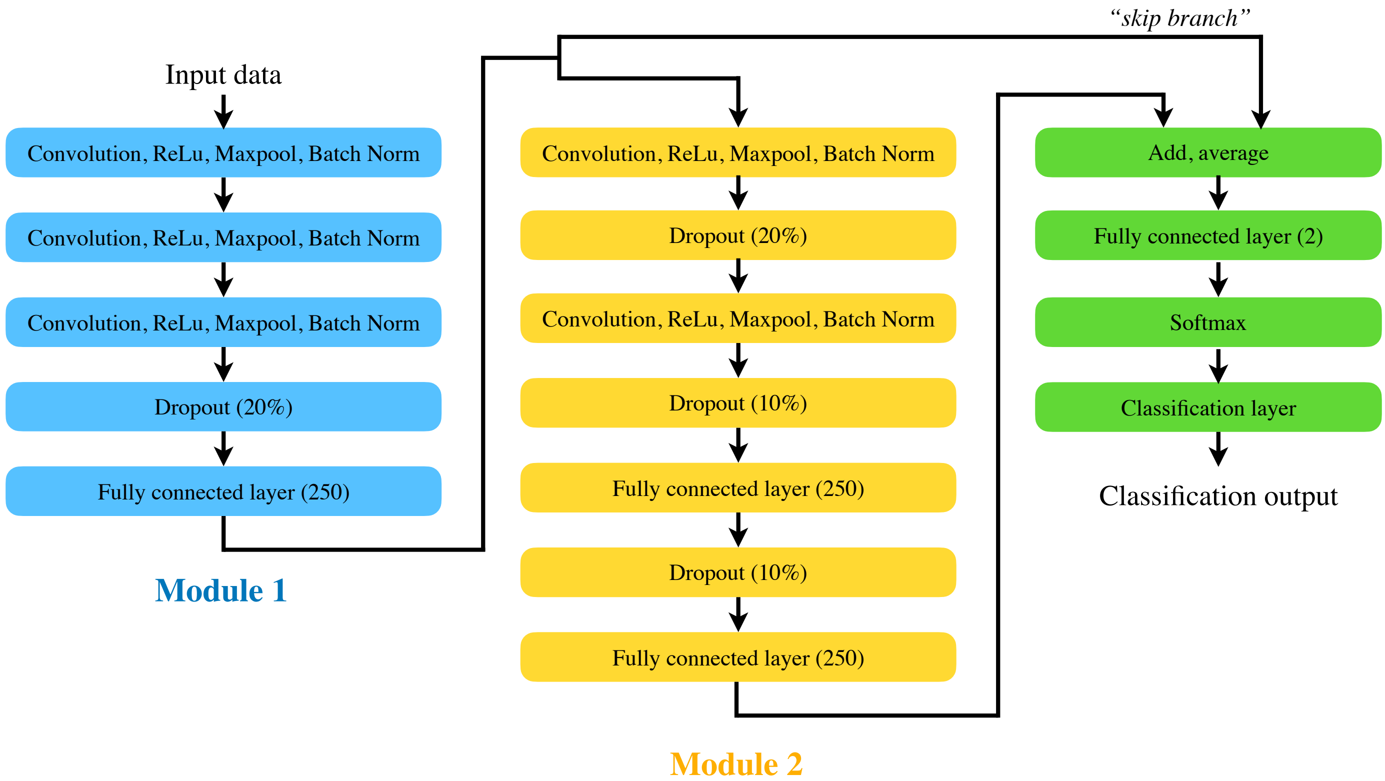

FIGURE 5.3: The modular deep residual network structure.

The first module comprises the first five layers of the trained backbone neural network from Fig 5.2. It predicts the $N-1$ stability for the original topology by capturing the critical features to predict the transient stability of a specific three-phase fault. In order to apply transfer learning to predict the stability of three-phase faults in the presence of topology changes, we remove the last three layers of the pre-trained backbone model that are designed to classify and output a binary stability status. Hence, the first module includes three convolution layers and one fully connected layer and incorporates the weights and biases of the trained model for the three-phase faults on the original power network (i.e. without topology change).

The output of the first module feeds into the second module. The task of the second module is to compensate for the new patterns in the topology change dataset by training it to predict the TSA of three phase faults under the topology change (NAR) scenarios. It has a smaller structure, compared to the first module, with only two series of convolutional (with filter size of 3 and 1) and max-pooling layers followed by two fully connected layers. To avoid over-fitting, we inserted dropout layers between layers.

The output of both modules is fed into an addition layer that sums multiple inputs element-wise, followed by average pool. This feeds into a fully connected layer, a softmax, and the cost-sensitive classification layer, detailed in (4.1), to output the classification prediction. The skip branch enables output from Module 1 to bypass Module 2, which has been shown to make it easier to optimise deep neural networks and to improve accuracy by resolving accuracy saturation issues [81].

5.5.5 Experiments

To show the impact of the network-based transfer learning (i.e. usage of the learnt biases and weights of the backbone model during the training process), we designed four experiments.

5.5.5.1 Experiment 1

To examine the performance of a model that was trained on the original power network and tested on the network topology change dataset, we only train the backbone network from Fig. 5.2 on $N-1$ scenarios, but test it on the NAR scenarios. This experiment demonstrates that the accuracy of trained models significantly deteriorates if the network is not adapted to topology changes.

5.5.5.2 Experiment 2

In this experiment we use the standard initialisation of the deep network (that sets weight values for the neural network and defines the starting point for the optimization) and train the entire ResNet structure from Fig. 5.3 from scratch. This experiment corresponds to the standard deep learning approach from the literature [8, 31, 45], and serves as the baseline for our comparisons.

5.5.5.3 Experiment 3

In this experiment we use transfer learning while we freeze the biases and weights of the trained backbone model (i.e. Module 1) to the values from the initial $N-1$ training, and only train Module 2 with the new NAR dataset.

5.5.5.4 Experiment 4

In this experiment we use transfer learning while initialising the weights of the trained backbone model based on the initial $N-1$ training, but allow them to be updated during the training of the ResNet structure with the new NAR dataset. We refer to this as *warm start*.

5.6 Results and discussion

The results from our first experiment show that topology changes will compromise the classification performance of a machine learning model that was trained on a dataset that does not include topology changes.

We used the trained backbone model from Fig. 5.2 and tested it on the full NAR dataset, which includes six network augmentation or reduction (NAR) scenarios. Table 5.2 shows the performance of the backbone model for four different contingencies.

TABLE 5.2: Performance of backbone model on topology change dataset.

Contingency	**False Positives**	**Accuracy**
Line 21-22	0.10%	87.81%
Line 14-15	10.40%	87.62%
Line 3-4	5.30%	89.70%
Line 25-26	7.85%	85.22%

The results indicate that the backbone model cannot reliably predict the stability of topology change scenarios, with an overall accuracy of less than 90%. In particular, the results show large variations in *False Positives* (*FP*), which correspond to unsafe misclassifications where the model predicts an unstable scenario as stable. The results demonstrate that a different method is required to accommodate topology changes.

We now present results that show the advantage of our proposed transfer learning approach. As described above, we use a pre-trained model as the backbone neural network model and then train the full ResNet on a smaller set of samples that include NAR scenarios. We compare the training effort and the accuracy of the resulting classifier with the standard approach of training the entire ResNet structure from scratch.

Table 5.3 shows the results of experiments 2–4, i.e., our baseline of training the entire ResNet from scratch, transfer learning with fixed biases and weights for Module 1, and transfer learning with warm-starts for Module 1. The table reports the results for four contingencies on the 39 bus test case in terms of training time (T_{training}), false positives (FP) and accuracy ($Acc.$).

The reported training time (T_{training}) is the average time it takes to train the ResNet structure for the available options of the grid search for each contingency with all the 30,000 training instances for the six topology change scenarios. The reported accuracy is the maximum value over the grid search. It is important to highlight that were unable to complete the grid search for all values of alpha and beta, due to ADAM optimisation algorithm not converging for some parameter configurations [55]. This issue was also discussed as one of the drawbacks of deep learning in Chapter 4. Therefore, we ensured a similar number of options are collected for the three frameworks.

All models are trained on three parallel GPUs (TESLA-V100-PCIE-16GB) using the adaptive moment estimation (ADAM) optimisation algorithm with a batch size of 32, maximum number of epochs equal to 300, and the patience argument of 100.

Table 5.3: Comparison of different initialisation frameworks.

Contingency on line 21-22				
Framework	**Backbone**	T_{training}	**FP**	**Acc.**
Deep Learning	Standard	6631s	1.52%	95.22%
Transfer Learning	Frozen	4347s	1.57%	95.71%
Transfer Learning	Warm start	5565s	1.89%	95.70%
Contingency on line 14-15				
Framework	**Backbone**	T_{training}	**FP**	**Acc.**
Deep Learning	Standard	7723s	1.93%	95.07%
Transfer Learning	Frozen	4027s	2.30%	95.15%
Transfer Learning	Warm start	7240s	2.22%	95.01%
Contingency on line 3-4				
Framework	**Backbone**	T_{training}	**FP**	**Acc.**
Deep Learning	Standard	7989s	2.19%	95.01%
Transfer Learning	Frozen	4996s	2.07%	95.10%
Transfer Learning	Warm start	7539s	1.96%	95.03%
Contingency on line 25-26				
Framework	**Backbone**	T_{training}	**FP**	**Acc.**
Deep Learning	Standard	6732s	2.06%	95.31%
Transfer Learning	Frozen	4221s	1.95%	95.72%
Transfer Learning	Warm start	5739s	1.83%	95.78%

It is evident from Table 5.3 that freezing the pre-trained backbone model parameters in the transfer learning framework leads to significantly faster training with higher or equal overall accuracy, compared to the standard deep learning approach. Comparing the frozen weight transfer learning versus the standard deep learning, the training time across the four contingencies is improved in a range from 38% to 48% and by 40% on average (4,470s for transfer learning with frozen weights compared to 7,410s for deep learning with standard backbone weights).

Moreover, Fig 5.4 shows the different training time (the y axis is in seconds) for the three studied initialisation frameworks. It indicates lower variance and mean training time of the proposed transfer learning frameworks compared to the standard approach. This translates into a significant improvement in computation effort when the size of the datasets grows for larger power networks.

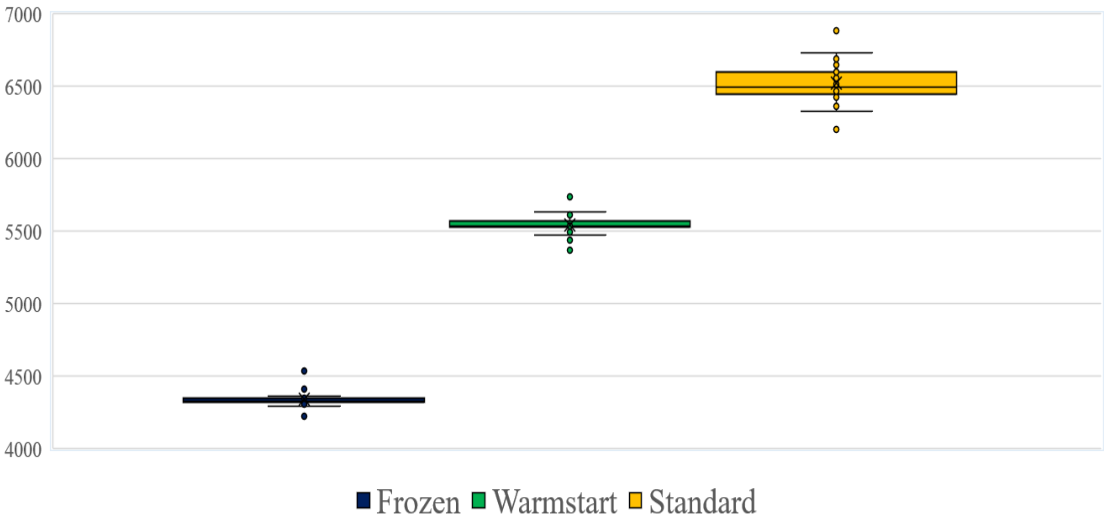

FIGURE 5.4: The comparison of training time for contingency on line 21-22 for the three initialisation frameworks.

Moreover, it is evident that freezing the backbone parameters consistently meets the overall accuracy for each of the four contingencies compared to the standard deep learning framework as well as the warm start approach.

In short, our experiments show that transfer learning (i.e. fix and warm start weights) will drastically reduce the training effort required, with fixing the weights yielding consistently bigger improvements and in addition appears to improve (or in the worst case scenario meet) the overall accuracy as well. These benefits manifest the merits of the proposed approach over the standard approach in the off-line training process.

5.7 Conclusion

This chapter presented a novel method for supervised data-driven transient stability assessment in the presence of network topology changes, that includes network reductions as well as additions. Our method takes advantage of a deep neural network-based transfer learning approach using a deep Residual Network (ResNet) structure with two modules.

We first train a module (Module 1) for $N-1$ transient stability assessment of theephase faults on the original power network without topology changes. A second module (Module 2) is then trained, along with the pre-trained layers of Module 1, on a new dataset to predict the stability of the same contingency (as in Module 1) while the topology of the network is changed. The second module enables adaptation to the new dataset that includes new patterns as a result of topology changes. From a data science point of view, the first module captures and extracts generic features of the problem, while the second module captures features for the specific task of dealing with topology change scenarios.

The main advantage of this method is that the combination of the two modules leads to a significant reduction in computational effort required for training the deep learning models (up to 48%), while also improving their classification accuracy. Our experimental works reinforce this when compared to the standard deep learning approach that trains the deep neural network structure from scratch.
The results also highlight that the proposed supervised learning approach outperforms the only existing literature that addresses the frequent update requirements of the trained models using a semi-supervised learning approach that achieved up to 12% improvement in training speed compared to a standard supervised learning approach.

To the best of our knowledge, this is the first attempt at using deep neural network-based transfer learning by incorporating a trained model for predicting the TSA of three-phase faults while the topology of the system changes.

In this chapter we explored the robustness of trained models by adding and removing transmission lines as probable topology change scenarios and introduced a novel and efficient algorithm to address that. We consider taking some generators offline or adding new generators at different locations in the network as the natural extensions of the current topology change framework, which remain as important directions for future research. This will require a larger test case with more generators available in the network, so that the exit of one generator does not significantly endanger stability or lead to blackout for the majority of operational scenarios.

Chapter 6

Conclusion and future work

6.1 Conclusion

This thesis describes the development of a range of innovative ideas, that are reliable, versatile and robust, to facilitate the use of data models to predict the transient stability of power systems. We set out to develop a clear framework for electrical engineers as well as data scientists to use conventional machine learning and deep learning models to improve the pre-fault transient stability assessment of power systems. Our initial approach was to use simple and off-the-shelf training algorithms and data models to be as straight-forward as possible, while leveraging the knowledge of power systems dynamics.

In Chapter 3, a novel hybrid machine learning approach including a shallow neural network with one hidden layer and ten hidden neurons along with a non-binary classifier are used to predict the transient stability status as well as the time to instability as a severity index of the fault. Since we utilised a small shallow neural network structure, the number of tunable parameters are small. Therefore, although the model performs well for the small test case (IEEE 9 bus system), it does not generalise well for bigger test cases (such as the IEEE 39 bus system) where more complex models are required to capture the data patterns.

In Chapter 4, to improve the reliability of predictions for larger test cases while leveraging the knowledge of power system dynamics, a novel data collection strategy in an instance transfer learning framework is introduced. To the best of our knowledge this is the first attempt at leveraging the understanding of the power system dynamics and how the fault effect propagates in the system into the data collection process in an instance transfer learning framework. This proved to be effective in improving the performance of data models, for both conventional machine learning and deep learning.

In Chapter 5, it is shown that topology changes in the power network will compromise the performance of the trained models. These topology changes include addition or outage of transmission lines, referred to as network augmentation and reduction (NAR). We therefore proposed a novel algorithm to train models that are robust to topology changes in a deep neural network-based transfer learning framework. We take advantage of the pre-trained models for $N-1$ stability assessment in a deep transfer learning framework to accommodate the TSA of three-phase faults for scenarios with network augmentations and reductions. This is the first attempt at using deep neural network-based transfer learning by incorporating a trained model for predicting the transient stability of three-phase faults while the topology of the system changes.

6.2 Future work

In this thesis we introduced novel methods to improve reliability, versatility, and robustness of machine learning models to predict the transient stability of power systems. This thesis surveyed the transient stability problem from a new point of view addressing Electrical Engineers as well as Data Scientists. Therefore it is just a new beginning as it brings the opportunity to further research in this domain.

This can remind one of Thomas Stearns Eliot's famous quote:

"What we call the beginning is often the end.
And to make an end is to make a beginning."

Here we list a number of innovative ideas for enthusiastic researchers as possible research directions:

- In this study we approximated the impact of renewable sources with negative loads (i.e., large load variation ranges), and the dynamic impacts of IBRs were not included.

  Currently, there are challenges regarding IBR modelling and control in terms of steady-state as well as dynamic stability. As discussed in Chapter 2, these challenges pinpoint the fundamental differences of IBRs and synchronous generators. From a Data Science and Machine Learning point of view; however, we hypothesise that predicting the pre-fault transient stability by capturing the data patterns in training datasets for power systems with a high penetration level of IBRs should theoretically be similar to a power system with no renewable source. This is based on the idea that a RMS (or EMT) model of IBR would include a number of DAEs with a level of non-linearity similar to that of a synchronous generator[1]. Hence, no exhaustive tuning of the proposed deep learning approach detailed in Chapter 4 and Chapter 5 should be required. Nevertheless, it is interesting to test the developed algorithms in larger test cases with different penetration of IBRs to explore the limitations and extensions of the proposed algorithms in this thesis.

- A larger test system with more generators would enable taking some generators offline or adding new generators, so that the exit of one generator does not significantly endanger stability or lead to blackout for the majority of operational scenarios. This needs to be studied as an extension of the current topology change framework.

  This is a crucial research question for future power systems where fossil fuel power plants would be disconnected from the grid during the day, lowering the total inertia, which can lead to larger and faster rotor swings, amongst other new issues.

- Another important remaining work is to add the trained machine learning models to the generation schedule problem (known as AC Optimal Power Flow). This could be conducted by generating linear constraints online, to reassure the security of operational scenarios in the planning process.

  It should be noted that there is a trade-off between the cost of operation and the level of security of the operational scenarios, as detailed in Chapter 3 where conventional ML and ANN are compared. This should be explored further and

[1] This holds true as long as the model is trained on a dataset with a range of diversified scenarios in the training set that covers the range of features in the test set.

addressed for this application. As discussed in Chapter 5, the currently applied approaches lead to generation schedules that are generally overly conservative which leads to higher cost of operation.

- Above, we discussed adding machine learning models to the optimisation problem. In retrospective, the generation schedule problem itself could potentially be modeled as a reinforcement learning problem that can output the generation schedules while maximising the security of operational scenarios. This can introduce a brand new chapter in the automated design of dispatch scenarios.

  This could significantly change the way that the electricity market is being operated, enhance power system operation tools, and open new horizons to power system operators and analysts.

Appendix A

Transient stability governing equations

A synchronous generator is driven by a prime mover. The equation governing the rotor motion is given by:

$$J\frac{d^2\theta_m}{dt^2} = T_a = T_m - T_eN - m$$

Where:

J: is the total moment of inertia of the rotor mass in kg-m2

θ_m is the angular position of the rotor with respect to a stationary axis in (rad)

t: is time in seconds (s)

T_m: is the mechanical torque supplied by the prime mover in N-m

T_e: is the electrical torque output of the alternator in N-m

T_a: is the net accelerating torque, in N-m

The angular position θ_m is measured with a stationary reference frame. Representing it with respect to the synchronously rotating frame gives:

$$\theta_m = \omega_s t + \delta_m$$

where, θ_m is the angular position in radian with respect to the synchronously rotating reference frame.

The derivative of the above equation with respect to time is:

$$\frac{d\theta_m}{dt} = \omega_s + \frac{d\delta_m}{dt}$$

The above equations show that the rotor angular speed is equal to the synchronous speed only when dm/dt is equal to zero. Therefore, the term dm/dt represents the deviation of the rotor speed from synchronism in rad/s.

In steady state mode, the machine angular speed is equal to the synchronous speed and hence ω_m can be replaced in the above equation by ω_s. Since P_m, P_e and P_a are given in MW, dividing them by the generator MVA rating S_{rated} gives these quantities in per unit. Dividing the above equation on both sides by S_{rated} gives:

$$\frac{2H}{\omega_s}\frac{d^2\delta}{dt^2} = P_m - P_e = P_a \text{ per unit}$$

This equation is also referred to as the swing equation.

Appendix B

ACOPF formulation

Equation (B.1) is the objective function that attempts to minimise the power generation costs[82], is expressed as follows:

$$\underset{P_{g,n}}{\text{minimize}} \sum_{n\in\mathcal{N}} \mathbf{c}_{n2}P_{g,n}^2 + \mathbf{c}_{n1}P_{g,n} + \mathbf{c}_{n0} \tag{B.1}$$

subject to (B.2) − (B.7).

Where c_0, c_1, and c_2 are generation cost coefficient of each generator.

Power plant physical limits are defined by minimum and maximum active and reactive power (P_g, Q_g) capabilities shown in (B.2) and (B.3). Equation (B.4) bounds the voltage angle θ at each bus n, while (B.5) defines bus voltage limits. Equation (B.6) sets the apparent power flow limits on power lines.

$$\mathbf{P}_{g,n}^{\mathbf{min}} \leq P_{g,n} \leq \mathbf{P}_{g,n}^{\mathbf{max}} \quad \forall n \in \mathcal{N} \tag{B.2}$$

$$\mathbf{Q}_{g,n}^{\mathbf{min}} \leq Q_{g,n} \leq \mathbf{Q}_{g,n}^{\mathbf{max}} \quad \forall n \in \mathcal{N} \tag{B.3}$$

$$\theta_{g,n}^{\mathbf{min}} \leq \theta_{g,n} \leq \theta_{g,n}^{\mathbf{max}} \quad \forall n \in \mathcal{N} \tag{B.4}$$

$$(\mathbf{V}_n^{\mathbf{min}})^2 \leq |V_n|^2 \leq (\mathbf{V}_n^{\mathbf{max}})^2 \quad \forall n \in \mathcal{N} \tag{B.5}$$

$$S_{nk} \leq \mathbf{S}_{nk}^{\mathbf{max}} \quad \forall n \in \mathcal{E} \tag{B.6}$$

$$
\begin{aligned}
P_{g,n} &= \sum_{k=1,k\neq n}^{\mathcal{N}} |V_n||V_k|\Big(\mathbf{G}_{nk}cos(\theta_n-\theta_k)+\mathbf{B}_{nk}(sin(\theta_n-\theta_k)\Big) \\
Q_{g,n} &= \sum_{k=1,k\neq n}^{\mathcal{N}} |V_n||V_k|\Big(\mathbf{G}_{nk}sin(\theta_n-\theta_k)-\mathbf{B}_{nk}(cos(\theta_n-\theta_k)\Big)
\end{aligned}
\tag{B.7}
$$

Appendix C

Generation cost coefficients

Below table indicates the generation cost coefficient used in Equation (B.1), for the IEEE 39 bus test case:

Generation coefficients	C_2	C_1	C_0
Generator 1	0.006	8.00	220
Generator 2	0.009	11.29	200
Generator 3	0.009	8.8	220
Generator 4	0.0095	8	250
Generator 5	0.0085	11.4	220
Generator 6	0.0075	10.45	190
Generator 7	0.009	10.03	200
Generator 8	0.009	10.15	210
Generator 9	0.007	7.98	230
Generator 10	0.105	15.37	240

Table C.1: Generation cost coefficients

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