FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

BIFANA - Bayesian Information Fusion in Advanced Network Assessment

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Resumo

A presente tese de mestrado desenvolve um novo modelo avançado de um estimador híbrido de fusão, baseada em inferência Bayesiana, para uma avaliação do sistema elétrico de potência em tempo real. O trabalho apresentado constitui uma contribuição para a progressão do estado da arte. A metodologia descrita habilita a integração total de PMUs nos sistemas SCADA. A solução proposta baseia-se em princípios de inferência Bayesiana para extender o conceito de distribuição à priori a um grupo alargado de informações dos estados do sistema em múltiplos instantes passados. Deste modo, este método introduz informação adicional valiosa ao processo de estimação de estados, em tempo real, referente às PMUs. Por fim, este trabalho propõe ainda um processo de transformação de coordenadas rectangulares baseado no método Jacobiano, auxiliando a integração consistente das estimações em coordenadas polares no modelo linear das PMUs (em coordenadas rectangulares)

Os sistemas elétricos de potência estão a evoluir para ambientes de extrema variabilidade por numerosos motivos entre os quais a progressiva penetração de fontes de energia renovável. Deste modo, o estimador de estados convencional, baseado em medidas SCADA de baixa taxa de amostragem, irá tornar-se obsoleto e incapaz de fornecer estimações precisas para suportar a operação do sistema. Consequentemente, revela-se urgente o desenvolvimento de uma infraestrutura operacional capaz de capturar o comportamento dinâmico do sistema, emergindo a necessidade da integração de informação em tempo real, capturada por PMUs, no processo de estimação de estados. Estimadores de estado híbridos, e em particular os de fusão, têm vindo a ser desenvolvidos na tentativa de endereçar as considerações supratranscritas. No entanto, estes métodos revelam falhas em explorar o máximo benefício proveniente da incorporação de informação de instantes anteriores no procedimento de estimação de estados.

O estimador de fusão baseado em inferência Bayesiana, proposto em [1], sugeriu a consideração de dados históricos no procedimento de estimação de estados. No entanto, este método considera apenas o conjunto de dados referentes a um único instante no passado. Por outro lado, os estimadores baseados no filtro de Kalman utilizam recursivamente informação passada no seu processo de estimação mas revelam-se incapazes de produzir uma estimação precisa em ambientes com elevada variabilidade. Os benefícios de uma abordagem intermediária entre os métodos supratranscritos, considerando um aumento de informações passadas, não foram estudados.

Os parâmetros da solução são primeiramente "afinados" através da análise da sua resposta a comportamentos estacionários e transitórios do sistema. Por último, é construído um ambiente de simulação baseado em séries temporais de PMUs e diagramas de carga/geração reais.

Os resultados obtidos demonstram um excelente *trade-off* entre melhorias na precisão e na estabilidade, quando comparados com o método de fusão sugerido em [1] e o estimador baseado no filtro de Kalman. Exemplos ilustrativos são apresentados no Capítulo 5, facilitando a interpretação de resultados das simulações realizadas. Concluindo, torna-se evidente o valor adjudicado à estimação pela consideração de um conjunto de dados passados e a melhoria

proveniente da solução proposta é quantificada, cumprindo com sucesso os objetivos delineados para esta dissertação.

Abstract

This master's thesis develops a new advanced Bayesian fusion hybrid estimation model for real-time assessment of power systems. The presented work constitutes a contribution to the progress of the state of the art. The described methodology enables the full integration of the Supervisory Control and Data Acquisition (SCADA) system with Phasor measurement units (PMUs). The proposed solution is based on Bayesian inference principals and extends the concept of the prior distributions to accommodate a broad set of past state conditions. Therefore, it introduces valuable additional information into the real time PMU estimation process. This document also proposes a rectangular coordinates transformation, based on the Jacobian method, to consistently integrate polar coordinates estimations in the PMU linear model (in rectangular coordinates).

Electric power systems are evolving into extremely variable environments for numerous reasons such as the increasing penetration of renewable energy resources. Therefore, the conventional state estimator which is based on SCADA measurements with low sapling rates will rapidly become obsolete and unable to provide accurate estimations to support the power system's operation. Thus, it is of primary urgency to design an operating infrastructure capable of capturing the system's dynamic behavior. In this sense, the need to accommodate the real-time data obtained by synchronised phasor measurement devices in the state estimation framework emerges. Hybrid state estimators, and measurement fusion estimators in particular, have been proposed in order to tackle the above stated. However, the referred methods seem to fail at fully exploiting the benefits of incorporating previous state information in the state estimation procedure.

The Bayesian Fusion estimator proposed in [1] initiated the path towards historical data consideration in the SE framework. Nevertheless, the referred method only considered a set of data from one particular instant in the past. Kalman filter-based estimators, on the other hand, recursively use past information in the estimation procedure, but reveal inability in producing effective responses in highly variable environments. The benefits of an intermediary approach between the above stated methods, considering a broader but limited historical prior, was yet to be assessed.

The proposed solution's parameters are firstly tuned through the analysis of its response to both stationary and transient behaviors of the system. Consequently, a simulation environment is built, based of real PMU time series and load and generation diagrams of real power networks.

The obtained results provide an excellent trade-off of improved accuracy and stability estimations in comparison to the primary Bayesian fusion [1] and Kalman filter estimators. Illustrative examples provided in Chapter 5 ease the interpretation of the simulation outcomes. Therefore, the value of considering a broader prior becomes evident and this procedure's enhancement is quantified, fulfilling the proposed objectives for this dissertation.

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Francisco Camões

“The older I get, the more I think the only barometer for intelligence is how kind you are.”

Josh Malerman

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Acronyms and Abbreviations

AI	Artificial Intelligence
BD	Bad Data
CI	Computational Inteligence
CSE	Conventional State Estimation
CB	Circuit Breaker
COI	Center Of Inertia
DC	Direct Current
DAE	Differential-algebraic Equation
DER	Distributed Energy Resource
DSA	Dynamic Security Assessment
DSE	Dynamic State Estimation
EKF	Extended Kalman Filter
EMS	Energy Management System
EnKF	Ensemble Kalman Filter
FASE	Forecasting-Aided State Estimation
FDI	False Data Injection
GPS	Global Positioning System
HMI	Human Machine Interface
HSE	Hybrid State Estimation
KF	Kalman Filter
LAN	Local Area Network
LNRT	Largest Normalized Residual Test
LSE	Linear State Estimation
MAP	Maximum a Posteriori Estimation
MCC	Maximum Correntropy Criterion
MDF	Multisensor Data Fusion
ML	Machine Learning
MLE	Maximum Likelihood Estimation
MCEKF	Maximum-correntropy-based extended Kalman filter
MTU	Master Terminal Unit
NN	Neural Networks
OPP	Optimal PMU Placement
PCKF	Polynomial-chaos based Kalman Filter
PDF	Probability Density Function
PMF	Probability Mass Function
PMU	Phasor Measurement Unit

PP HSE	Post-processing Hybrid State Estimation
PSO	Power System Operator
PV	Photovoltaics
RTU	Remote Terminal Unit
RUKF	Robust Unscented Kalman Filter
SCADA	Supervisory Control and Data Acquisition
SE	State Estimation
SSE	Static State Estimation
TSO	Transmission System Operator
UKF	Unscented Kalman Filter
UTC	Coordinated Universal Time
WAN	Wide Area Network
WAMS	Wide Area Monitoring System
WLAV	Weighted Least Absolute Value
WLS	Weighted Least Square
WWW	*World Wide Web*

Chapter 1

Introduction

1.1 Context and Motivation

Digitalization: The path for carbon neutrality and enhanced operability of power systems

The European Green Deal set ambitious goals towards a decarbonized short-term future. The proposed objectives require significant vertical changes to the power system's architecture whilst considering the increased necessities of the electric energy end-consumers. The designed route to achieve the referred targets has digitalization, through cutting-edge research and innovation, as one of its core leveraging points [2]. The progressive digitalization of modern power systems will play a pivotal role as enabler of the full scale integration of renewable energy resources, smart grids implementation and interoperability of emerging complex loads (electric vehicles, smart homes, energy storage devices, to name a few).

The future power infrastructures operation will require continuous and accurate monitoring of the network. The energy management systems will be supported by real-time data collected throughout the grid at both transmission and distribution levels. Recent developments towards the use of Artificial Intelligence (AI) and Machine Learning (ML) for multiple applications such as to reduce the cognitive load of system operators in the control centers [3] will demand a considerable larger amount of data to be collected. Hence, the measurement technology currently in use will have to be progressively replaced by new devices capable of meeting these demands. Smart-meter technology has been developed to address this issue at the distribution level, having a crucial impact in pioneer smart-grid implementations. However, due to their modest sampling rates, they are unable to fulfill the request of a real-time data collection of the system's dynamic events data. Therefore, phasor-measurement units (PMUs) have been gaining attention in what appears to be the main protagonist technology in the measurement framework of the future power systems. Its applicability in the monitoring and control operation of the transmission level network has been strongly recognized for the past decades and is one of the main subjects of study in this research project.

Concluding, it evident that the revision of the measurement architecture in contemporary power systems is of undoubtable importance to accommodate the emerging technologies that will lead to a sustainable, zero carbon emission future.

How long will the power grid's monitoring maintain an accurate real-time representation of its more than ever dynamic state with the tools currently in use?

In the past, power systems operation and control were characterized by beforehand planning as well as the recursive execution of real-time control functions. [4]

This methodology, though meeting the network operation necessities at the time, proved to be ineffective and unable to respond to the ever-growing behavioral complexity of the power grids. Problems such as the miscalculation of load flows and lack of covered operating scenarios started to show and the unreliability of the power grid operation became evident. [5] It was then necessary to implement a tool capable of giving the Power System Operators (PSO) the needed resources to effectively manage the Power Network in real time.

Fred C. Schweppe introduced the first State Estimation formulation in 1969 to tackle these issues. Schweppe stated that "the static state of an electric power system is defined as the vector of the voltage magnitudes and angles at all network buses", named state variables. [6, 7, 8] In order to determine the superscript variables, the State Estimation formulation makes use of the network model, its parameters and an amount of redundant real-time measurements of the grid, applied to a weighted least square (WLS) problem. Due to its robustness and reliability, the conventional State Estimation quickly became one of the fundamental core functions of real-time operation and monitoring of power networks, implemented in the energy management system (EMS).

The array of measurements (inputs) in the State Estimation algorithm is typically formed by bus voltage magnitudes, bus injected powers and active/reactive power flows in the branches of the network. These measurements are obtained through devices displaced over the network and collected periodically by the Supervisory Control and Data Acquisition System (SCADA).

Most of the monitoring and control functions implemented in the network managing systems presume a steady-state model and the conventional SE formulation follows the same premise. The continuous development and implementation of Distributed Energy Sources (DERs), the increasing power penetration share of renewable energy (mostly solar pv and wind plants - with spasmodic generation) and the rise in complex loads deployment are leading to unpredictable and instantaneous variations in the generation-demand scheme. [9] Despite sufficiently accurate in resembling the network state, from a steady-state point of view, the conventional SE is unable to capture these system dynamics.

In this sense, PMUs are devices capable of providing both voltage and current phasor measurements with a GPS synchronized time-tag, acquired with high precision and sampling rates when compared to the conventional SCADA measurements. The maturing of this technology and its incremental distribution over the power networks, even though costly, made possible the capture of the above-mentioned network dynamics. [10]

The development of new methodologies to integrate both conventional SCADA measurements and PMU measurements has been characterizing the investigations in the area of state estimation for the past decade [1, 11, 12], with a consensus still to be achieved in the scientific community.

This masters thesis proposes a new formulation for the application of SCADA and PMUs derived measurements in a State Estimation algorithm, applying Bayesian principles to ensure the measurement fusion and the use of historical (*a priori*) data from these different sources. Throughout the course of the investigation, the applicability of this methodology in today's control centers, with minimal economic and modus operandi impact, is considered of imperative importance.

1.2 Document Structure

The present document is organized in the following chapters:

- **Chapter 2** - [Literature Review and State of the Art]: Review of the conventional State Estimation fundamental concepts and functions. Chronological exploration and discussion of the different developed methodologies mainly addressing the recent research efforts towards PMU measurements integration.
- **Chapter 3** - [Bayesian Inference Main Concepts]: Presentation of the key principles to Bayesian Inference followed by its applicability in a state estimation framework. Description of the previously proposed Bayesian Fusion estimator on which this research project is based upon.
- **Chapter 4** - [Advanced Network Assessment Through Improved Prior Information]: Description and explanation of the developed solution for the objective of this research project, detailing its algorithm and Bayesian fusion framework.
- **Chapter 5** - [Numerical Tests]: Simulation environment detailing. Illustration of the achieved results through the implementation of the proposed solution. Evaluation of parameters influence and accuracy comparison to other methodologies.
- **Chapter 6** - [Conclusion & Contributions]: Conclusion of the research work highlighting its main outcomes and contributions. Discussion of relevant future work.

Chapter 2

Literature Review and State of the Art

2.1 State Estimation

2.1.1 Historical Background and Development Motivation

The management of real-time control functions used to be a fundamental part of the work of the system operator. The control actions were based on sets of load flow calculations and results [4] which were limited and often failed to comprehend unusual and unexpected events [13]. Besides the difficulty associated with covering most of the possible scenarios from a system state point of view, relying on load flow calculations for this matter was inefficient and failed to accommodate the measuring technologies capabilities in its' methodology. This was mainly due to [6, 14]: the inability to perform the load flow calculation with non-existing measurements of either injected active and/or reactive power or voltage magnitude; the influence of measurements with gross errors in the results; the inefficiency in taking advantage of redundant/other measurements as a result of multiple meter deployment in common areas [13]. Some of the above mentioned limitations of the past monitoring and control operation could theoretically be resolved with the extensive deployment of metering equipment throughout the grid. However, this solution wouldn't be either technically or economically doable for obvious reasons [15].

Taking into account the superscript difficulties and limitations, research effort was made in order to progress towards a flexible solution capable of operating with different available measurements while increasing the reliability of the system operation. Power system state estimation was developed for this purpose, resulting in accurate results while making use of the accessible measurements [16].

2.1.2 Conventional State Estimation Framework

The state estimation has played a pivotal role as the establisher and one of the main functions of the Energy Management System (EMS) [4], enabling the implementation of many other important applications in the power system control operation and energy markets of today [17].

Therefore the Conventional State Estimation has been one of the main pillars for the evolution of power systems management and control, while maintaining its initial implementation in most of the energy network control centers. The reasons why other variations haven't been largely implemented will be further detailed and referenced.

As a fundamental tool for the on-line security assessment of the grid, the estimator relies on other functions namely, the topology processor, parameter and structural error processing, observability analysis and bad data processing [4]. A systematic explanation of these application functions and the correlation between them in the on-line static security analysis assessment can be found in [4] and summarily represented in the diagram illustrated in Figure 2.1. The fundamentals of on-line security analysis and control have been divided in three different elements: monitoring, assessment and control, which are bonded and interconnected in a clear framework, thoroughly presented in [18].

As previously stated in the Introduction, the estimator makes use of available measurements, grouped in a redundant set, in order to accurately estimate the power system's state. Pseudo-measurements are used if the set of given measurements doesn't result in a fully observable system [19]. Observability analysis and the definition of pseudo-measurements is further discussed in section 2.1.3. The defined system state is established with the resulting bus voltage phasors, alluding to the necessity of a clear knowledge of the network topology and its parameters, which in fact not always happens. This is caused by different local events such as faults, line disconnections, switching events, etc. [20]. The development of new state estimation methodologies addressed the identification of topological errors such as the Generalized State Estimation (GSE) [14, 21] at the transmission system level and as examples, other methodologies presented in [22, 23] at the distribution system level. Data-driven and probabilistic methods identifying topological variations have also been proposed to remit this issue in state estimation at the distribution systems level in [24, 25] with Bayesian approaches, in [26] with auto-encoders, as well as many others. The work in [20] also addresses the evolution of different proposed methodologies to tackle this issue.

The quality of the measurements have a direct impact in the accuracy of the state estimation results [27, 28]. Therefore, to guarantee a reliable estimation, the noise present in the measurements set, which leads to considerable errors when measurements are compared to the real values (bad data), must be filtered and corrected. Through the redundancy in the measurement set and the use of defined weights associated to the type of measurements, by applying the weighted least-squares process (WLS), the conventional estimator improves the accuracy of its results. The bad data detection and identification will be further discussed in section 2.1.4. Nevertheless, in some cases (types of networks), this alone may not be enough to achieve a satisfactory accuracy in the estimation process and small noise affected measurements as inputs to the estimator may still lead to considerable divergences from the real values [16] and the formation of an ill-conditioned power system. Research effort has been put in to find novel alternative methodologies [29, 30] to solve the above mentioned problems.

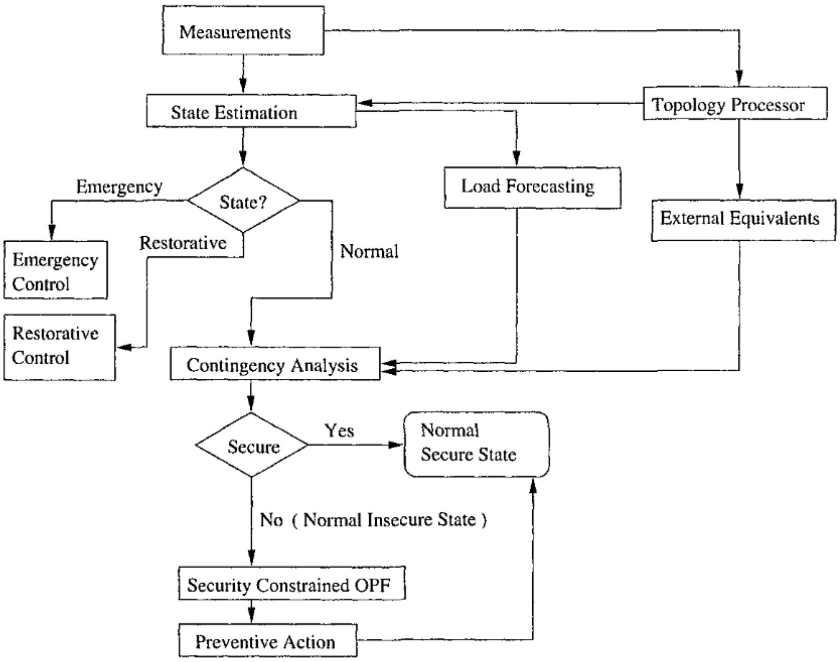

Figure 2.1: Diagram of the application functions for on-line Static Security Assessment [4].

2.1.3 Network Observability Analysis

As stated in the previous chapters the state estimation application relies on a group of important functions for its operation. Owing to is crucial importance, the observability analysis function is briefly described in the present section. The theoretical background is fully detailed in [4].

Preceding the state estimation, the observability analysis function confirms that a unique solution can be achieved with the accessible set of measurements [31]. The system's observability is directly influenced by the number of measurements, the measuring devices' locations and types [32]. This function is also utilized *off-line* accompanying the installation of the state estimator, to ensure the correct configuration of the existing measuring system. In case of the system being not observable, the network is split into multiple observable islands with unobservable branches as its boundaries. The deployment of supplementary meters in specific locations may be necessary to reestablish the system's full observability [4]. If the network is deemed observable, the system's critical measurements, which are measurements that lead to the unobservability of system if eliminated, should be identified [32]. It is possible to include pseudo-measurements in order to solve the lack of measurements in the state estimation input set. These values are based on historical data (load prediction and generation scheduling [17]), and should be regularly updated to avoid additional inaccuracy [13]. On the other hand, this approach may lead to possible numerical problems besides increasing the computational complexity [33].

Defining the observability of a network, given determined specifications, is achieved through topological or numerical methods [34] or through hybrid methods [35, 36, 37], which typically use the topological method to simplify the network scale and consequentially apply the numerical

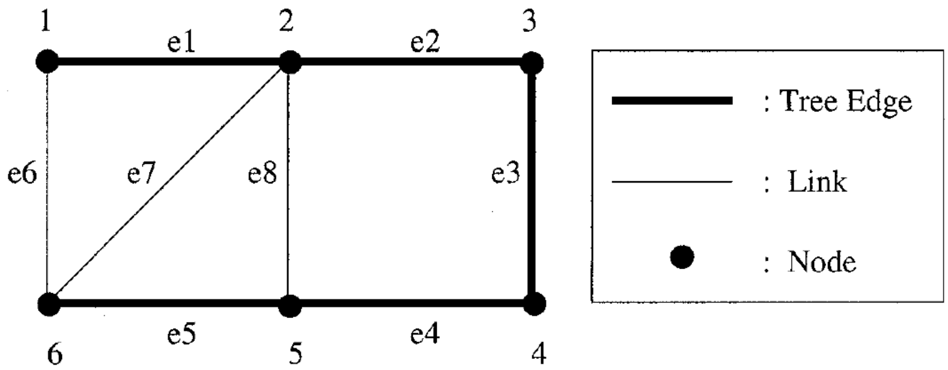

Figure 2.2: 6 Nodes Network Graph [4].

observability analysis.

Topological observability in power systems state estimation was proposed in [38] being later developed in [39]. Topological analysis methods are based on the graph theory, since it is adequate to resemble the networks and their respective equations and solutions. An example of a network graph is represented in Figure 2.2.

The numerical observability analysis was primarly addressed in [31] and improved in [40]. Due to their computational efficiency and increased compatibility with other state estimation functions, the numerical methods have been the main focus of research in the observability analysis field [5]. Conventional numerical observability methods can be divided in three groups [5]: the gain matrix method [40, 41, 42], the gram matrix method [43, 44, 45] and lastly the method of the test matrix [46, 47, 48, 32]. The above mentioned methods are based on the decoupled DC model [49, 31] which is a simplified network model for observability analysis that does not lead to a lack of topological knowledge of the grid. With the increasing implementation of phasor measurement technologies, novel state estimation methodologies for the improvement of network observability with the integration of PMU measurements have been developed [50, 51, 35].

2.1.4 Bad Data Handling

The state estimator must be adroit at detecting, identifying and eliminating measurement errors whenever possible. This section aims to provide a brief declaration of bad data (BD) handling processes applied to the conventional Weighted Least Squares (WLS) estimation, based on the detailed description and formulation in [4]. Other proposed methodologies as well as novel ones are also briefly enunciated as a way of referencing the state of the art on this subject.

Random measurement errors have different natures namely the finite accuracy of the measurement devices and the telecommunication channels of the signals. Large errors also appear due to wrong connections, telecommunication system failures and interference noise. The error filtering procedure depends on the estimation method implemented. Given enough measurement redundancy, the estimator should be capable of filtering these errors.

Bad data can be generally classified as single or multiple bad data, i.e only one measurement in the measurement set with a significant error or more than one, respectively. Multiple bad data can also be classified in different groups, based on the correlation between their errors and the way they conform with one another.

The bad data detection and identification functions in the WLS estimator are called as a post-processing block of the estimation, considering the measurement residuals and their probability distribution.

Bad Data Detection - Chi-squares Distribution: The *Chi-squares* test is one of the conventional methods for bad data detection. It is based on the assumption that measurement errors are normally distributed random variables with zero mean. In a simplistic explanation, values that exceed a predefined threshold, which is based on the chosen error sensitivity, correspond to bad data.

Bad Data Identification - Largest Normalized Residual Test: As its name points out, this test is based on the normalized residuals of the measurements. The method is typically able to identify bad data corresponding to redundant measurements (critical measurements or pairs are not identified) and is commonly described as the succession of the following steps:

1. Calculation of the measurement residuals and its normalised residuals.

2. Identification of the largest normalised residual.

3. If **2.** is bigger than the predefined threshold, the measurement is flagged as bad data. If there's no threshold exceeding normalised residual, the identification test ends.

4. Deletion or substitution of the identified measurement.

5. Return to **1.**

Inaccurate topology information, interpreted as bad data by the estimator, may also result in a significant estimation deviation. As mentioned in section 2.1.2, the Generalized State Estimation (GSE) [14, 21] addressed this problem, adapting the conventional state estimation methodology with novel features namely: the improvement of statistical models of suspected measurements, the aptitude to consider better estimates for the data base values of the suspected measurements; the ability to estimate non-telemetered variables and to determine unknown status of circuit breakers (CBs) while detecting topology errors.

The handling of bad data was viewed as a robustness factor for the estimator. Hence, different state estimation methodologies that remained insensitive to this errors, thus robust, were proposed in [52, 53, 54]. The referred methodologies integrated the bad data detection and identification as an internal process of the estimation.

Novel proposed methods to deal with bad data could be divided into two different groups: methods for BD handling with SCADA measurements and PMU aided enhancement of SCADA bad data processing [55]. Robust estimators with PMU aided bad data methods were proposed in [56] with dynamic adjustment of measurement weights based on PMU readings comparison and also in [57] creating an extra estimation block for PMU based judgement of the measurement set, in [58] by utilizing the results of observability analysis to enhance optimal PMU placement in order to transform critical measurements (or pairs) into non-critical, as well as many others. The majority of the proposed methods, like the above mentioned, typically rely on the assumption that the measurement noise follows a Gaussian distribution, which in fact is not commonly verified. This distribution is usually undetermined diverging from the assumed Gaussian model, yielding outliers [10].

A robust two-stage estimator with PMU measurement BD detection enhancement is proposed in [59] considering non-gaussian distribution (heavy-tailed) of noise in the measurement set. It revealed better results in dealing with this type of errors while mantaining efficiency when compared with a non-robust two-stage estimator proposed in [60]. Recent research towards robust estimators for dealing with bad data and non-Gaussian noise are presented in [61, 10]. The authors in [62] identified vulnerabilities in the former methods, regarding the lack of consideration for the abrupt dynamic changes in the system state, proposing a new formulation based on a maximum-correntropy-based extended Kalman filter (MCEKF) to tackle this issue. A novel method for state estimation based on the Generalized Error Correntropy and interior point method algorithm is presented in [63], providing better results when compared with the classical Largest Normalized Residual Test (LNRT) in case studies characterized by up to five gross errors in the measurement set, including gross errors in critical measurements or sets and leverage points.

Closing this section, the author would like to state that the bad data (BD) handling process is of great interest in the state estimation area. Although this document does not heavily focus on this subject, further reading of bad data detection and robust estimators is advised for better understanding on this subject as this section only briefly described the evolution, referring some of the most important research outcomes. False data injection (FDI), resulting from cyber attacks, in distribution networks and smart-grids, strongly impact the state estimation process. The former were not detailed, although being of utter importance in today's modern distribution power systems. [64] presents a survey on fundamentals of this subject.

2.2 State Estimation with SCADA and PMU Measurements

First and foremost, the author would like to point that an important revision of fundamental concepts and the framework of Supervisory Control and Data Acquisition (SCADA) systems as well as modern network monitoring through Phasor Measurement Units (PMUs) are summed up in Appendix A and B respectively.

The development of PMUs lead to its establishment as the pillar for power systems monitoring data and situational awareness. It is clear, however, that the integration of PMU measurements in the conventional state estimation, characterized by measurements from the

Supervisory Control and Data Acquisition (SCADA), presents complications. This is mainly due to the fact that PMUs and SCADA devices present a wide difference in terms of both sampling rates [65] and precision. It is important to note, as previously mentioned, that PMU measurements are synchronized according to a global positioning system (GPS) time reference [66]. Owing to its significance, several different approaches have been developed and proposed over the past years in order to accelerate the progressive integration of PMUs in the contemporary power systems state estimation. This chapter aims to describe these methods, evolution, adaptations and their astonishing results, proving the effectiveness and necessity of a successful implementation in future power systems monitoring and control.

2.2.1 Hybrid State Estimation

Phasor measurement units (PMUs) provide high sampling rates of measurements (voltage and current phasors) which are linearly related to the states of a system [67]. Assuming full observability of the grid (2.1.3) with these devices, a linear state estimation (LSE) could be applied. The mass deployment of PMUs over the grid, achieving full PMU observability, is not economically feasible at the moment [68], dismissing the idea of a contemporary implementation of a linear estimator and enhancing the necessity for an intermediary solution. Taking the above mentioned into account, hybrid state estimation (HSE) algorithms began to be developed, as a contemporary middle step between conventional and the linear state estimators of the future.

Hybrid State Estimators make use of both SCADA conventional measurements and PMU measurements, to increase the estimation accuracy, robustness and efficiency. HSE methods differentiate by the process used for the integration of PMU measurements. Research efforts in the HSE field could be split in different categories as following [69]:

- Alternative procedures for state estimation (not WLS)
- HSE applications
- Optimal PMU Placement (OPP) for HSE
- Processes for SCADA and PMU measurement integration in HSE

This section will be mainly focusing the first and last category. The reader can find extensive literature references of each in [69].

Taking into consideration the significant difference between sampling rates of PMU and conventional SCADA measurements, new estimation methods were proposed in order to address this issue. Methods like the forecasting of measurements [70] focusing on the steady state estimation (which will be further discussed in section 2.2.3), the weighted least absolute value estimator (WLAV) processing the estimated states if new PMU measurements are posted [65] as well as many others were proposed, enhancing the robustness of the estimator against gross errors [1].

The different type of measurements between SCADA conventional (voltage magnitude, active/reactive power flow and injection) and PMU (voltage and current phasors) also challenged researchers into finding ways of effectively integrating the two in a single framework of HSE. These can be grouped in the following categorization, according to its formulation [69]:

- *post-processing HSE* (PP HSE): methodology that uses the outputs of the conventional state estimator as pseudo-measurements [1] forming part of the input set of a following linear state estimator (LSE). In this formulation, each of the two type of measurements are processed separately.

- *fusion HSE*: like the former method, the fusion HSE also utilizes both conventional and linear estimator. It simultaneously processes each type of measurement in the respective estimator, combining the outputs according to the fusion formulation.

- *integrated HSE*: this type of HSE combines both measurements class in a unique processing block.

First research effort was put into enabling the concomitantly processing of both PMU and SCADA measurements [66, 71]. Even though simultaneous processing methods, like the former, reveal satisfactory performance in a power system steady-state condition, due to the different sampling rates of both measuring systems, the accuracy of the estimator significantly decreases when the network state changes [12]. It is also important to state that the implementation of an integrative PMU and SCADA measurement scheme in a single model would require the substitution of the existing SE softwares of contemporary EMS at control centers [72] which, due to economic reasons may push back the adoptability of such solutions. An algorithm considering a multi-stage formulation (i.e PP HSE) was then proposed in [73]. Fusion Hybrid State Estimators (fusion HSE) were presented in [12, 74] by establishing a Bar-Shalom-Campo fusion model. Data Fusion methodology in hybrid state estimators will be further discussed in section 2.2.2. Finally, the use of extended Kalman filter model in [61, 75] and the unscented Kalman filter model in [76] were proposed for dynamic state estimation, using a state space model for the state variables and often following smoother results [1]. Dynamic state estimators will also be discussed in section 2.2.4.

2.2.2 Data Fusion in Hybrid State Estimation

This section is based on and describes the formulation proposed in [12] presenting the Data Fusion model for hybrid state estimation. Before this methodology, most of the research outcomes were based on either: the decoupling of the sate estimation process in two separate stages, addressing the SCADA measurements in an initial block, followed by the use of PMU measurements in a second block or in the simultaneous processing of both measurement types in a common estimator, requiring significant changes to the pre-existing systems in some cases. Novel propositions are also briefly referred, exhibiting state of the art applications and developments on this formulation.

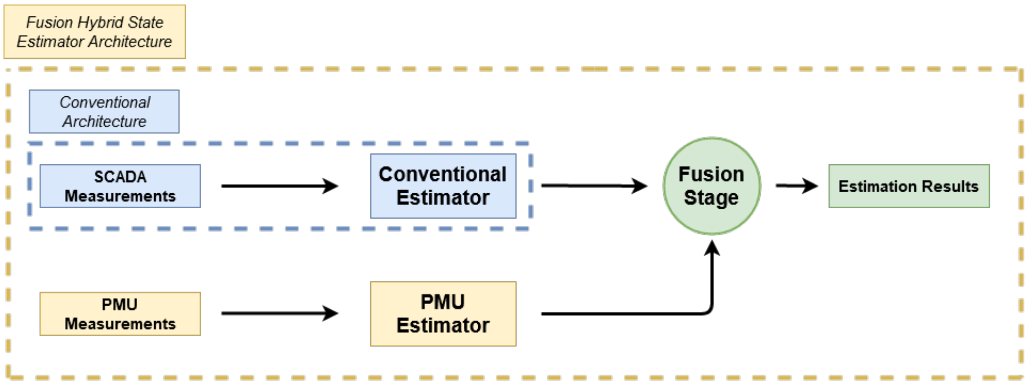

Figure 2.3: Fusion Hybrid State Estimation Architecture.

In [12] the authors claim that the proposed method does not require structural changes to the pre-existing conventional state estimator. Instead, the former architecture is enhanced with a second estimator, in parallel, uniquely designed for the processing of PMU measurements. The outputs of both estimators are then *fused* in a final stage, based on *Multisensor Data Fusion* (MDF) theory [77], producing the set of estimated state variables that resemble the current condition of the system. Figure 2.3 illustrates the estimation architecture. MDF is a recent research field regarding frameworks monitored by *sui generis* classes of sensors.

Relevant features of the implementation of this method are described in the literature as following:

- The PMU measurement estimator algorithm is free of restrictions, processing measurements in parallel hence independently of the conventional SCADA estimator. A linear state estimator (LSE) (section 2.2.1) can, therefore, be implemented in the PMU stage. As previously stated, this architecture greatly benefits the gradual transition of the current Energy Management Systems towards PMU integration, since it does not require structural replacements to the current implementation.

- Observability problems regarding the PMU estimator are dismissed. The authors recognize the availability of pseudo-measurements but, instead, design the referred model based on *a priori* information, implementing artificial observability through former saved data. This data set can either be recent estimation outputs or "standard expected values" of complex voltages of the network buses. This approach also leads to minimal computational effort since there's existing Givens rotation-based estimators that process *a priori* information at boot stage, resulting in data that can be assigned to network buses which are not PMU observable.

- If the measurement set is free of gross errors, the fusion resulting estimation is bias-free and truly reflects the state values with small deviation due to the use of the minimum variance criterion [78].

- Depending on the PMU deployment locations and relying on significant redundancy, bad data prevention and detection for errors present in critical measurements or sets can be achieved with the fusion strategy.

Assuming full observability (both SCADA and PMU) as well as the uncorrelation between measurement classes it was concluded that this estimation method yields the same estimation results as (simultaneous) integrated hybrid state estimators. Furthermore, in cases where full PMU observability is not verified, fusion HSE still ensures significant improvement in the estimation results when compared with the conventional SCADA estimator.

Innovative methodologies were proposed in the last years based on the fusion hybrid estimator previously referred. In [79], it is proposed a hybrid two-stage fusion architecture with a Maximum Correntropy Criterion (MCC) based estimator combined with adjustable Parzen windows instead of the conventional WLS, demonstrating a resilient effect against outliers right from the estimation stage and dismissing heavy computational efforts for bad data handling.

A robust unscented Kalman filter (RUKF) is proposed in [11]. The formulation is based on the unscented Kalman filter (UKF) for the fusion of assynchronous measurements and the utilization of a gain matrix correction method for the bad data detection and filtering of PMU measurements. Results demonstrate a substantial improvement in estimation accuracy when compared with the tradition UKF and extennded Kalman filter (EKF) methods.

2.2.3 Forecasting-Aided State Estimation (FASE)

The present section describes the generic concepts of the Forecasting-Aided State Estimation (FASE) methods surveyed in [80, 81].

The process of future values estimation based on previous observed/estimated ones is refered to as *a priori* estimation or forecasting. It has been widely recognized that the conventional state estimation process can be effectively upgraded with incorporation of state/measurement forecasts. Therefore, a vast amount of research effort has been put into finding novel alternatives to integrate this concept in the state estimation field. The FASE formulation has been consolidated by means of correct dynamic modeling, forecasting methods and data validation schemes. The method's flowchart is illustrated in Figure 2.4.

Conventional State Estimation (CSE) supports its process on the measurement redundancy. Nevertheless, due to the costs of mass implementation of metering devices, it is commonly observed that power grids are not monitored with sufficient redundancy, leading to inaccurate estimation results. Another important aspect to denote in the CSE methodology is that the estimated state vector is obtained from a single scan of measurements so the redundancy is timely concentrated. Therefore, valuable information from previous estimations/measurements is completely disregarded and situations where the redundancy level significantly decreases are not effectively addressed with the available information.

The Forecasting-Aided State Estimator addresses the above-mentioned problems due to its ability of relating the successive system states. Through mathematical formulations, it forecasts a

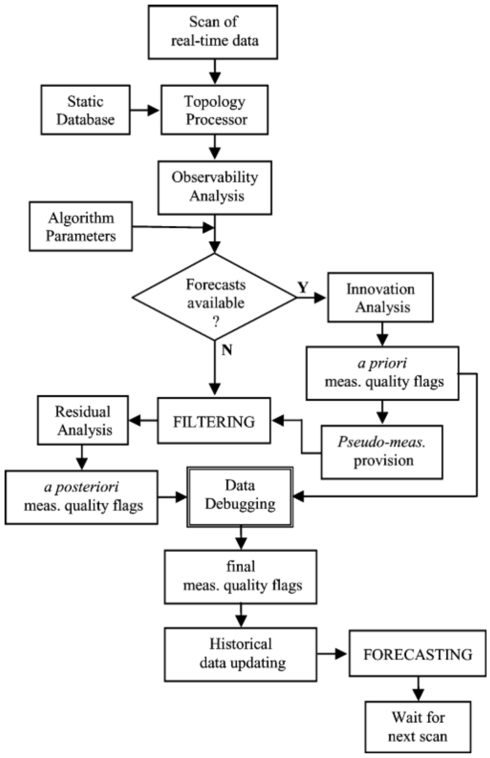

Figure 2.4: Fluxogram of the FASE methodology [81].

significant amount of variables (system state/measurements) to be added to the conventional raw SCADA estimation inputs (or used as pseudo-measurements for unmeasured variables and enhancing network observability), resulting in a wider information set to be processed i.e. increasing redundancy. Innaccurate estimations can result from errors present in the conventional measurements. With the simultaneous use of forecasted values (*a priori* information) and conventional measurements, the FASE methods can result in filtered estimated states (*a posteriori information*). The mentioned additional filtering requires further computational effort investment. To address this aspect, formulations characterized by the integration of extended Kalman filter (EKF) with reduced gain matrix or the adoption of hierarchical estimation procedures were proposed in the literature.

Since it is designed as a real time function of the Energy Management System, the forecasting step should be characterized by easy implementation and maneuverability, fully automatic and computationally fast. The authors state that an efficient way of dealing with the raising data redundancy whilst upgrading the state estimation process is through the definition of a *predictive database* which should be an output of the FASE method thus not requiring the further implementation of new equipment. This database should be upgraded automatically through the *innovation analysis* function dismissing the need for the operator's frequent intervention. The *innovation analysis*, implemented in FASE algorithms, is responsible for scanning the new measurement set that is acquired by the system and deciding whether new and relevant/considerably different information is present. The improvement of data debugging, measurement and network configuration errors problems with the use of *predictive databases* are widely declared on the existing literature. It has become clear that it is essential to integrate the dynamics of the system-state in the state estimation process to achieve a reliable monitoring of the power grid since the power system is naturally dynamic. Without this time based evolution, the state estimation results in an inaccurate picture of the power system. Dynamic State estimation will be further addressed in the next section (2.2.4). Adopting the FASE methodology brings significant value to the security analysis as well. By predicting the short-term evolution of the system state, system operators can pre-program control actions in advance. The forecasting step in the FASE approach does not significantly increase the estimation process computational effort. The processing burden of this step is trifling when compared with the full estimation framework and, if correctly implemented, may in fact reduce the overall execution time (specially in the data validation and state filtering steps).

In order to maintain the section's briefness, the FASE methodology was succinctly described. Nevertheless, the author would like to point out that the concept of forecasting associated to state estimation, even though a topic of discussion for the past decades, has opened doors to numerous applications, developments and concepts in this field. The implementation of Computational Inteligence (CI) and Neural Networks (NN) [82, 83] to enhance the forecasting capabilities of such methods and thus the estimation efficiency and accuracy, for example, has been demonstrating fascinating results.

2.2.4 Dynamic State Estimation

The present section is based on and aims to describe the important aspects of the Dynamic State Estimation (DSE) framework, thoroughly described in [9] in a unified framework.

As previously described, power system applications responsible for its monitoring and control are based on the steady-state model of the system. Even though viable for the past years, this approach is inaccurate since there's frequent variations in generation and demand, resulting in a dynamic behavior of the system. Modern power systems have become extremely dynamic due to the increasing incorporation of DERs, loads of high complexity and microgrids, emphasizing the need to implement a novel methodology that deals with these variations. Dynamic State Estimation (DSE) was proposed to reassess this paradigm, contemplating the modern power systems necessities and its continuous evolution in complexity and behaviour.

With the recent development in PMU technology and its extensive disposition, the DSE evolves into a fast and robust function that is able to record the system's dynamics with considerable accuracy.

The DSE makes use of multiple non-linear filters based on the Kalman filter [84] to estimate the dynamic state vector or model parameters of the state space model. Some of the different Kalman-filter-based approaches applied to the DSE framework are: the extended Kalman filter [85], the unscented Kalman filter (UKF) [86], the cubature Kalman filter [87], the H-infinite extended Kalman filter [88], robust extended Kalman filter [61], polynomial-chaos based Kalman filter (PCKF) [11] among many others.

Kalman filter based architectures usually consist of two sequential steps, the prediction step and the update (filtering) step.

Dynamic state variables are variables related to the time derivatives in the group of differential-algebraic equations that illustrate the power system dynamics. The state variables connected to synchronous generators are correlated to its electromechanical and electromagnetic processes and controllers. The non-synchronous types have state variables related to its main source of energy [89].

Taking the state estimate and its covariance matrix, the predicted state is obtained directly or along a set of points from the probability distribution. In the update/filtering step, the resulting predictions are combined with measurements from a determined time-step in order to estimate the system-state and its covariance matrix. Due to its formulation, the Dynamic State Estimator can be implemented in any system, assuming sufficient computational capacity as well as the correct use of equality and inequality constraints.

In the DSE field, observability analysis characterizes systems as strongly, weakly or non-observable, instead of the usual binary result (observable or non-observable). This classification typically relies on the computation of the smallest singular value of the observability matrix based on the Lie derivatives. The highest values of the smallest singular value of the referred matrix indicates *stronger* observability for a determined measurement set and vice-versa [89].

Bearing in mind the method's correlation with the time and non-linearity, observability classification also varies accordingly to it, being time dependent. As previously referred, optimal PMU placement (OPP) methods have been proposed to increase the network observability.

DSE can be implemented in two different architectures, according to the system's full or partial observability: centralized and decentralized. The centralized dynamic state estimator, implies full PMU observability of the system, where proper reductions can be applied. Besides, it assumes wide-area PMU measurements in real-time and precise system component parameters knowledge. The decentralized DSE takes a local approach. It solely makes use of local PMU measurements, presuming local observability of the dynamic state. If, for instance, a determined generator terminal bus is not PMU observable, a LSE should be primarily executed in order to estimate its value so that a DSE can properly initiate.

Contemporary literature typically considers a hierarchical/distributed DSE as opposed to the centralized DSE since the latter requires highly efficient computing techniques that are still in a premature development stage.

The successful implementation of the dynamic state estimator brings numerous advantages. Part of the referred advantages are briefly listed below, according to their description in [9].

- **Improved Oscillations Monitoring:** DSE execution results in estimated states of entire regions. These can be exploited for modal analysis, enhancing power system stabilizers (PSS) and leading to improved system stability (in cases where the generator has considerable impact) that would otherwise be conventionally limited by the systems' local observability.

- **Improved hierarchical decentralized control:** having dynamic estimates for both local and wide-areas, the dynamic state estimator allows for an enhanced local and wide-area control architecture.

- **Enhancement of protection systems:** analysing the coherence between the dynamical model and the PMU measurements of a determined area, the detection of faults can be achieved with no *a priori* protection settings. An enhanced protection system is achieved, more reliable than the conventional coordinated architecture based on pre-programmed settings. Besides, a wide-area protection scheme becomes available to the operator, that may accurately assess stability issues for the whole grid, instead of only relying on local protection schemes with a marginal oversight of the system.

A framework comparison between the Static State Estimator (SSE) and the Dynamic State Estimator (DSE) is illustrated in Figure 2.5.

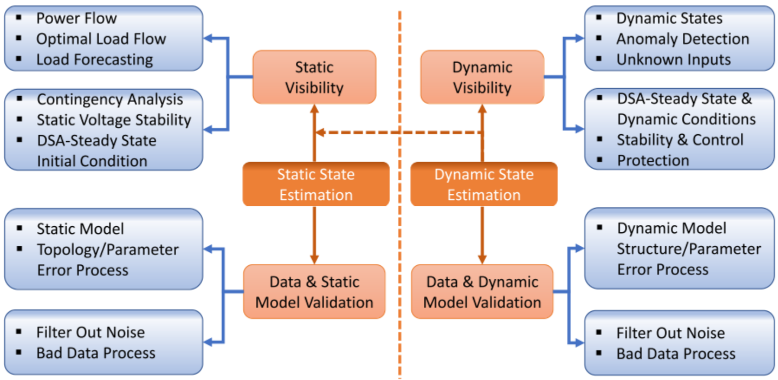

Figure 2.5: Comparison of SSE and DSE Frameworks [89].

Even though Dynamic State Estimation has resulted from intensive research effort in the scientific community for the past years, the author recognizes that there's still much to be developed and improved in this methodology. Future works in the DSE field are also addressed in [9] enlightening the path for future research.

2.2.5 State Awareness

The dynamic state estimator has an established position in the monitoring, operation and protection framework of the short-term future of power systems. This function reveals promising features crucially tracking the rapid variations in the system operating point significantly caused by, as previously stated, stochastic profiled renewable generation and distributed energy resources (DERs). Due to this capability of tracing the evolution of the system in a both local and general manner, the DSE provides a true *awareness* of the power system state, in real-time, to the operator.

The present section enunciates some of the most interesting and *avant-garde* applications of the dynamic state estimation implementation. These applications are listed and succinctly described based on their extensive report in [89]. The author eulogizes the document and emphasizes its importance as an essential "in-depth overview" of the Dynamic State Estimation fundamentals and state-of-the-art concepts.

The DSE will have a significant impact in three pillar application areas, specifically: system modelling, monitoring through enhanced dynamic visibility and system operation.

Regarding the **system modelling**:

The DSE can contribute to validate the implemented generator models. This achieved by recording the voltage phasor/frequency on the generator terminals through PMUs, using these records as model inputs in order to determine the response active/reactive power (*P/Q*) models as outputs. The latter are then compared with their respective measured values and the model's accuracy is determined. If this test reveals an inaccurate model, a calibration method is applied which typically follows a sequence of four different steps: initial checks, erasing obvious errors in parameters; sensitivity analysis, resulting in a parameter sensitivity map, flagging suitable parameters for calibration; parameter estimation, by performing a joint DSE method with the parameter vector and the original state vector; parameter validation test with other disturbances: guaranteeing the found solution is resilient to other events and not solely a local optimum. The above mentioned steps are heavily based on the extensive use of Kalman filter models.

Other components such as dynamic loads, wind farms and DERs with power-electronics interface can also be "parameter estimated" presuming availability of local measuring devices and their correct expression of differential-algebraic equations (DAEs).

Regarding the **enhanced dynamic visibility monitoring**:

There are numerous advantages in the implementation of the DSE in terms of the system monitoring. In order to maintain the present section brief, only a couple of the paramount will be enunciated. Readers can find an extensive description of the mentioned advantages in [89].

The dynamic state trajectory tracking is an integrated result of the DSE since it allows the visualization of time series of generators and respective controllers in circumstances of system disturbances. The tracking of the rotor's speed and angle has been used for oscillation detection and bus frequency estimation dismissing the deployment of further PMUs for this purpose. The center of inertia (COI) frequency can also be obtained through the execution of DSE, obtaining an online reference frequency for control and disregarding conventional techniques for this purpose that imply assumptions that lead to questionable accuracy.

The measurement error filtering is also enhanced in the DSE framework. There are robust DSE methods capable of filtering measurement noise, resulting in accurate data for further application use. The robust DSE automatically detects and disregards bad data with significant improvement when compared to conventional estimators. Cyber-attacks are a hot topic in the field of power system operation. Novel robust DSE methods are being developed, including machine learning-aided DSE, to tackle this growing modern issue.

Other key aspects related to the generator's excitation system visibility or the ever growing importance of thermal rating of lines and cables, to name a few, are also deeply enhanced with the implementation of the DSE.

Concerning the **system operation**:

Dynamic State Estimation enhances Energy Management Systems with dynamic security assessment (DSA) and dynamic stability assessment, which will be briefly described.

Conventional DSA is characterized by some drawbacks and initialization problems. This is due to the fact that the SSE can only properly determine the system's initial conditions if it evolves steadily over time. The latter remained true for the past power systems, but with all the above mentioned reasons contributing to a stochastic variable operating point of the system, the future DSA will require a new framework capable of dealing with such dynamics, representing an accurate vision of the system state. Simulation tests with multiple contingencies have proven that the model initialization for dynamic security assessment of the DSE is efficient in determining the real system behavior in opposition to the SSE-based DSA which indicates, for example, system stability loss under circumstances where the system remains stable.

Dynamic stability assessment has been executed through the comparison of real-time measurements with data-base event records from offline simulations. If an instability is encountered, control actions are executed. This approach, even though practical, is questionable since full simulation coverage of all scenarios can't be guaranteed. Since DSE can ensure a clear real-time image of the system state it can be used to compute transient stability indices, improving the dynamic stability assessment accuracy. This control framework is still in a premature but promising stage.

Even though not addressed in the present section, the author would like to state that there's another aspect of utter relevance in the deployment of DSE towards achieving power system state awareness in the modern and future networks. Renewable energy resources with power electronics interface constitute the inevitable future of power systems. The stochastic variations in production and generation in small time-windows point towards an absolute necessity for a dynamically visible power system both locally and as a whole and, therefore, the need for further DSE development and gradual implementation.

2.3 Conclusion

The present chapter establishes a clear overview of the vast state estimation field as a whole, defining the roles and correlations between different components and concepts. The fundamentals, chronological evolution of the main concepts and fields of study, the conventional methodologies and most importantly state-of-the-art developments were addressed. Important concepts regarding the architecture of Supervisory Control and Data Acquisition (SCADA) systems and PMU-based monitoring were opted out to appendixes for the sake of the chapter's concision. The brief reading of these chapters is advised for an overview of the State Estimation integration in the framework of power systems operation.

Regarding the latest proposed state estimation methodologies, the evolution of modern power systems and the advent of powerful synchronised measurement technology, it has become evident that the future trends point towards an application that embraces the true dynamic behavior of the power system. A consensus on which approach or combination returns the optimum implementation is still to be achieved.

Energy utilities and the scientific community have been investing in establishing a progressive smooth transition framework solution between conventional methods of state estimation with SCADA measurements and fully dynamic state estimators with full PMU deployment and integration of other measurement devices due to economical and technical limitations. The concept of hybrid state estimator has been the overall accepted solution. The main proposed methods in the literature for hybrid state estimation were referred and some concept gaps were identified. The consideration of *a priori* information from different moments related to the estimated states and their respective correlations/weights for the enhancement of the state estimator integrating a Bayesian fusion architecture hasn't been addressed.

This document proposes a new two-stage Bayesian fusion estimation perspective for addressing the dynamic behaviour of the modern power systems whilst considering multiple *a priori* data from different periods and sources enhancing the SE accuracy. Particular considerations related to variables correlation, which are often disregarded, are also addressed. The proposed methodology envisions a real-life applicability on the current Energy Management Systems with minimal structural changes and cost investments, ensuring a getaway transition solution to the conventional estimation architecture that has been predicted to become obsolete in a short-term future.

Chapter 3

A New Bayesian Perspective for State Estimation

3.1 Introduction

The use of probability models under the Bayesian perspective hasn't been thoroughly and widely recognized in the power system state estimation field even though recent literature demonstrates clear advantages in its adoption. The Bayesian Fusion HSE architecture [1], on which this research work has been based, addresses the referred particular lack of consideration. The Bayesian approach is also made use of in a multitude of different applications for power systems which are worth mentioning such as: aiding topology estimation [90]; supporting fault analysis [91]; enabling reliability analysis [92]; aiding selectivity in medium voltage protection [93]; short-term wind generation forecasting [94] and forecasting smart meter data [95].

Therefore, the present chapter is structured as follows: section 3.2 is a theoretical introduction to the fundamental concepts and terminology of the Bayesian inference, describing its main principles and assumptions; section 3.3 revises the conventional state estimation formulation, linking the current implementation with the Bayesian fusion hybrid architecture wich is further presented in section 3.4. Finally, a brief discussion of the presented concepts is addressed in section 3.5 defining the current stand point on which this research work evolves from.

3.2 Bayesian Inference Main Concepts

As previously stated in this chapter's introduction, the present section serves as an introductory elucidation on Bayesian theory concepts, describing its main principles and assumptions. The correct interpretation of the referred terms is necessary for its applicability to the proposed power system state estimation problem, which will be further addressed in section 3.4. The definitions and concepts presented in this section are mostly based on their extended descriptions found in [96]. Further reading of this document is advised for advanced Bayesian theory related studies and applications.

The concept of probability can viewed in two different ways: *frequentist* (classical) or *Bayesian*.

In the frequentist approach, parameters are treated as fixed but unknown quantities. These parameters can be estimated using samples from a population, but different samples lead to different estimates. The estimation is therefore determined by the relative frequency of outcomes for an infinite amount of similar trials. The distribution of the estimates is termed *sampling distribution* quantifying the uncertainty of the estimate whilst maintaining the parameter fixed.

In the Bayesian approach, parameters are treated as random variables (a variable which results from the outcomes of a random phenomenon [97]) which can be represented through a probability distribution, listing the possible outcomes and their respective probabilities. The function that describes the probability distribution of a discrete random variable is termed as probability mass function (PMF) whilst the probability density function (PDF) describes the probability distribution of a continuous random variable. The Bayesian approach is based on the state of knowledge resulting exclusively from the available information.

Bayesian inference is, therefore, a method for fixing a probability model to a data collection, representing its result through a probability distribution on the parameters of the model and on unobserved quantities (for example, predictions for new observations). Bayesian theory makes use of probability in order to evaluate uncertainty of inferences in respect to statistical data analysis, hence, easing the interpretation of statistical conclusions.

The principal framework of Bayesian statistics and data analysis is typically divided in a sequential procedure as follows:

- Firstly, a *full probability model* must be formulated. The referred model must be coherent with the knowledge of the problem, resulting in a probability distribution regarding all observable and unobservable quantities of the problem.

- Following up, the conditional probability distribution of the desired quantities of interest - *posterior distribution* - is calculated with respect to the observed information.

- Proceeding, the created model must be tested to determine its applicability and impacts on the results. These tests usually dictate whether: the model is suitable for the available information or not, if it resulted in proper conclusions and if it significantly impacts the results, i.e the results are sensitive to the constructed model.

- Lastly, the implementation or alteration of the proposed model considering the above mentioned steps.

Bayes' Rule:

As previously stated, in the interest of building probability statements of a parameter θ, given an observed value or set of values $\boldsymbol{y}$, one should construct a model for the *joint probability distribution* for θ and $\boldsymbol{y}$.

The PMF or PDF of the joint distribution - *p(θ,y)* - can be described as a product of two separate PMFs or PDFs, typically termed as the *prior distribution* - *p(θ)* - and the sampling distribution - *p(y|θ)* - as follows:

$$p(\theta, y) = p(\theta)p(y|\theta) \tag{3.1}$$

On the other hand, the joint probability distribution may also be expressed as:

$$p(\theta, y) = p(y)p(\theta|y) \tag{3.2}$$

Given equations (3.1) and (3.2), the terms can be rearranged yielding the equation known as the *Baye's Theorem*, expressed below:

$$p(\theta|y) = \frac{p(\theta)p(y|\theta)}{p(y)} \tag{3.3}$$

Where:

- *p(θ)* is the prior belief or prior probability on the hypothesis.
- *p(θ|y)* is the posterior probability for θ as soon as y has been observed.
- *p(y|θ)* is the likelihood for θ assuming the data to be true. The likelihood function describes the compatibility of the observed data with the regarded hypothesis.
- *p(y)* is the marginal likelihood for the observed data, which is independent of θ being verified or not. It represents the sum of all possible values (if discrete) or the integrate of the full range of outcomes (if continuous) for θ. It is also termed as *evidence*.

Since in (3.3), *p(y)* does not depend on θ, and therefore is constant, it is usually omitted, resulting in the *unnormalized posterior density*, which can be interpreted as the posterior distribution being proportional to the likelihood times the prior distribution. The *unnormalized posterior density* is expressed below in the right term of (3.4):

$$p(\theta|y) \propto p(\theta)p(y|\theta) \tag{3.4}$$

The Bayesian inference can be used as an iterative process, updating its parameters and estimations as fresh data is observed. After calculating the posterior distribution and as soon as new data is observed, the posterior can be used as the new prior and the likelihood can be re-determined enabling the calculation of a new posterior distribution. The flexibility and simplicity of the Bayesian framework results in its effective application to complex multi-parametered and multi-layered problems. In summary, Bayes's theory enables the continuous update of beliefs regarding an hypothesis as newly observed data is registered.

3.3 State Estimation Formulation

The power system at transmission level uses numerous devices to acquire measurements of different electric quantities. Inaccuracies or errors are inevitable in the measuring process, but these can be quantified in a statistical manner. The estimated values of the measured quantities, which result from the posterior estimation process, can be accepted or neglected, depending on their accuracy [98].

The classical Weighted Least Squares (WLS) estimator has been defining the control and monitoring operation of power systems for the past decades. As previously mentioned, its framework has been providing an effective way of assessing the network state with relative ease of implementation and robustness. The state estimation function addresses the problem of determining the voltage phasors at all of the network's buses through a set of redundant measurements and the posterior filtering of errors in the referred measurements.

The present section aims to describe the conventional state estimation algorithm as formulated in the classical literature [4, 99, 98].

First and foremost, one should regard the set of measurements, described by the vector z, as follows:

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix} = \begin{bmatrix} h_1(x_1, x_2, \dots, x_n) \\ h_2(x_1, x_2, \dots, x_n) \\ \vdots \\ h_m(x_1, x_2, \dots, x_n) \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_m \end{bmatrix} = h(x) + e \tag{3.5}$$

Where:

- $x^T = \begin{bmatrix} x_1, x_2, \dots, x_n \end{bmatrix}$ - the vector of the system state, consisting of voltage magnitudes and phase angles of all buses of the network.
- $h^T = \begin{bmatrix} h_1(x), h_2(x), \dots, h_m(x) \end{bmatrix}$ - $h_i(x)$ is the nonlinear function that relates the measurements i (typically line power and current flows and bus power injections and voltage magnitudes) to the state vector x.
- $e^T = \begin{bmatrix} e_1, e_2, \dots, e_m \end{bmatrix}$ - measurement errors vector.

It is important to denote that, since there is no synchronism between conventional SCADA measurements, the reference bus is usually the slack bus, with the set reference angle of 0 (which does not integrate the state vector).

Regarding the measurement errors, it is often assumed that:

- these display a Gaussian (Normal) distribution, with μ and σ^2 as the parameters of mean and variance respectively.
- $E(e_i) = 0\ ,\ 1 \leq i \leq m$ - the expected value of any measurement error is zero.

- $E[e_i\, e_j] = 0$ - measurement errors are independent.

Considering the latter, the covariance of the vector of measurement errors is expressed as follows:

$$Cov(e) = E[e \cdot e^T] = R = diag\left\{\sigma_1^2,\ \sigma_2^2,\ \dots,\ \sigma_m^2\right\} \tag{3.6}$$

The accuracy of the used measuring device, related to each measurement i, is assumed as its standard deviation σ_i.

Static state estimation consists of seeking the maximum of the likelihood function, l*(x | z)*, applied to the model of the measurements set (3.5) in order to achieve a state vector coherent with the measurement data and the network model. Assuming the above stated Gaussian assumption, the resulting Maximum Likelihood Estimator (MLE) of the referred model is expressed as:

$$\max\ l(x|z)\ = \prod_{i=1}^{m} \frac{1}{\sqrt{2\ \pi\ R_{ii}}}\ e^{-\frac{(z_i - h_i(x))^2}{2R_{ii}}} \tag{3.7}$$

Where R is the covariance matrix (m x m), with m being the number of measurements. By performing some algebraic modifications, and taking the maximum of the likelihood, yields:

$$\max\ l(x|z)\ = \prod_{i=1}^{m} \frac{1}{\sqrt{2\ \pi\ R_{ii}}} \prod_{i=1}^{m} e^{-\frac{(z_i - h_i(x))^2}{2R_{ii}}} \tag{3.8}$$

$$\max\ l(x|z)\ = \prod_{i=1}^{m} \frac{1}{\sqrt{2\ \pi\ R_{ii}}}\ e^{\sum_{i=1}^{m} -\frac{(z_i - h_i(x))^2}{2R_{ii}}} \tag{3.9}$$

$$\max\ \log(l(x|z))\ = \sum_{i=1}^{m} log(\frac{1}{\sqrt{2\ \pi\ R_{ii}}}) + log(\ e^{\sum_{i=1}^{m} -\frac{(z_i - h_i(x))^2}{2R_{ii}}}\ ) \tag{3.10}$$

The optimal estimation of the state expressed in (3.10) is determined when the Weighted Least Squares (WLS) estimator minimizes its objective function i.e. its derivative is zero. The referred objective function is expressed below:

$$\min J(x) = \sum_{i=1}^{m} \frac{(z_i - h_i(x))^2}{R_{ii}}\ =\ [z - h(x)]^T\ R^{-1}\ [z - h(x)] \tag{3.11}$$

Determined the minimum point, the first-order optimality conditions must be satisfied. These are compacted in the following expressions:

$$g(x) = \frac{\partial J(x)}{\partial x} = -\ H^T(x)\ R^{-1}\ [z - h(x)] = 0 \tag{3.12}$$

Where *H(x)* is the Jacobian matrix of the *h(x)* function:

$$H(x) = \left[\frac{\partial h(x)}{\partial x}\right] \tag{3.13}$$

Through the expansion of g(x) in its Taylor series around the state vector x^k and neglecting its terms of higher order, the iterative Gauss-Newton method is formulated as follows:

$$x^{k+1} = x^k - [G(x^k)]^{-1} \cdot g(x^k) \tag{3.14}$$

Where:

- k - iteration step.
- x^k - solution vector at iteration step k.
- $g(x^k) = -H^T(x^k) \cdot R^{-1} \cdot (z - h(x^k))$.
- $G(x^k) = \dfrac{\partial g(x^k)}{\partial x} = H^T(x^k) \cdot R^{-1} \cdot H(x^k)$ - gain matrix.

The gain matrix G(x) is sparse, symmetric and positive definite assuming the system's full observability. A revision of observability concepts can be found in section 2.1.3. Due to its characteristics, the gain matrix is decomposed into its triangular factors enabling the resolution of a sparse linear set of equations, commonly termed as *Normal Equations*, through the Newton-Raphson method. The referred calculations are recursively executed at each iteration step. The *Normal Equations* are expressed as follows:

$$[G(x^k)]\, \Delta x^{k+1} \;=\; H^T(x^k)\, R^{-1}\, [z - h(x^k)] \tag{3.15}$$

Where Δx^{k+1} is the difference between state estimates in sequential iteration steps.

$$\Delta x^{k+1} = x^{k+1} - x^k \tag{3.16}$$

The iterative process is finished once acceptable convergence ε is achieved.

$$Stop\ if:\ |\Delta x^k| \leq \varepsilon \tag{3.17}$$

3.4 Bayesian Fusion State Estimation

The aim of this section is to describe the Bayesian fusion state estimation formulation, based on the proposed method presented in [1] as it is the fundamental conceptual guide from where the explored solution arises.

The constructed model is characterized by a double staged Bayesian state estimator, which addresses SCADA conventional measurements and PMU synchronized measurements according to their respective sampling frequencies. The Bayesian inference fundamentals, presented in section 3.2, are used for the integration of the two types of referred measurements.

In the proposed framework, SCADA updated measurements are recursively treated in an independent stage (the first stage) through the use of the conventional weighted least squares

(WLS) estimation model, as described in section 3.3, expressed by (3.5). The outputs of this stage are the primary SCADA estimated state, $\hat{\mathbf{x}}_0$, and its specific covariance matrix $\mathbf{R}_{\hat{x}_0}$.

On the other hand, PMU measurements are addressed in an independent stage which is based on the FASE methodology and relies on a state space model to formulate the estimation problem. Forecasting-aided State Estimation (FASE) fundamental concepts can be reviewed in section 2.2.3, and its formulation is described in Appendix C.

Since this stage is solely built for synchronised phasor measurements from PMUs, its representation in rectangular coordinates, for both the state variables and the measured phasors (current and voltage), enables the linearization of (3.5) and the implementation of a linear state estimation (LSE) model.

The FASE model expressions (C.1, C.2) can be rearranged for the PMU measurements presuming a stationary processed state space and that the previous system state is given by the last executed estimation. The resulting adapted expressions are expressed below:

$$x_t = F\hat{x}_{t-1} + \omega_{t-1} \tag{3.18}$$

$$z_t = Hx_t + e_{PMU} \tag{3.19}$$

Where:

- z_t - vector of PMU measurements in the latest instant, t.
- x_t - state variables vector in the latest instant, t.
- $\hat{x}_{t-1}$ - SCADA-based estimation vector.
- ω_{t-1} - is the process noise associated with possible state variation between the arrival of new PMU measurements.
- H - (m x n) matrix, relating the m PMU measurements with the n state variables.
- e_{PMU} - noise error vector. These errors are presumed to be, similarly to the FASE approach, independent normally distributed random variables with zero mean and respective covariance matrix R_{PMU}.
- F - constant state transition matrix, assumed as an identity (n x n) matrix in order to closely relate the PMU measurement to the last yielded SCADA-based estimation.

The proposed state space model approach (3.18) regards x_t as a random variable due to its relation to the former estimated state through a forecasting model with a random error. Hence, and envisioning the Bayesian inference framework, it is adequate to analyse the referred state estimation problem in a Bayesian based manner, regarding measurements and system states as random variables [100]. Therefore, applying the Bayes' Theorem (3.3) to the stated problem, the posterior probability function of the state variables is expressed as a conditional probability distribution:

$$P(x_t \mid z_t) = \frac{P(z_t \mid x_t)P(x_t)}{P(z_t)} \tag{3.20}$$

Which is, as stated in 3.2, proportional to the *unnormalized posterior density*:

$$P(x_t \mid z_t) \propto P(z_t \mid x_t)P(x_t) \tag{3.21}$$

Where:

- $P(x_t)$ - prior distribution of x.
- $P(z_t \mid x_t)$ - likelihood function which results from the PMU measurement model expressed in (3.19).
- $P(z_t)$ - marginal likelihood constant or evidence, which is the value of the probability function of the measurements at the observed values.

Taking the above considerations into account, the state estimation can be addressed and settled with the use of the posterior probability distribution in opposition to the sole use of the measurement model. Therefore, the posterior probability is expressed as [1]:

$$Prior : x_t \sim \mathcal{N}(F\hat{x}_{t-1}, Q_{t-1}) \tag{3.22}$$

$$Likelihood : z_t \mid x_t \sim \mathcal{N}(Hx_t, R_{PMU}) \tag{3.23}$$

$$Posterior : x_t \mid z_t \sim \mathcal{N}(A, B) \tag{3.24}$$

Where:

$$A = (H^T R_{PMU}^{-1} H + Q_{t-1}^{-1})^{-1} (H^T R_{PMU}^{-1} z_t + Q_{t-1}^{-1} x_t\hat{_{-1}})$$

$$B = (H^T R_{PMU}^{-1} H + Q_{t-1}^{-1})^{-1}$$

The Bayesian architecture that is presented settles the prior distribution as the conventional estimation stage output with SCADA measurements. This prior distribution remains unchanged until the SCADA measurement set is updated again. Between SCADA updates, data (measurements) from PMUs is continuously being registered at a much faster rate. In other words, $\hat{x}_{t-1}$ as well as $R_{\hat{x}_{t-1}}$ are set as the estimates resulting from the SCADA measurement processing stage ($\hat{x}_0$ and $R_{\hat{x}_0}$ respectively) but expressed in the form of rectangular coordinates for its integration with the PMU registered samples. The state space model with respect to the proposed sequential stages is schemed in Figure 3.1.

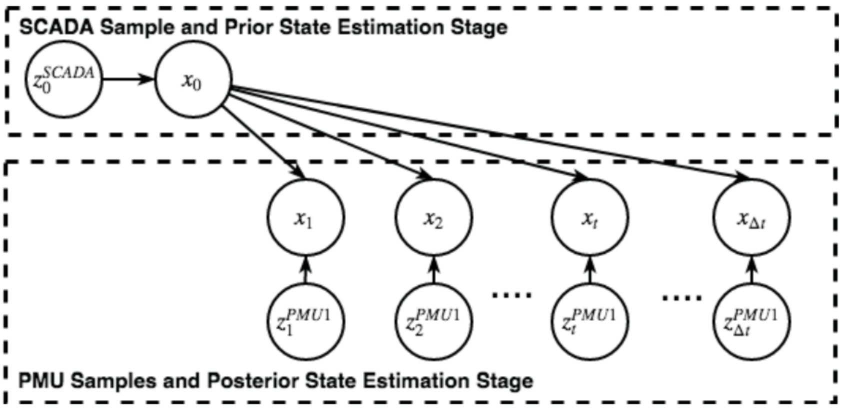

Figure 3.1: Bayesian State Estimation state space model. Initial stage is related to the processing of the conventional state estimation with SCADA measurements. The following stage takes into account newly registered PMU measurements to update the current state with the use of the defined posterior distribution [1]. Δt is the number of PMU samples registered between sequential SCADA measurements.

Accordingly to the Bayesian concepts presented in 3.2, one should now be able to correlate the proposed methodology to the "previous posterior as new prior" Bayesian updating scheme i.e. x_0 is the prior to the estimation of x_1, and x_1 will be taken into account as the prior to x_2, continuously, untill a new SCADA estimate update is encountered.

3.4.1 Maximum a Posteriori (MAP) State Estimation

The PMU stage relies on the *Maximum a Posteriori* (MAP) state estimation to enable the resolution of the estimated state. This procedure is expressed as follows:

$$\hat{x}_t = \arg\max_{x_t} f_{X|Z}(x_t \mid z_t) \tag{3.25}$$

Assuming a joint multivariate Gaussian prior model and according to the Bayesian inference fundamental concepts addressed in 3.2, the resulting MAP estimate is the expected value of the posterior multivariate normal distribution. This conceptualization is fundamental for the theoretical applicability of the proposed solution presented in Chapter 4. The resolution of the linear system yields the estimated state of the PMU measurement addressing stage as follows:

$$(H^T R_{PMU}^{-1} H + Q_{t-1}^{-1})\, \hat{x}_t = (H^T R_{PMU}^{-1} z_t + Q_{t-1}^{-1} F \hat{x}_{t-1}) \tag{3.26}$$

The single requirement for the resolution of an estimation in a determined time-step (for example, t = 1) is the system's observability with respect to SCADA measurements, that is, the network observability for an initial SCADA estimation (t = 0), what is commonly the case in power systems. The same requirement applies to every estimation procedure in the presented model.

A descriptive demonstration of the deduction of the normal distribution of the posterior (3.24) is presented in Appendix D.

3.5 Discussion

The above sections addressed the fundamental concepts of the Bayesian inference and its applicability to the state estimation problem in a fusion-based architecture. The conventional Weighted Least Squares estimator was also described in order to emphasize the differences between these two approaches.

The appropriation of Bayesian principles to the state estimation problem demonstrates promising advantages. Considering both system states and measurements as random variables (a reasonable approach in the Bayesian domain) and introducing a state space model enables the use of SCADA measurements as a fixed part of the prior distributions in its further use for the joint posterior estimation with updated PMU measurements.

Since the Bayesian fusion state estimation relies on the use of a prior distribution with a clear impact on the posterior, it is necessary to implement a Maximum a Posteriori (MAP) estimator instead of the conventional Maximum Likelihood Estimator (MLE). Even though similar in a practical manner, the MAP estimator applies a determined "weight" to the likelihood function. The referred "weight" is, therefore, imposed by the used prior. One can think of MLE as a singular case of MAP, where the prior is constant and equal to one i.e. the prior has no impact in the posterior. The MAP estimator collects the information of the latest SCADA-based estimated state and considers it, alongside the covariance, as a state prior relating to the likelihood of the PMU measurement set at a given moment.

The Bayesian fusion state estimation is presented as an effective solution towards the progressive integration of PMU measurements and the enhancement of the sate estimation accuracy and robustness. Furthermore, it does not require significant substitutions to the currently installed software/hardware. Since it relies on the use of two parallel stages (conventional SCADA-based estimator and PMU-based estimator) the designed architecture only requires the installation of the needed components for the latter. As previously stated, one of the main goals of this research work was to propose an economically viable solution and so, this architecture fulfills that intention.

The presented Bayesian fusion estimator does not allow the consideration of multiple SCADA and PMU priors in the same framework. In other words, making use of multiple historical data, which is typically already registered, extending the concept of the prior distributions and enabling the incorporation of previous different states into the estimation. This methodology would, if applied correctly, enhance the estimation accuracy even further. The proposed solution that resulted from this research, presented in chapter 4, envisions the above mentioned considerations building a multi-prior bayesian fusion estimator.

Chapter 4

Advanced Network Assessment Through Improved Prior Information

4.1 Introduction

The integration of PMU measurements alongside conventional SCADA measurements in the state estimation technology has been thoroughly discussed in the present document. In fact, highlighting the Fusion estimation approach, several challenges arise related to its correct formulation, implementation and to what extent should the intervening variables affect the estimation process.

The present section describes the proposed solution for the referred problem, a Bayesian fusion state estimation framework that simultaneously considers the behaviour of the power system through two different perspectives: an over viewed window of the system's evolution, with a high time constant, mostly characterized by smooth transitions captured by the conventional SCADA measurements; and an in-depth view of the stochastic variations of the dynamical power system captured by the PMU measurements, that can be achieved considering its extremely fast time constants.

Furthermore, the proposed method uses registered data regarding both types of measurements to enrich the prior information of the fusion model, enhancing the estimation accuracy.

Relevant unconventional approaches, specific to this formulation are also presented throughout this chapter.

4.2 Temporal Behavior of the State in Power Systems

As previously stated, power systems have been conventionally monitored through the acquisition, processing and display of SCADA measurements. These measurements are updated with a frequency of two to ten seconds. The referred sampling frequency has proven to be sufficient for the "accurate" representation of the system's state evolution for the past decades. However, for numerous reasons such as: the progressive integration of renewable stochastic generation in the grid, the installation of decentralized DERs resulting in bilateral power flows and the development of complex loads, to name a few, the power system state has evolved into a rapidly changing environment. Therefore, events that would be captured within a time-frame of minutes, are now undergoing volatile expressions within seconds. If the monitoring framework remains unchanged, it'll soon become obsolete, and the real-time representation of the power system will provide insufficient and inaccurate information to the PSO, leading to an inoperable network. Phasor measurement units (PMUs) are devices capable of capturing this rapidly changing dynamic state of the short-term future power systems. With a sampling frequency of 50 or 100 Hz, PMUs can provide a near real-time image of the system's state, enabling the continuous perception of the events occurring in the network.

In summary, maintaining the implemented monitoring system which relies solely on SCADA measurements, will incur into the imperception of the power system's events and both the state estimation function as well as all the EMS functions that rely on it, will be compromised i.e. the power system operation will be compromised. The present section aims to elucidate to the above stated considerations demonstrating illustrative examples of monitoring records of a real power system for practical evidence.

First and foremost, it is important to establish a practical relation between the sampling frequencies of SCADA conventional measurements and PMU measurements. As stated before, SCADA measurements are typically refreshed every two to ten seconds. On the other hand, PMU devices are capable of refresh frequencies from 50 Hz ($= 20ms$) up to 100 Hz ($= 10ms$).

For the present analysis, the following sampling rates are considered:

$$SCADA\ update\ rate : 1\ measurement\ per\ 10 seconds$$

$$PMU\ update\ rate : 1\ measurement\ per\ 20 milliseconds\ (50Hz)$$

In Figure 4.1 the discrepancy between sampling rates is emphasized. Between each SCADA measurement, five hundred PMU measurements are collected. The increased amount of collected data, with enhanced accuracy and synchrony, enables the projection of a clear picture of the system's dynamic behavior.

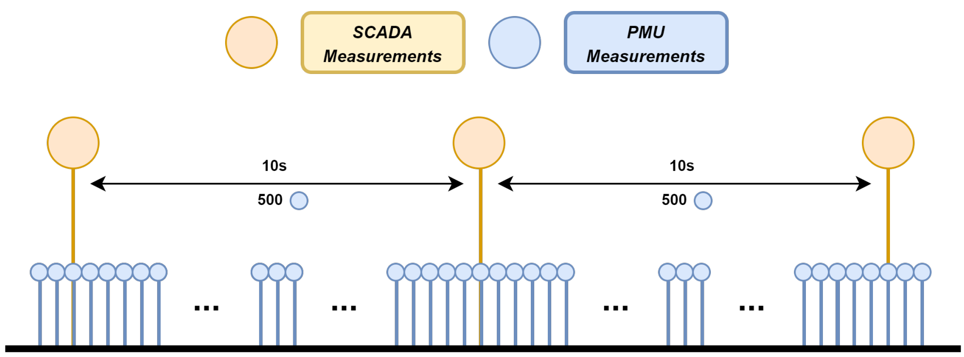

Figure 4.1: Schematic of the different sampling frequencies of conventional SCADA meters and PMUs.

Another interesting aspect to be considered has to do with the security and stability assessment functions that operate according to the state estimation process outputs. Adverse events to the correct operation of the grid are often observed and, as stated in Appendix A, control actions are required to be performed in order to reestablish the secure system state. If, for instance, an adverse event takes place in a determined location just as the last SCADA measurements of that area are surveyed, the system operator will only be able to take manual restorative actions as newly SCADA measurements are obtained for that area of the network.

One could argue that for extremely adverse situations the system's relay protections would activate due to transient events. However, if pro-stability actions (that rely on the state estimation outputs) were performed, the system would recover its secure state faster or without compromising its optimal operability. This could only be achieved with an increased measurement sampling rate.

In other words, it'd might happen that an adverse event would only be pictured and assessed up to 10 seconds after it had taken place which for the above stated reasons is not desired. On the other hand, assuming the update rate of PMU devices, these events would only go unnoticed for a maximum of 20ms (or 10ms depending on the sampling rate).

Following, an example of the pictured behaviour of electrical quantities under the sampling frequencies of PMU and SCADA devices is demonstrated. The analysed data was accessed through a data base which resulted from measurements extracted from multiple PMU devices deployed on the grid of *École Polytechnique Fédérale de Lausanne* (EPFL) campus integrating an "innovative monitoring infrastructure" by *IEEE PES Subcommittee On Big Data & Analytics For Power System* [101].

Through the observation of Figure 4.2 it is possible to visualize how conventional SCADA meters would capture the temporal evolution of the state of the system.

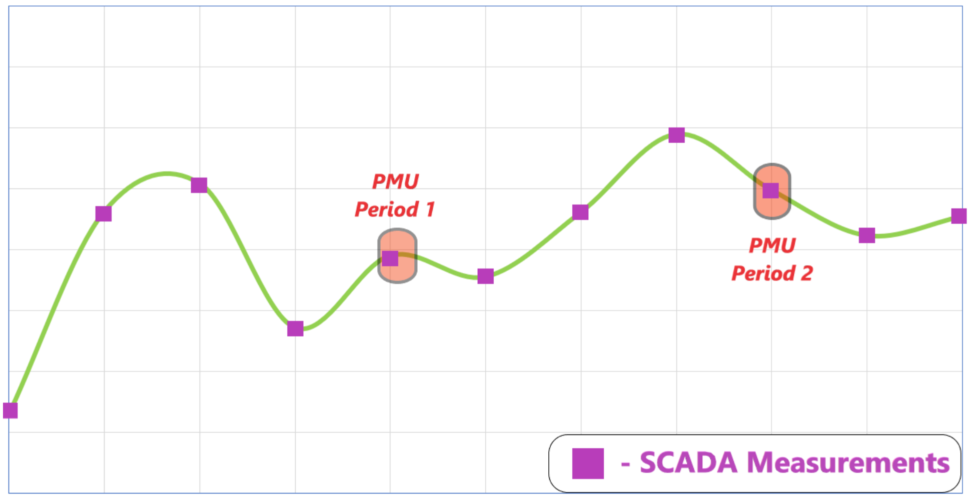

Figure 4.2: Fictional representation of registered measurements of voltage magnitude, considering data values [101], for a time window of 10 seconds. Two 1 second time-windows are also marked pointing the further PMU measurement illustrations (Figures 4.3, 4.4).

Two different time windows are also marked which are related to Figures 4.3 and 4.4, respectively. These demonstrate how the deployed PMU devices captured the system dynamics throughout different sampling periods of two seconds. Considering that Figure 4.2 demonstrates a time window of ten seconds and that both Figures 4.3 and 4.4 are related to different time windows of one second (1000ms - 50 samples with a 50 Hz sampling rate) it becomes unquestionable that the same system state evolution can have completely different perspectives and interpretations based on the sampling rate, accuracy and definition of the viewing time window. A self explanatory example of this situation can be seen in *PMU Period 2* marked window. The SCADA exhibiting figure shows a continuous voltage magnitude decrease at this particular instance when in fact it is increasing as it can bee seen in Figure 4.4.

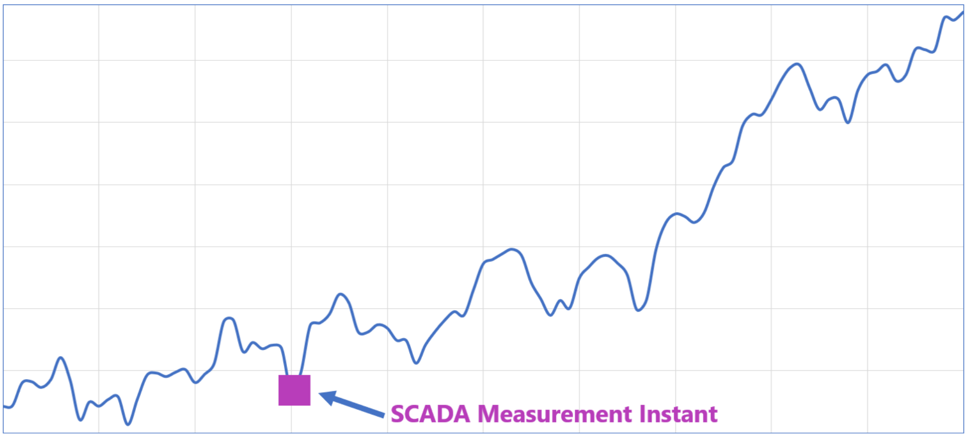

Figure 4.3: Registered values [101] of voltage magnitude of a PMU with 50 Hz sampling rate for a time window of 1 seconds, marked in 4.2 as PMU Period 1.

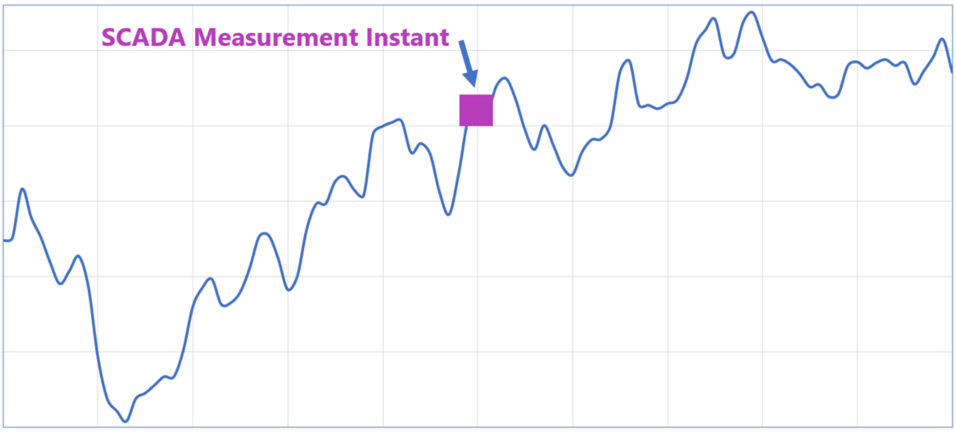

Figure 4.4: Registered values [101] of voltage magnitude of a PMU with 50 Hz sampling rate for a time window of 1 seconds, marked in 4.2 as PMU Period 2.

Concluding, the positive impact of PMUs deployment in the perception of the system state evolution is undeniable. It presents an emergent necessity for the enhancement of the state estimation process on which multiple EMS functions and overall operation of the network depend.

4.3 Bayesian Inference Historical Fusion

The present section addresses the formulation of the Bayesian fusion process designed for the proposed solution. The Bayesian approach to the state estimation problem, as previously stated, relies on the definition of the state variables as random variables. This consideration enriches the concept of state variable, relating its probabilistic model to different conditions that may be verified in the power network instead of a conventional fixed vector for a determined instant.

The proposed method evolves and deviates from the previous research effort towards Bayesian inference based fusion estimation [1], described in section 3.4, by extending the prior distribution from a single set of estimated states (which resulted from the latest SCADA stage estimation) to an agglomerate of independent previous states by accessing an historical database of recent PMU-based estimates and former SCADA-based estimates. A schematic of this concept is illustrated in Figure 4.5.

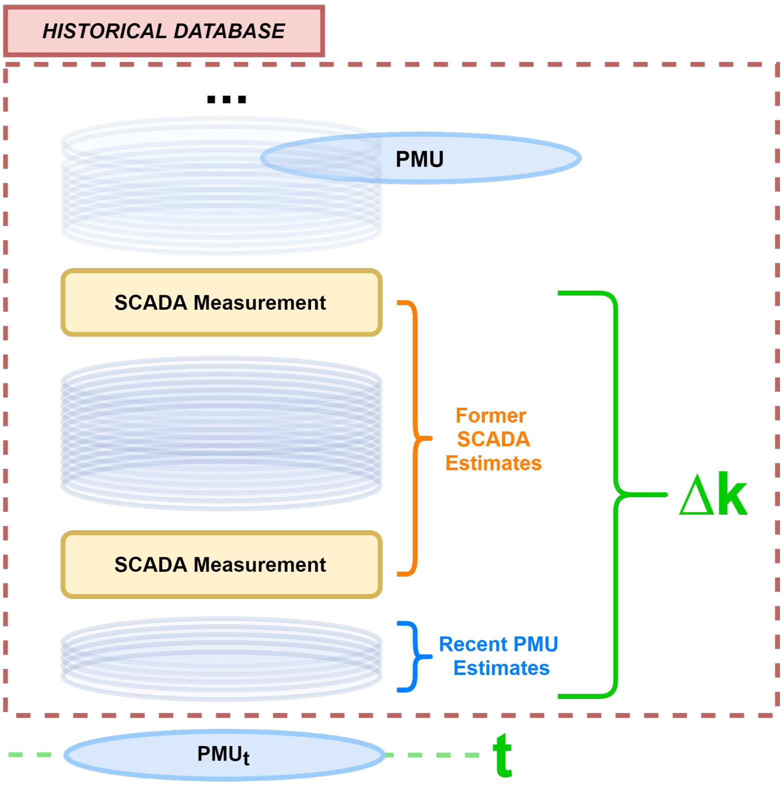

Figure 4.5: Consideration of multiple priors with recent PMU-based estimates and former SCADA-based estimates.

Therefore, a set of past state vectors comprises part of the Bayesian prior where each element (vector) is related to a given set of observations:

$$x_{t-1} = \left\{ x_0,\ x_1,\ \ldots,\ x_{k-1},\ x_k,\ x_{k+1},\ \ldots,\ x_{\Delta k} \right\} = x_k|_{k\in\Delta k} \tag{4.1}$$

Where:

- Δk - time window of considered state vectors for the prior.
- k - past instant inside Δk time window.
- x_k - former state vector at instant k.
- x_{t-1} - set of former state vectors in the time interval Δk.

Therefore, a single prior distribution and an independent multi-period prior distribution that provides the state variables characterization is given by the following expressions respectively:

$$\pi(x_k) = \frac{1}{(2\ \pi)^{n/2}\ det(Q_k)^{1/2}}\ e^{-(x-\hat{x}_k)^T Q_k^{-1}(x-\hat{x}_k)} \tag{4.2}$$

$$\pi(x)\ =\ \prod_{k=0}^{\Delta k}\pi(x_k)\ =\ \prod_{k=0}^{\Delta k}\frac{1}{(2\ \pi)^{n/2}\ det(Q_k)^{1/2}}\ e^{-(x-\hat{x}_k)^T Q_k^{-1}(x-\hat{x}_k)} \tag{4.3}$$

Where Q_k is the covariance matrix of the prior at instant k.

Applying the Bayes Theorem (3.3) to the Bayesian Fusion PMU measurement model previously presented (3.18,3.19) with the above stated prior results in the following:

$$p(x|z,x_{t-1})\ \propto\ \prod_{i=1}^{m} e^{-\frac{(z_i\ -\ H_{ii}x_t)^2}{2R_{ii}^2}}\ \ \prod_{k=0}^{\Delta k} e^{-(x-\hat{x}_k)^T Q_k^{-1}(x-\hat{x}_k)} \tag{4.4}$$

Taking the above mentioned developments, and similarly to (3.22 - 3.24), the state estimation procedure will rely on the extension of the prior distribution to using multiple correlated previous estimations from different instants and types (4.3), expressing the posterior distribution as follows:

$$Prior: x_t \sim \prod_{k=0}^{\Delta k}\mathcal{N}(\hat{x}_k,Q_k) \sim \mathcal{N}((\sum_{k=0}^{\Delta k} Q_k^{-1})^{-1}\ \ \sum_{k=0}^{\Delta k} Q_k^{-1}\hat{x}_k, (\sum_{k=0}^{\Delta k} Q_k^{-1})^{-1}) \tag{4.5}$$

$$Likelihood: z_t \mid x_t \sim \mathcal{N}(Hx_t, R_{PMU}) \tag{4.6}$$

$$Posterior: x_t \mid z_t \sim \mathcal{N}(A,B) \tag{4.7}$$

Where:

$$A\ = (H^T\ R_{PMU}^{-1}\ H\ +\ \sum_{k=0}^{\Delta k} Q_k^{-1})^{-1}(H^T\ R_{PMU}^{-1}\ z_t\ +\ \sum_{k=0}^{\Delta k} Q_k^{-1}\ \ \hat{x}_k)$$

$$B\ = (H^T\ R_{PMU}^{-1}\ H\ +\ \sum_{k=0}^{\Delta k} Q_k^{-1})^{-1}$$

Through the Bayesian perspective, the estimate of x is given by the *Maximum a Posteriori* (MAP) estimation of (3.25). Hence, taking into account the above stated formulation and after algebraic modifications, in a similar manner as presented in Appendix D (where a demonstration of the posterior distribution is presented), the estimation becomes an unconstrained minimization problem, as expressed below:

$$\hat{x}_t \;=\; \underset{x_t}{\arg\min}\; (z - Hx)^T\; R_{pmu}^{-1}\; (z - Hx_t) \;+\; \sum_{k=0}^{\Delta k} \; (x_t \;-\; \hat{x}_k)^T\; Q_k^{-1}\; (x_t \;-\; \hat{x}_k) \tag{4.8}$$

Considering the joint multivariate Gaussian prior model and the presented formulation, the MAP estimate is the expected value of the posterior multivariate normal distribution.

$$(H^T\; R_{PMU}^{-1}\; H \;+\; \sum_{k=0}^{\Delta k} Q_k^{-1})\; \hat{x}_t \;=\; (H^T\; R_{PMU}^{-1}\; z_t \;+\; \sum_{k=0}^{\Delta k} Q_k^{-1}\;\; \hat{x}_k) \tag{4.9}$$

4.3.1 Rectangular Coordinates Transformations

The proposed method relies on the consideration of a linear model, which can only be applied when both state variables and the measurement set are expressed in their corresponding rectangular coordinates. However, the state variables and SCADA and PMU measurements are usually expressed in polar coordinates.

The present subsection addresses the lack of consideration for the coordinates transformation method that is typically encountered in previous versions of the Fusion State Estimators. Consequently, this document presents a second practical contribution which is the incorporation of a technique for proper coordinates transformation. Both the measurement vector and prior state vectors (from PMUs and SCADA), as well as their respective covariance matrices, have their coordinates transformed while maintaining statistical consistency.

PMU Measurements:

Firstly the measurement vector z, which is originally recorded by the PMUs in the form of polar coordinates is addressed. In order to obtain the real, z^{re}, and imaginary, z^{im}, parts of the phasors, the following nonlinear transformation T($\dot{z}$) is applied to each measured phasor $\dot{z}$ in polar coordinates (magnitude and phase angle):

$$z^{re} = T(\dot{z}) = |\dot{z}|\; \cos(arg(\dot{z})) \tag{4.10}$$

$$z^{im} = T(\dot{z}) = |\dot{z}|\; \sin(arg(\dot{z})) \tag{4.11}$$

Following, the statistical Jacobian method is used on the above stated non linear transformations to obtain the corresponding measurement error covariance matrix:

$$R_{pmu}^{rectangular} = \nabla T(\dot{z})\; R_{pmu}^{polar} \nabla T(\dot{z})^T \tag{4.12}$$

As an example, the following matrix represents such transformation for a phasor measurement, initially with a diagonal measurement error covariance matrix, as assumed in the state estimator formulation.

$$R_{rect} = \begin{bmatrix} \cos(arg(\dot{z})) & -|\dot{z}|\ \sin(arg(\dot{z})) \\ \sin(arg(\dot{z})) & |\dot{z}|\ \cos(arg(\dot{z})) \end{bmatrix} \begin{bmatrix} \sigma_{z_{polar}} & 0 \\ 0 & \sigma_{z_{polar}} \end{bmatrix} \begin{bmatrix} \cos(arg(\dot{z})) & -|\dot{z}|\ \sin(arg(\dot{z})) \\ \sin(arg(\dot{z})) & |\dot{z}|\ \cos(arg(\dot{z})) \end{bmatrix}^T \tag{4.13}$$

SCADA Estimated States:

In a similar manner, under the same premise, the state variables estimated in the SCADA stage, the voltage phasor $\dot{V}$, also need to suffer a coordinates transformation, since they are typically represented in polar coordinates as well (voltage magnitude V and voltage phase angle Θ). Applying the same principle as in (4.10, 4.11) yields:

$$V^{re} = T(\dot{V}) = |\dot{V}|\ \cos(arg(\dot{V})) \tag{4.14}$$

$$V^{im} = T(\dot{V}) = |\dot{V}|\ \sin(arg(\dot{V})) \tag{4.15}$$

Furthermore, applying the statistical Jacobian method to the state covariance matrix Q_k in polar coordinates, as in 4.12, yields its corresponding state covariance matrix in rectangular coordinates:

$$Q_k^{rectangular} = \nabla T(\dot{V})\ Q_k^{polar} \nabla T(\dot{V})^T \tag{4.16}$$

As an example, the following matrix represents such transformation for the state variables in a particular node. Note that, initially, the state covariance matrix is already correlated due to intrinsic connections between different buses on the system.

$$Q_k^{rectangular} = \begin{bmatrix} \cos(arg(\dot{V})) & -|\dot{V}|\ \sin(arg(\dot{V})) \\ \sin(arg(\dot{V})) & |\dot{V}|\ \cos(arg(\dot{V})) \end{bmatrix} \begin{bmatrix} q_{VV} & q_{V\Theta} \\ q_{V\Theta} & q_{\Theta\Theta} \end{bmatrix} \begin{bmatrix} \cos(arg(\dot{V})) & -|\dot{V}|\ \sin(arg(\dot{V})) \\ \sin(arg(\dot{V})) & |\dot{V}|\ \cos(arg(\dot{V})) \end{bmatrix}^T \tag{4.17}$$

Through the execution of this method, the final measurement covariance matrix becomes correlated with the above mentioned transformations. Concerning the prior state covariance matrices, these were formerly correlated, but it is assumed that these rotations result in additional unaddressed correlations. Therefore, the proposed method ensures the statistical consistency between each of the estimator implemented in the bayesian fusion estimation framework that addresses measurements with different phasor coordinates specifications.

4.4 Proposed Solution

Throughout the present chapter, the contextual concepts needed to interpret the proposed solution were addressed as well as the theoretical background and its formulation adaptations.

Therefore, the present section aims to outline the architecture and algorithm of the proposed solution in a detailed manner through a closer look at its framework illustrations and respective descriptions. According to the aforementioned architecture, the proposed Bayesian Fusion State Estimator is composed by two different and independent stages, each one addressing a specific type of measurement: SCADA or PMU. Firstly, the SCADA measurement estimation stage is revised alongside with the newly proposed adaptations. Secondly, the PMU measurement stage, where the Bayesian Fusion process is integrated, is addressed. Finally, the complete Bayesian fusion state estimation algorithm is over viewed with the use of an explanatory flowchart. For the sake of convenience the SCADA State Estimation Stage and PMU & SCADA State Estimation Stage will be addressed as SCADA Stage and PMU/SCADA Stage respectively.

4.4.1 SCADA Stage

In the present subsection, the SCADA State Estimation Procedure of the Bayesian Estimation architecture is described. In Figure 4.6 a schematic of this stage is illustrated as a visual support for a clearer understanding of the algorithm processing sequence.

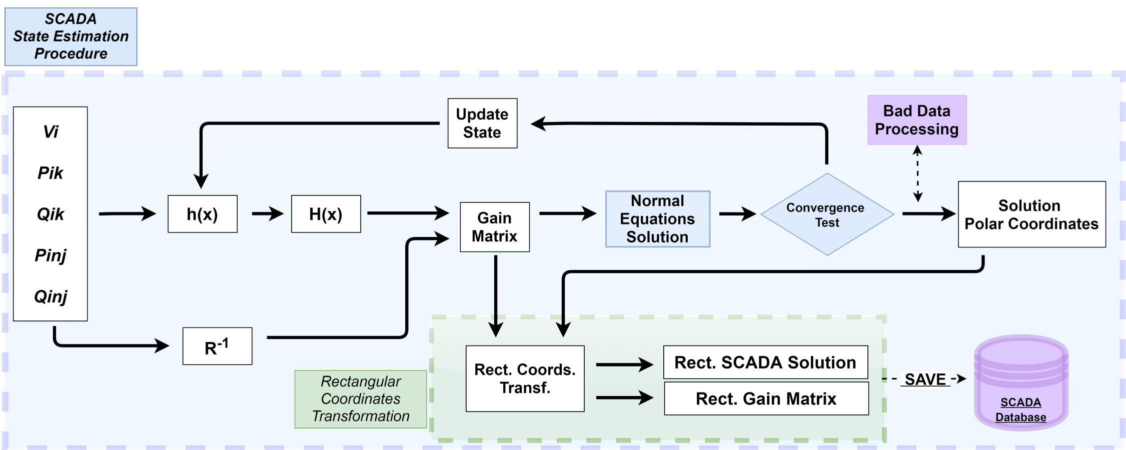

Figure 4.6: SCADA measurement estimation stage.

The SCADA Stage begins whenever a new set of SCADA measurements is received. As previously stated, it is considered that SCADA Measurements are surveyed every ten seconds. According to the network model and metering system type and location, *h(x)* is determined following its Jacobian matrix *H(x)* (3.13). Simultaneously, the measurement errors are defined with respect to the accuracy of the measuring devices in use (recall the assumptions - Gaussian normally distributed and zero mean) and the weight matrix (R^{-1}) is determined (3.6). Following, the gain matrix *G(x)* is determined with use of the equation subscript to (3.14). Finally a recursive use of the Normal Equations (3.15, 3.16) concludes the estimation process. Note that a

Bad Data (BD) processing block is demonstrated before the "*Solution Polar Coordinates*". The implementation of a BD processing method wasn't addressed in the present study, therefore it is illustrated merely to indicate that this step should integrate the final application to the real power system operation, ensuring some level of robustness against gross errors. Bad data processing methods are succinctly described in section 2.1.4.

The solution is, as illustrated, expressed in polar coordinates. Therefore, according to the proposed method in section 4.3.1 and aiming for its use in the Bayesian fusion procedure, it must be transformed into rectangular coordinates. Furthermore, the weight matrix (hence the gain matrix as well) is also transformed for later use in the Bayesian fusion. Once both are transformed, the latest SCADA estimate is updated and the estimation solution and respective gain matrix are uploaded onto the SCADA Historical Database.

4.4.2 PMU & SCADA Bayesian Fusion Stage

The PMU & SCADA state estimation procedure is described in the following section. An overview of this procedure's framework is represented in Figure 4.7.

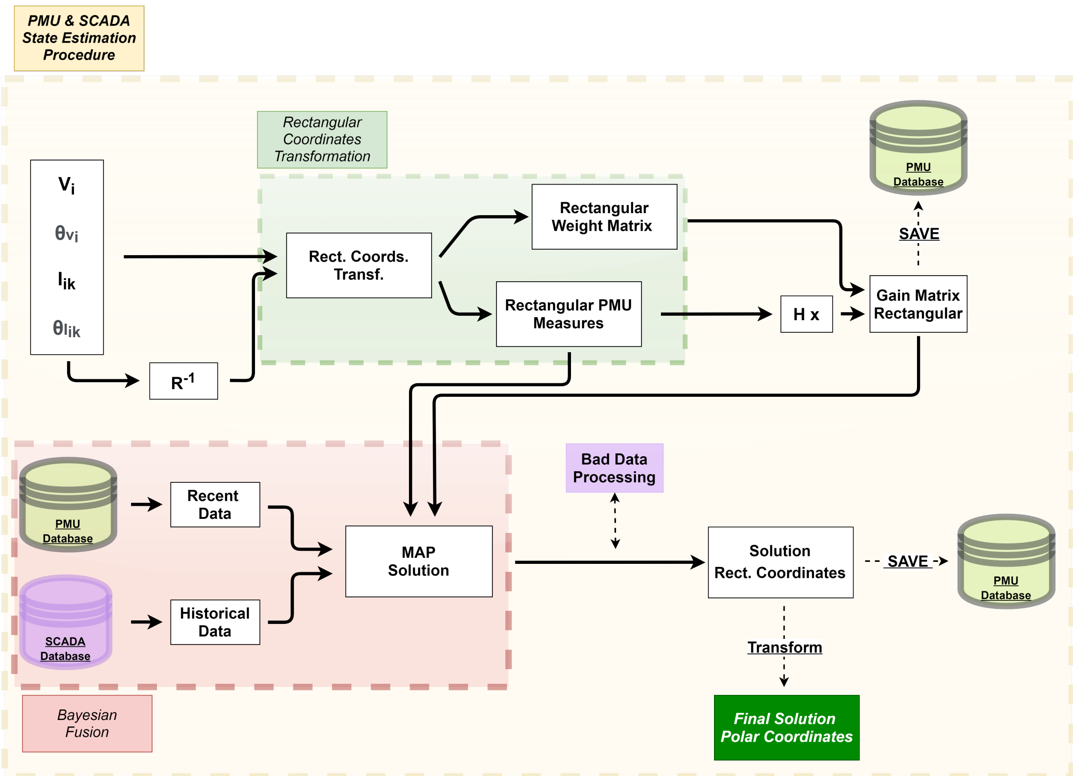

Figure 4.7: PMU & SCADA Bayesian Fusion stage.

The stage begins with a newly updated set of PMU measurements (voltage and current phasors, hence in polar coordinates). Aiming for its use in a Linear State Estimator (LSE) and similarly to the transformation applied to the SCADA stage parameters, they are immediately transformed into their respective rectangular form with the use of the rectangular transformation process described in section 4.3.1. The weight matrix simultaneously suffers the same transformation. Sequentially, defined the respective Jacobian *H(x)*, the gain matrix is determined in rectangular coordinates and uploaded onto the PMU recent database.

Once the gain matrix and the PMU measurements are transformed into rectangular coordinates the Bayesian Fusion process begins as previously described in section 4.3. The prior distribution of the *Maximum a Posteriori* Estimation (section 3.4.1) is composed of multiple independent priors of historical data from the former SCADA estimates (SCADA Stage - 4.4.1), recent data from Bayesian Fusion estimates and the newly updated PMU measurementss. The referred former priors are taken from their respective databases (SCADA and PMU Databases in the figures) which are updated at the end of each estimation stage. It is relevant to denote that since the prior is partially formed by a full SCADA observable system, the MAP estimator overcomes the implementation problem of a Linear State Estimation that would require a full PMU observable system which, as previously stated, isn't a viable situation yet. Finally and similarly to the description of the SCADA stage, it is illustrated a bad data processing block for the estimated state even though not being the scope of research for the present work and, therefore, not implemented. Recent literature have been profoundly addressing this step as prevously mentioned in section 2.1.4, namely [63, 102].

The solution (still in rectangular coordinates) is uploaded onto the recent PMU database and simultaneously transformed into polar coordinates to ease the monitoring analysis.

The flowchart in Figure 4.8 demonstrates an overview of the proposed Bayesian Fusion State Estimation algorithm. Indeed, since each stage is treated separately and independently, the SCADA stage requires minimal changes to the currently in use installed architecture at the Energy Management System. The proposed framework presents an interesting solution to energy utilities and operators for its economical viability as well as its minimal technology R&D necessities for a near-future implementation.

4.5 Discussion

The present chapter described the needed concepts and theoretical formulation for the implementation of the proposed solution.

The illustration of the temporal evolution of a real power system and its dynamics through different time windows disclosed interesting information. Indeed, data collected purely from SCADA measurements lead to the assumption that the power system displayed a smooth variation over time due to its modest sampling rate. Between measurements, the time series interpolation of the electrical parameters (such as the voltage magnitude for the given example) leads to a display of gradual increase/decrease in these parameters. Through the time window "zoom" obtained by phasor-measurement units high sampling rate, it becomes clear that the system does not evolve in a smooth manner, nor does it constantly increase or decrease over time between SCADA measurements sampling instants. Therefore, the lack of PMU deployment leads to not only a blackout of reliable information between SCADA measurements but also induces

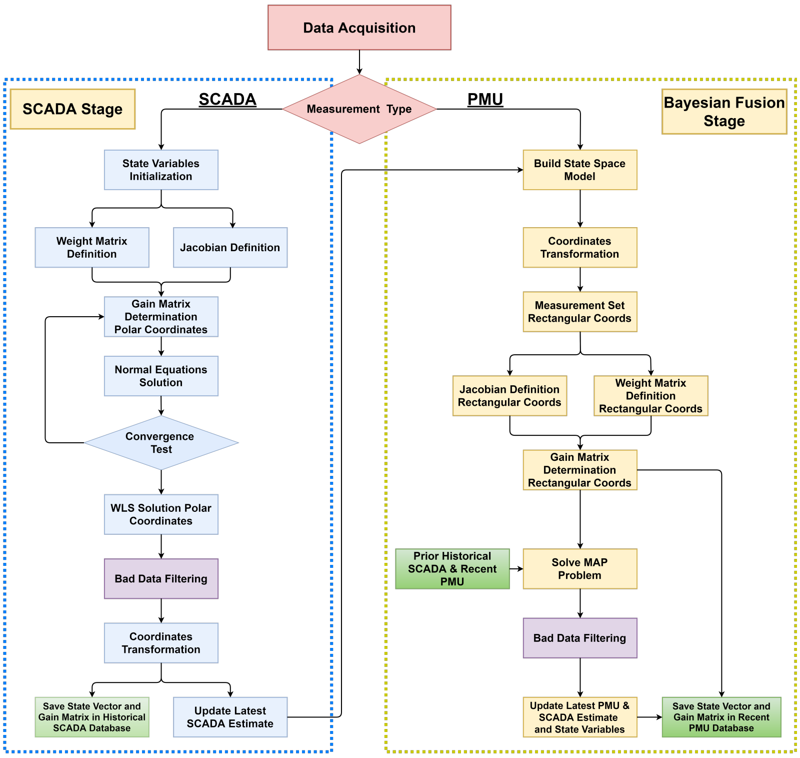

Figure 4.8: Flowchart of the proposed Bayesian Fusion State Estimation algorithm.

the system and its operators into assuming a determined upward/downward development of the state when the opposite is taking place. The used database from EPFL's campus will be used to integrate part of the reference scenario in the simulation environment described in the results chapter.

The Bayesian Inference Historical Fusion estimator relies on the use of multiple, independent, former estimates to constitute a robust enhancer of the measured state for the formation of the *Maximum a Posterior* estimation prior. However, it is important to consider the needed precautions related to the impact given to each prior since the state space can be overly influenced by it. In other words, it is sensible to admit that the probability of the systems state to be in the neighboring area of the previous states is relatively high. Nevertheless, and as previously stated, the dynamical behavior of the modern systems make it possible that in a matter of a glimpse, the system state evolves to a completely different scenario. If the priors in use have excessive impact in the posterior expected estimate, the estimator will fail to consider the real operating scenario as a plausible system state, resulting in inaccurate estimation results.

The taken assumptions of the proposed solution seem reasonable under the Bayesian context and its theoretical conceptualization induces speculation towards enhanced results when compared to the primary research developed in [1]. A relevant contribution of this research concerning the coordinates transformation method has also been addressed, diminishing the impact of previously renounced considerations in the literature. The proposed methodology grants enhanced statistical coherency in the transformation process.

Concluding, and as one of the main objectives of this research work, the proposed solution reveals to be *implementation friendly* by treating each stage separately. This means that it does not require significant changes to the currently installed EMSs or SCADA monitoring architecture. Instead, the formulated method relies on the enhance of the systems metering infrastructure through optimally placed PMUs (which is a short-term future reality) and the further installation of aditional *software/hardware* to ensure the Bayesian Fusion SE architecture.

Chapter 5

Numerical Tests

5.1 Introduction

The following chapter discusses the implementation and results obtained from the simulation of the proposed Bayesian Fusion State Estimator. Since this method evolves from the solution presented in [1], it will stand as the main comparison point for the following tests. For the remaining portion of this chapter, the latter solution will be designated as *"Powertech"* whereas the proposed algorithm *"BIFANA"* for the sake of convenience.

The BIFANA algorithm as well as others implemented for comparison were entirely developed and simulated in *PyCharm*, a Python environment distributed by *Anaconda*. *PandaPower*, a powerful *pandas* and *PYPOWER* based open source tool was used for the power systems modeling and optimal power flow (OPF) calculations.

5.2 Simulation Description

The present section briefly describes the assembling procedure of the simulation environment.

The simulation power system was modeled with the use of *PandaPower*. It is characterized by three buses (Bus 1 resembling a wind farm, Bus 2 a conventional thermal plant - reference bus - and Bus 3 a load bus), five lines and measurement devices/types available in determined locations as illustrated in Figure 5.1.

In order to build the reference scenario, real values obtained from [103] were used to interpolate the generation and load time series of Bus 1 and 3 respectively. The generation time series of Bus 2 was determined after. All of the former were properly scaled and normalized coherently. With the use of *PandaPower* optimal power flow function, the simulation values of the reference scenario were obtained and filtered according to the SCADA measurement architecture, illustrated in Figure 5.1.

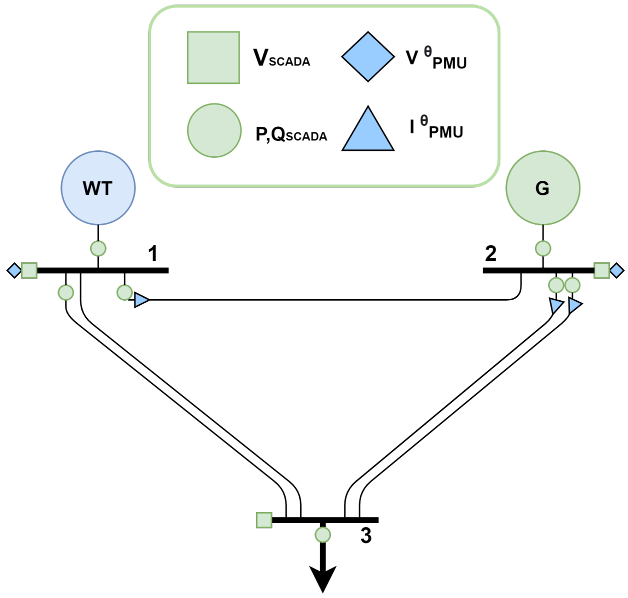

Figure 5.1: Modeled 3 Bus System.

The measurement values are then created with a random gaussian distribution, simulating noise in the measurement process, according to the precision class of the respective meter, as follows:

$$\text{std.dev} = \frac{|\,\text{ref.value}\,| \times \text{precision.class}}{3} \tag{5.1}$$

$$\text{measurement} = \text{random.gauss}(\text{ref.value}\ ,\ \text{std.dev}) \tag{5.2}$$

Where the precision class is:

- 1% - for measurements of bus voltage magnitude for SCADA measurements;
- 2% - for measurements of active and reactive bus injected power and line power flow from SCADA measurements;
- 0.1 % - for measurements of bus voltage magnitude and phase angles, and current magnitude and phase angles from PMUs;

Once the SCADA measurements time series is determined, the SCADA Stage of the BIFANA estimator (Figure 4.6) is enabled. To ensure an automatic estimation procedure, the Weighted Least Square (WLS) built-in estimator of *PandaPower* is used and the estimated state is determined. Since the proposed measurement fusion procedure requires both the SCADA stage gain matrix and estimated state of previous instants in rectangular coordinates, these are simultaneously determined (4.14 - 4.16) and stored in their respective databases. A diagram of the reference scenario and measurement emulation procedures is illustrated in Figure 5.2.

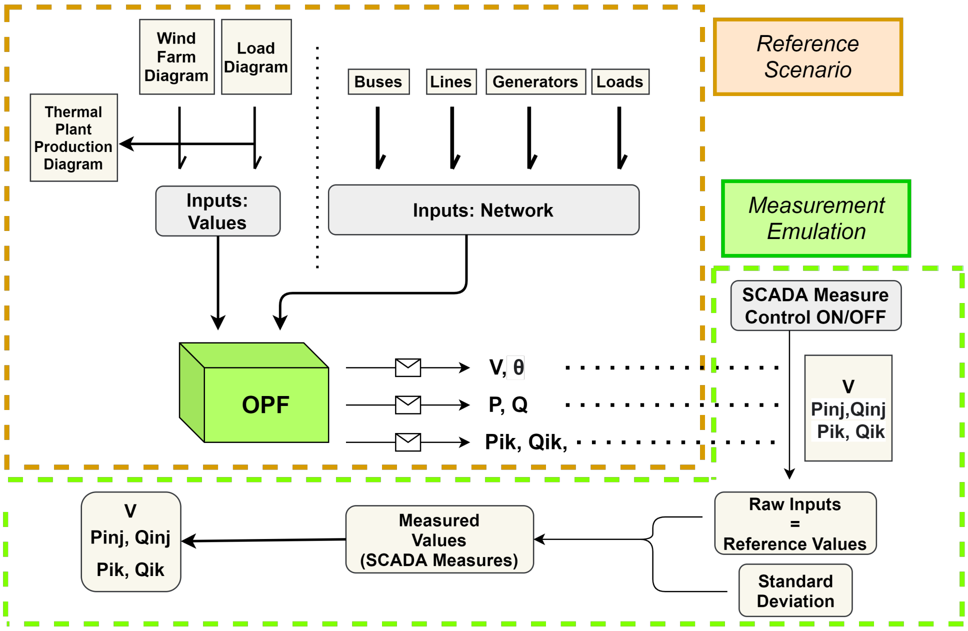

Figure 5.2: Reference scenario creation and SCADA measurement emulation.

Regarding the PMU reference scenario, it was considered the sampling rate difference between these devices (one sample per 20ms) and SCADA conventional meters (one sample per 10s). Therefore, the OPF resulting values that formed the reference scenario for the SCADA stage are linearly interpolated to establish a larger time series coherent with the referred sampling rate. In order to create a reference scenario that resembles the true dynamic behavior of the grid, EPFL's PMU database values [101] are used and scaled by the interpolation value. This way, the reference scenario results of a time series of dynamic and scaled values. With the establishment of the main reference scenario, the PMU measurement values are determined in a similar manner to the SCADA measurements (5.1) suffering a further coordinates' transformation. Once the measurement time series is determined, the Bayesian Fusion Stage (4.7) and the overall simulation of the proposed solution are fully enabled. Figure 5.3 demonstrates the reference scenario and measurement emulation framework.

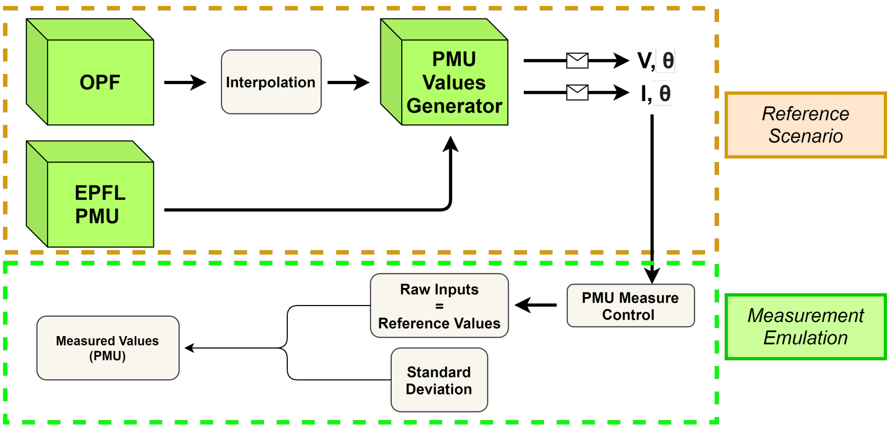

Figure 5.3: Reference scenario creation and PMU measurement emulation.

5.3 Influence of Recent PMU Information

The BIFANA estimator relies on the use of recent PMU information to build part of the Bayesian prior distribution in the MAP estimation process. Therefore, the impact of the defined range of recent values in the estimation accuracy was assessed. As an algorithm "tuning" step before its simulation in the built scenario, the present section will be used to analyse and discuss the impact of different ranges of the PMU prior time window, in response to stationary and transient typical events. The results regarding these tests will be compared with the obtained from both the Powertech algorithm and a typical Kalman filter implementation (which were both developed in the simulation environment).

The following simulations considered five different ranges of PMU samples building the Bayesian PMU prior set. The range established for each simulation is described in Table 5.1. Recalling the main goal of this research, to assess the benefits of considering both a PMU and a SCADA prior, when compared to the Powertech implementation (which only considers the latest acquired SCADA sample as a prior). One SCADA sample integrated the estimation prior for every simulation thus maintaining coherence in the obtained results.

	Powertech	**BIF - 1**	**BIF - 2**	**BIF - 3**	**BIF - 4**	**BIF - 5**
SCADA Samples	1	1	1	1	1	1
SCADA Coeficient	0.1	0.1	0.1	0.1	0.1	0.1
PMU Samples	-	1	3	5	10	100
PMU Coeficient	-	1	1	1	1	1

Table 5.1: Description of tested Parameters.

As a pivotal keynote for the interpretation of the following results, one should recall the relation between sampling rates of SCADA measurements and PMUs (10s to 20ms - 1 sample to 500 samples, respectively). Therefore, the time scale of the demonstrated graphs is based on the instant of a PMU sample acquisition. Hence between x = 0 and x = 1, for example, 20ms have elapsed.

5.3.1 Response to Stationary Operating Points

Primarily, the different described parameters were applied to estimate the system state variables in a scenario of a stationary operating condition. Figure 5.4 demonstrates the estimation of Bus 1 voltage magnitude of a typical Kalman filter estimator and the Powertech estimator in comparison to the reference stationary values. The time window [9000;9500] reflects that these values are a result of the estimation between two SCADA samples (at PMU Samples = 9000 and PMU Samples = 9500).

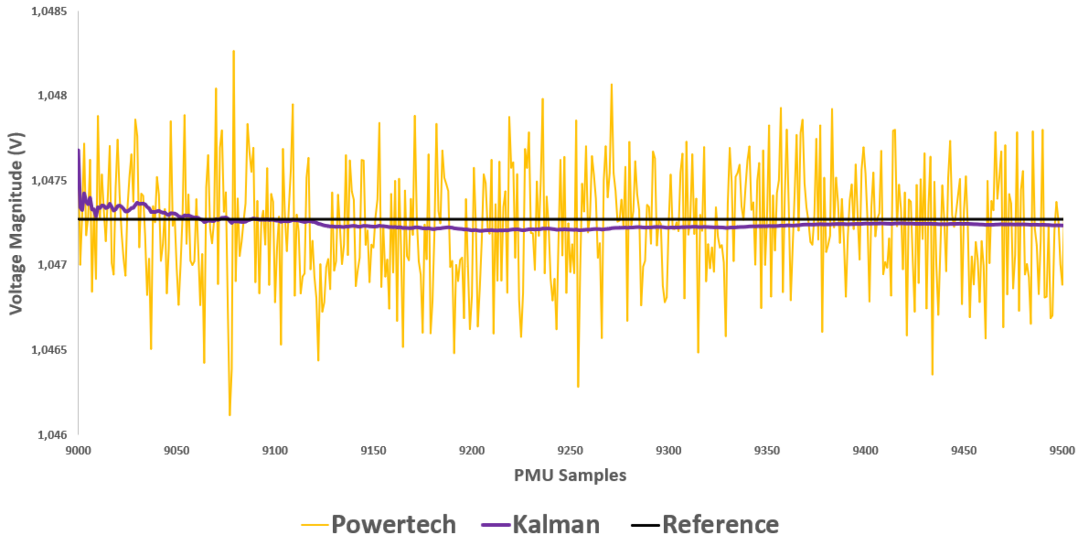

Figure 5.4: Estimation comparison between the Powertech algorithm and Kalman Filter estimator.

Following, Figure 5.5 illustrates the estimation time series of the different tested BIFANA algorithms with the previously described parameters. It becomes clear that considering a wider range of previous PMU estimates leads to a less variable evolution of the estimated states. The wider PMU prior leverages the estimation inertia, being less affected by the newly acquired PMU measurements' high variability. Hence, the BIFANA algorithm with a wide PMU-based prior leads to a similar response of a Kalman filter estimator. In a stationary operating point, this effect benefits the estimation accuracy as can be seen in the error distribution of the voltage magnitude presented in Figure 5.6 and the mean absolute error of each algorithm in Table 5.2.

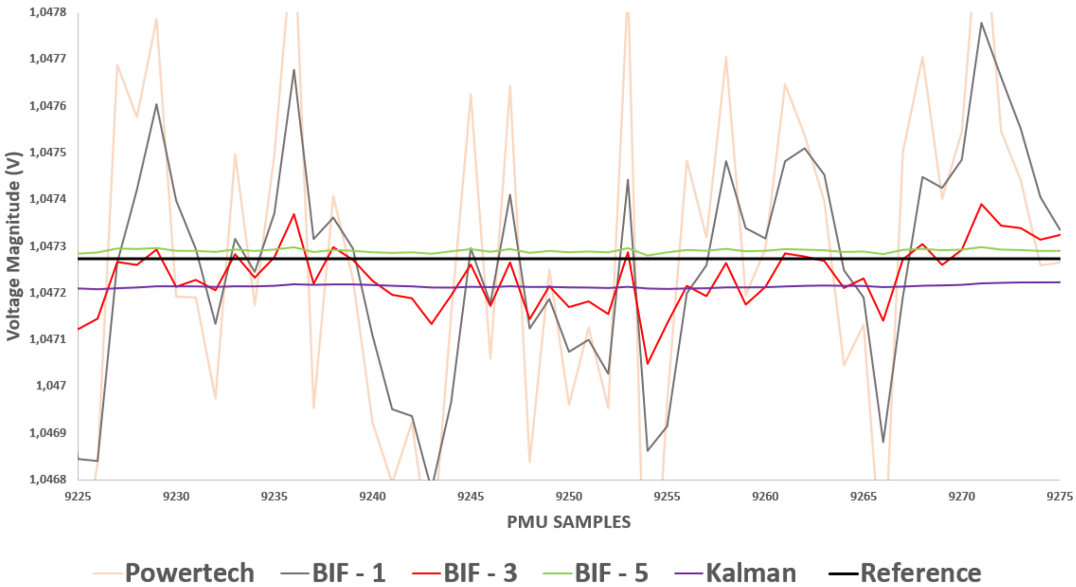

Figure 5.5: Response to a stationary operating condition between the tested algorithms.

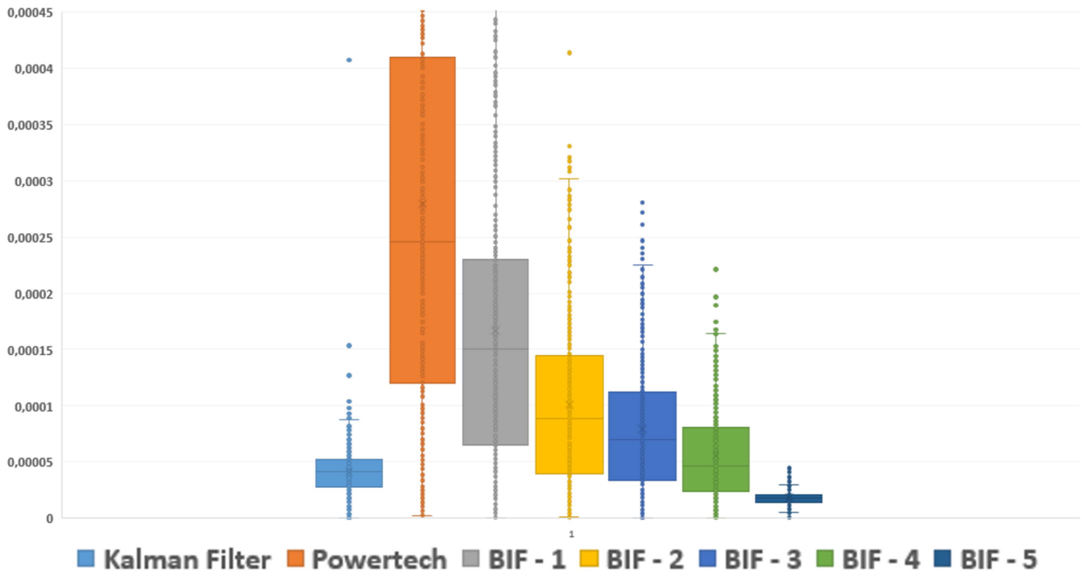

Figure 5.6: Error distribution of the Bus 1 voltage magnitude estimation for the tested algorithms.

Estimation Method		Mean Absolute Error	
		Voltage Magnitude	Phase Angle
Kalman Filter		4.1 E-05	7.3 E-07
Powertech		2.7 E-04	1.1 E-05
BIFANA	BIF-1	1.7 E-04	6.2 E-06
BIFANA	BIF-2	1.0 E-04	3.5 E-06
BIFANA	BIF-3	7.9 E-05	2.4 E-06
BIFANA	BIF-4	5.6 E-05	1.5 E-06
BIFANA	BIF-5	1.8 E-05	8.3 E-07

Table 5.2: Mean Absolute Error of the compared algorithms' estimation of Bus 1 voltage magnitude in response to a stationary operating point.

5.3.2 Response to Transient Events

The following section demonstrates the response of the described algorithms to a transient event. The reference values remain constant for half the time window until a voltage step of 10% increase is applied. Similarly to the previous simulation regarding the stationary operating point, a primary illustration of the Kalman filter estimator and the Powertech estimator is demonstrated in Figure 5.7.

Since the Powertech estimator considers only one SCADA prior with low coefficient, it has a smaller inertia. Therefore, it is able to rapidly react to the transient event and reestablish the estimation accuracy. On the other hand, the Kalman filter is characterized by a higher inertia. It takes into consideration the convolution of the past events in its estimation procedure leading to a slow response to the transient event and inaccurate estimation results.

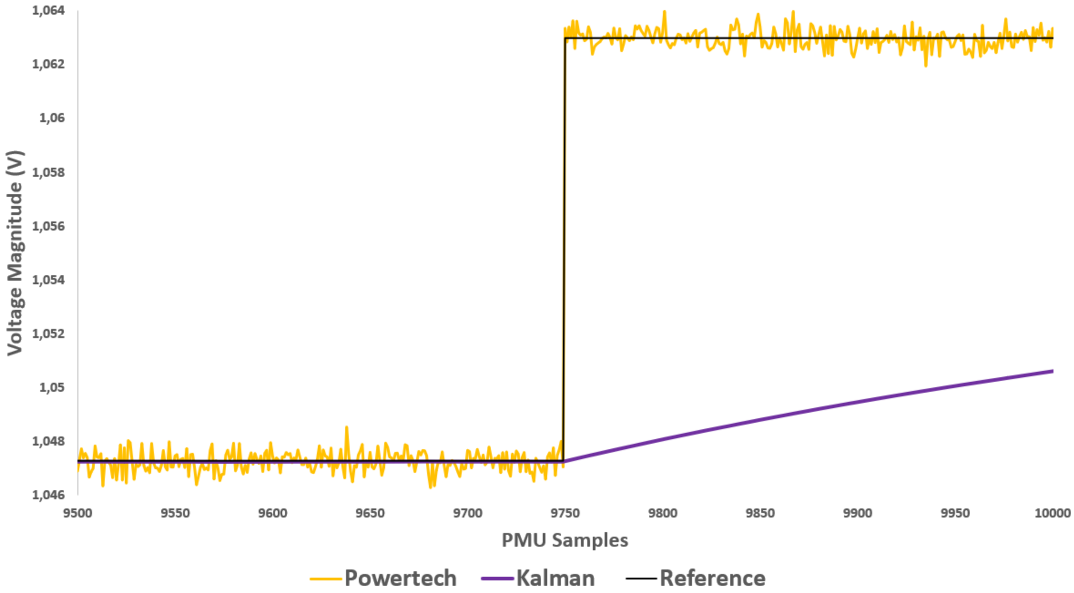

Figure 5.7: Estimation comparison between the Powertech algorithm and Kalman Filter estimator.

Taking into account the previous example, it becomes evident that a smaller time window PMU prior, hence smaller inertia, will lead to a faster response to the transient event. In fact, through the observation of Figure 5.8, the above stated conclusion takes evidence. **BIF-2**, the BIFANA simulation with the consideration of only the latest three PMU samples, is able to rapidly react to the transient event, reestablishing its stability and enhanced accuracy when compared to Powertech and BIF-1. The other implemented simulations take longer to react according to their increased prior consideration. Once the estimator surpass the transient time, the previous considered response to a stationary operating point is observed. Figure 5.9 illustrates the error distributions of the voltage magnitude for each simulation and Table 5.3 presents both voltage magnitude and phase angle errors.

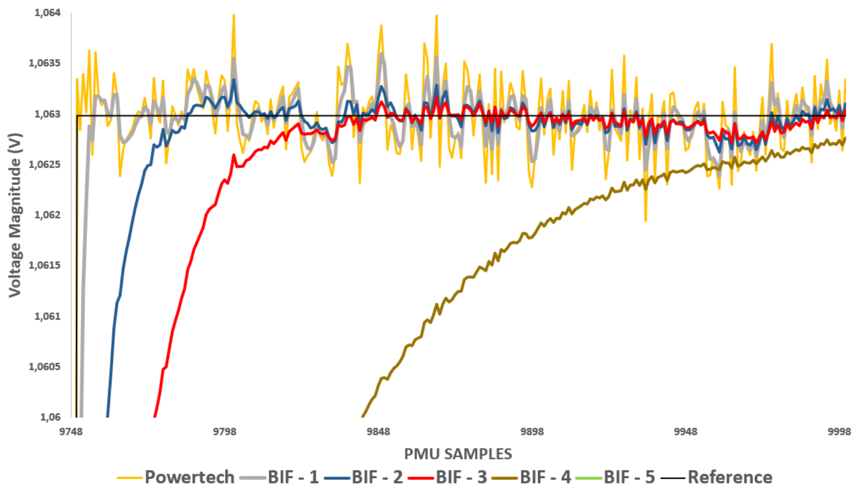

Figure 5.8: Response to a transient event between the tested algorithms.

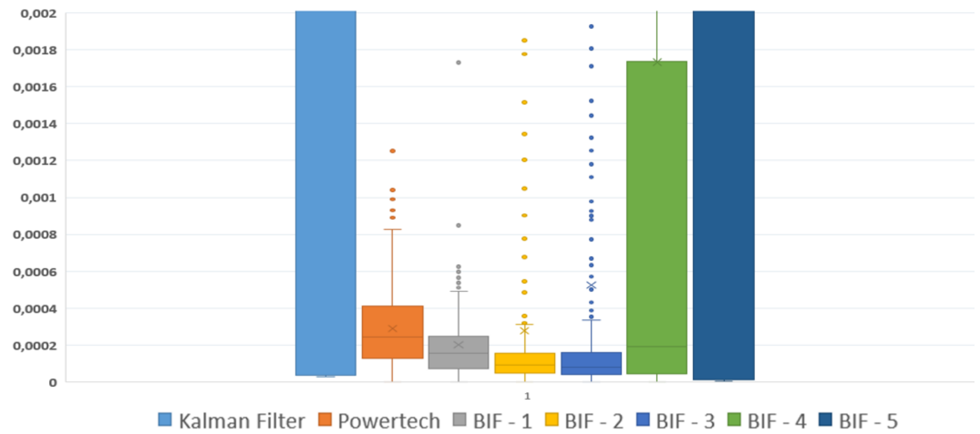

Figure 5.9: Error distribution of the Bus 1 voltage magnitude estimation for the tested algorithms.

Estimation Method		Mean Absolute Error	
		Voltage Magnitude	Phase Angle
Kalman Filter		7.0 E-03	9.0 E-04
Powertech		2.9 E-04	1.2 E-05
BIFANA	BIF-1	2.0 E-04	1.1 E-05
BIFANA	BIF-2	2.8 E-04	2.9 E-05
BIFANA	BIF-3	5.2 E-04	6.4 E-05
BIFANA	BIF-4	1.7 E-03	2.2 E-04
BIFANA	BIF-5	7.6 E-03	1.0 E-03

Table 5.3: Mean Absolute Error of the compared algorithms' estimation of Bus 1 voltage magnitude in response to a period containing a transient event.

5.3.3 Defined PMU Prior Time Window

In the previous sections the impact of a PMU prior broadening in the state estimation accuracy was analysed for two different operating scenarios. It became clear that an increase in the past information time window leads to a more inert estimator. This consequence proves to be beneficial for situations where the system is undergoing slow transitions, smoothing the stochastic variability that characterizes the PMU measurements' behaviour whilst increasing the estimation accuracy.

On the other hand, for transient events i.e situations where the system state rapidly varies, a wider PMU prior reveals to be inefficient in capturing the system's dynamics and the estimation accuracy is heavily compromised.

Even though not being addressed in this research, the influence of the coefficient of each prior should also be studied. It is expected, however, that an increase/decrease in the referred coefficient will lead to an increase/decrease in the estimator inertia.

Taking into account the above stated conclusions, the choice of the PMU prior range is of utter importance and should be thoroughly analysed depending on the expected system behaviour before its implementation. Since the main goal of this research work is to address a state estimation solution for the near-future power systems, strongly characterized by stochastic dynamics, the PMU prior range defined in **BIF-2** is chosen for the remaining tests. It demonstrates an effective trade-off between rapid response to transient events whilst maintaining overall stability and accuracy for regular operating scenarios.

5.4 Influence of Historical SCADA Information

Once established the range of PMU prior for the estimator, it becomes relevant to assess the impact of a broader historical SCADA information as well.

In a similar manner to the previous section, the referred influence was observed with the use of the same scenarios: stationary and transient operating points. Since there was no significant differences in the stationary operating point simulation, the respective results are omitted from this chapter and succinctly presented in Appendix E. The number of historical SCADA samples used in the following simulation were limited to ten. It is expected that a broader SCADA prior range would induce a negative effect on the estimation accuracy. Since the time constants of both SCADA and Fusion stages are completely different, considering more than ten samples of historical SCADA estimates would mean to consider information regarding 5 000 PMU estimated samples before. In a highly dynamic system, as previously stated, this would lead to an inaccurate estimation of the state variables and additional unwanted inertia.

The next simulations were performed with the parameters presented in Table 5.4.

	Powertech	**BIF - 2**	**BIF - 6**	**BIF - 7**	**BIF - 8**
SCADA Samples	1	1	3	5	10
SCADA Coeficient	0.1	0.1	0.1	0.1	0.1
PMU Samples	-	3	3	3	3
PMU Coeficient	-	1	1	1	1

Table 5.4: Description of tested Parameters.

5.4.1 Response to Transient Events

The present simulation took place in the same manner as described in section 5.3.2. The voltage step of 10% increase was applied to the reference values measured by the PMU devices.

As stated in the introductory note of this section, the use of a broader SCADA prior lead to a decrease in the estimation accuracy even with a small coefficient of 0.1. The historical estimations of previous instants not only did not contribute to a significant improvement on the response time but also lead to a decrease in the absolute value of the estimated state variable. The latter is explained by a decreased value of the estimated voltage magnitude in the corresponding instants where the referred SCADA estimations took place (before the voltage step). This situation can be observed in Figure 5.10 where the different responses to the voltage step are illustrated. Figure 5.11 expresses the error distributions obtained for each of the different parametered BIFANA estimators and the Powertech and Kalman filter estimators.

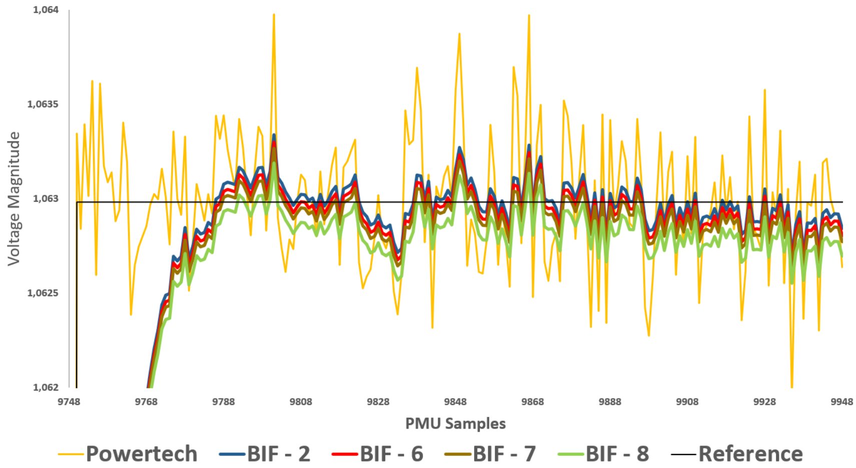

Figure 5.10: Response to a transient event between the tested algorithms.

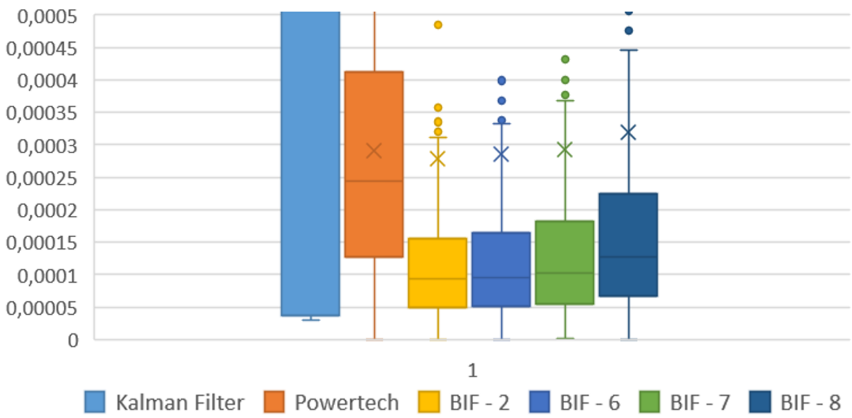

Figure 5.11: Error distribution of the tested algorithms.

Concluding the "tuning" step of parameters for the BIFANA estimator, the selected combination for the next simulation remains **BIF - 2**. When dealing with stationary operating points it results in accurate estimations. It is also effective in diminishing the variability of the results, when compared to Powertech, leading to a more stable evolution of the estimated state variables. Therefore, it proves to have a balanced trade-off between inertia and response time when compared to the other tested SCADA prior ranges.

5.5 Three Bus System Accuracy Analysis

The present section aims to illustrate the results obtained from the implementation of the BIFANA state estimation framework in the simulation environment described in section 5.2. These results are compared with the ones obtained from both the currently in use conventional state estimator and the Bayesian inference fusion estimator (Powertech) from where the proposed solution evolves.

In order to completely assess the effectiveness of the BIFANA algorithm in comparison to the above stated, and envisioning the main goals of this dissertation, the presented analysis is executed in a time window where the system operating state is demonstrating high variability. On a side note, from PMU Sample = 0 to PMU Sample = 9000, both a Conventional WLS State Estimator and a Linear State Estimator were performed to create the SCADA and PMU historical databases which were used for other prior broadening tests.

First and foremost, one should consider the evolution of the reference scenario throughout the analysed time window. Figure 5.12 illustrates the voltage magnitude of Bus 1 (Wind Farm Bus), the captured PMU measurements and the results of the conventional WLS estimator which only uses SCADA measurements.

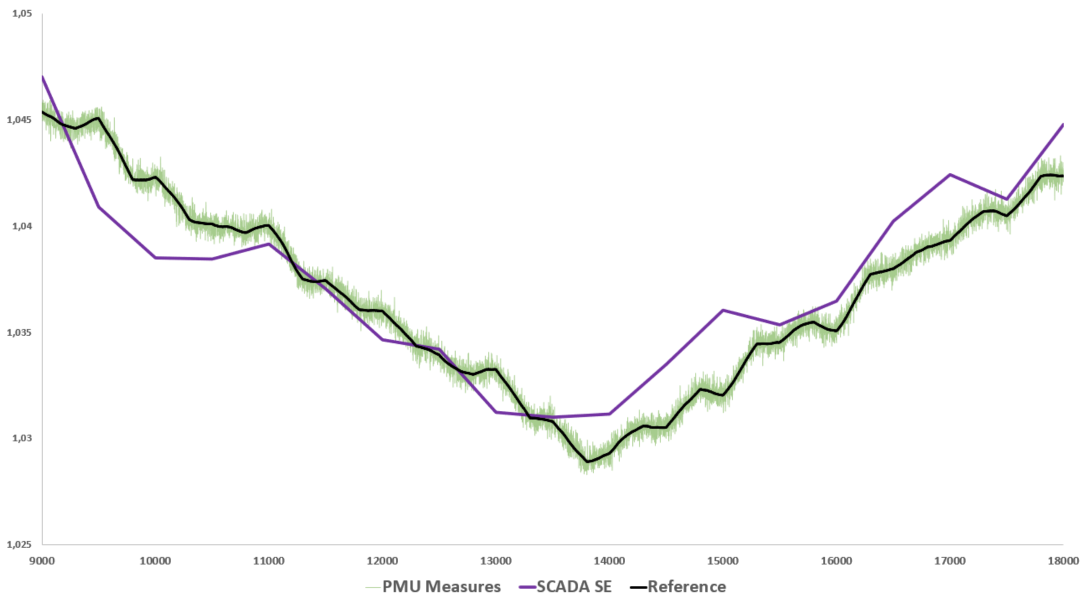

Figure 5.12: Bus 1 voltage magnitude evolution: Reference values, PMU measurements and SCADA based estimates.

Through the observation of the above illustration, the lack of accuracy in conventional state estimation is once again emphasized. Furthermore, in the same time window where 18 SCADA measurements were taken, the PMU device located in Bus 1 acquired 9000 samples, each one with a higher precision than any of the latter.

Following, the estimation results of the BIFANA and Powertech estimators are presented. In Figure 5.13, the evolution of the estimated state variable V1 demonstrates an unquestionable enhancement of the BIFANA algorithm when compared to its previous version Powertech. Relying on both recent and historical estimation data, the BIFANA algorithm is able to react to the system dynamics whilst improving the overall stability. A closer look at the turning point near PMU Sample = 13 800 is illustrated in Figure 5.14.

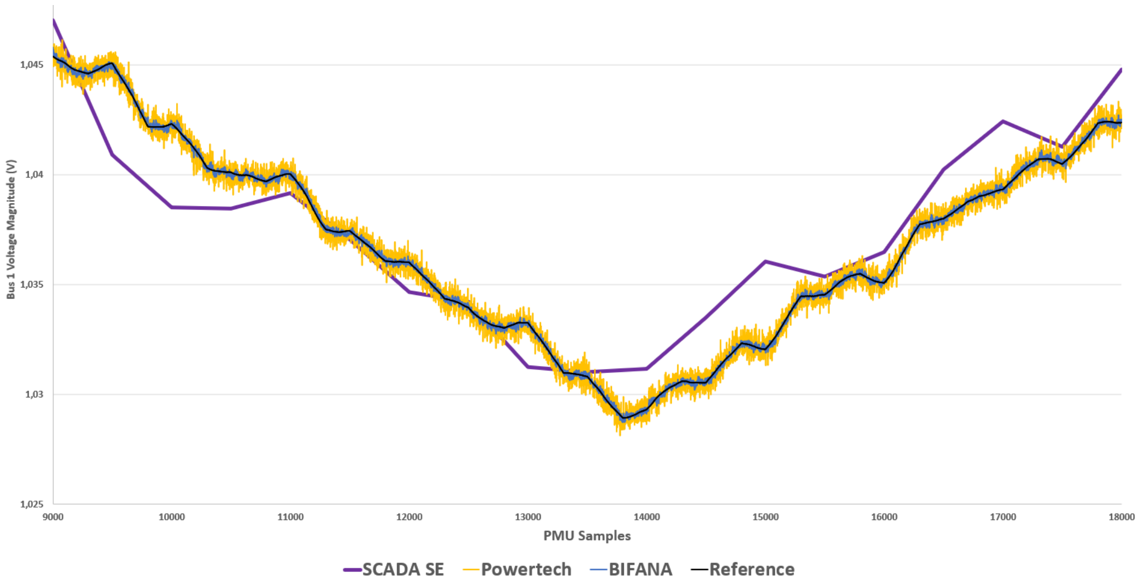

Figure 5.13: Bus 1 voltage magnitude evolution of the compared estimators.

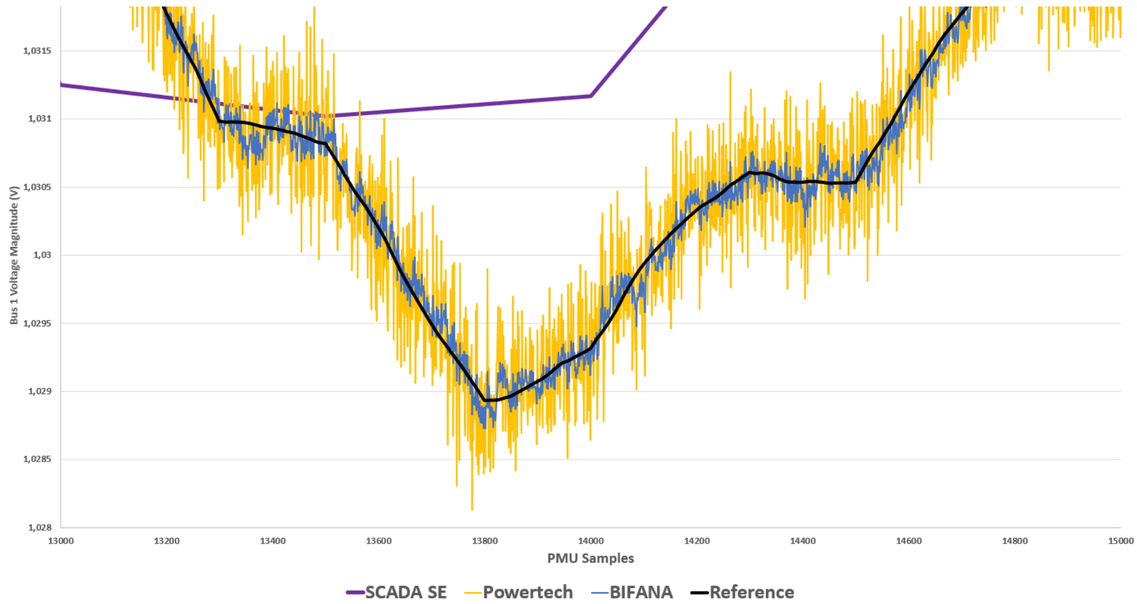

Figure 5.14: Zoom around the turning point of the voltage magnitude evolution of Bus 1.

Regarding the voltage angle, both BIFANA and Powertech estimators present a high accuracy as illustrated in Figure 5.15. The differences aren't statistically significant as it can be seen in the boxplot of errors presented in Figure 5.17 and their respective evolution in Figure 5.16.

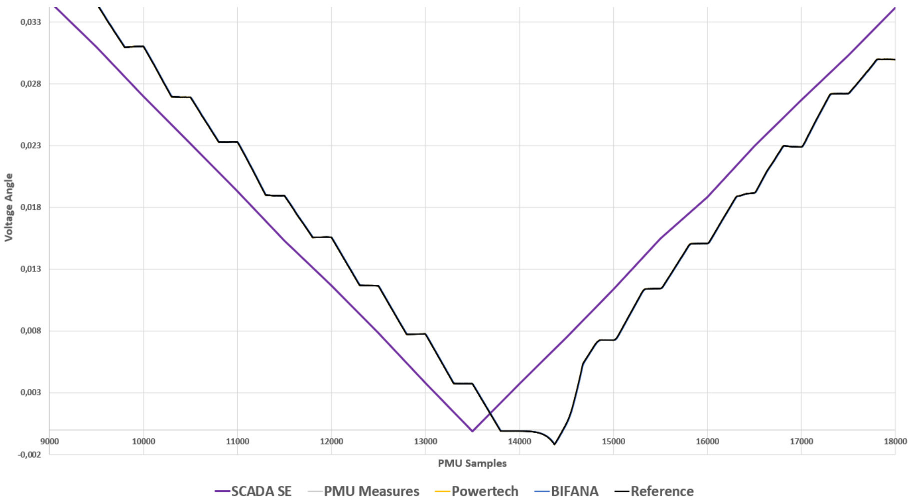

Figure 5.15: Bus 1 phase angle evolution: PMU measurements, Powertech estimates and BIFANA estimates are overlaid by the reference values.

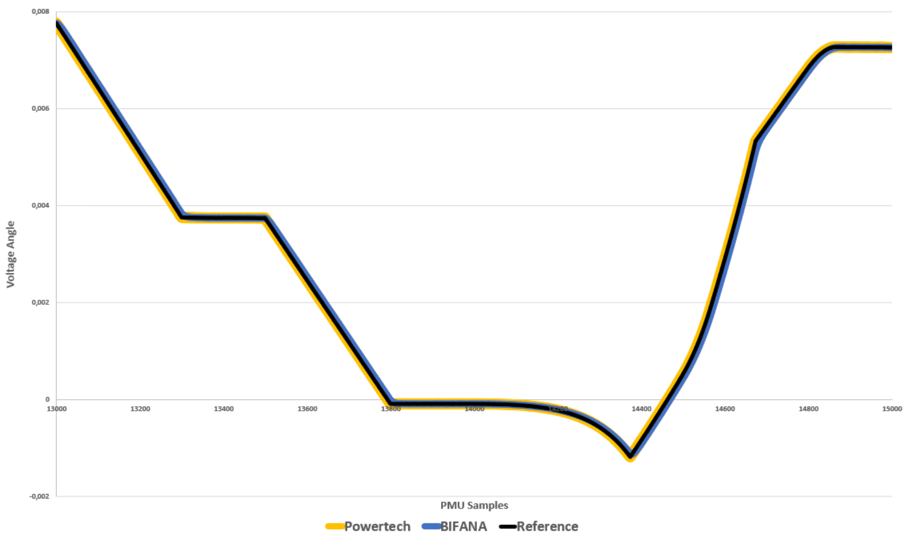

Figure 5.16: Bus 1 phase angle evolution of BIFANA and the Powertech algorithms.

The illustration of the remaining state variables' estimates are presented in Appendix F.

According to the distribution of the voltage magnitude errors expressed in Figure 5.17, the enhanced accuracy of the BIFANA algorithm is also resembled. The referred enhancement is further emphasized in the error distribution regarding the voltage magnitude of Bus 1 (Figure 5.18), where the simulated wind farm is connected. Therefore, the BIFANA estimator proves its ability do deal with and capture the stochastic profiled variations of renewable generation.

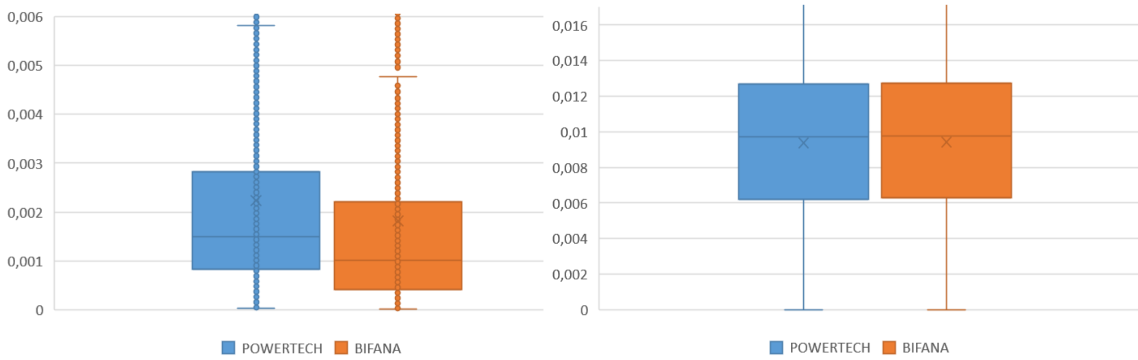

Figure 5.17: Comparison of average error distribution of voltage magnitudes (left) and phase angles (right).

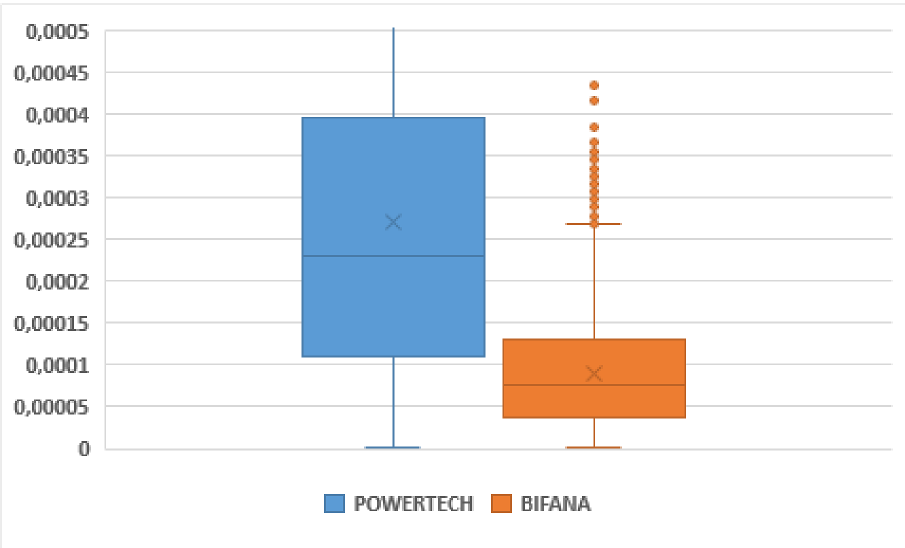

Figure 5.18: Estimation error distribution of the voltage magnitude in Bus 1 of Powertech and BIFANA algorithms.

5.5.1 Sensitivity to Gross Errors

The present subsection aims to succinctly describe a secondary contribution to the further development of the proposed solution. Whilst implementing the BIFANA estimator algorithm, its sensitivity to gross errors in the measurement set was detected. Even though a bad data processing method was not the aim of this research work, it became necessary to filter outliers in the used input data.

Recall that for the present simulation, EPFL's PMU Database was used to simulate the system's PMU measurements behavior. The results obtained from the primary estimation tests demonstrated that the successful implementation of this algorithm will heavily rely on the use of a robust bad data detection and filtering procedure, especially due to the propagation of errors in locations where no PMU measurements are available (in this simulation, Bus 3). Figure 5.19 demonstrates the behavior of the BIFANA estimator in the presence of extremely corrupted data and the propagation of error in the estimation of non available PMU measurement state variables. The outlier has a minimal impact in the Bus 1 voltage magnitude estimation. Since the implemented BIFANA algorithm considers a prior of only three PMU measurements, once the instant related to that error stops integrating the estimator prior, it immediately reestablishes stability and accuracy. On the other hand, since there's no PMU available in Bus 3, the estimation error might propagate throughout many estimations after the error has elapsed, possibly leading to catastrophic control actions.

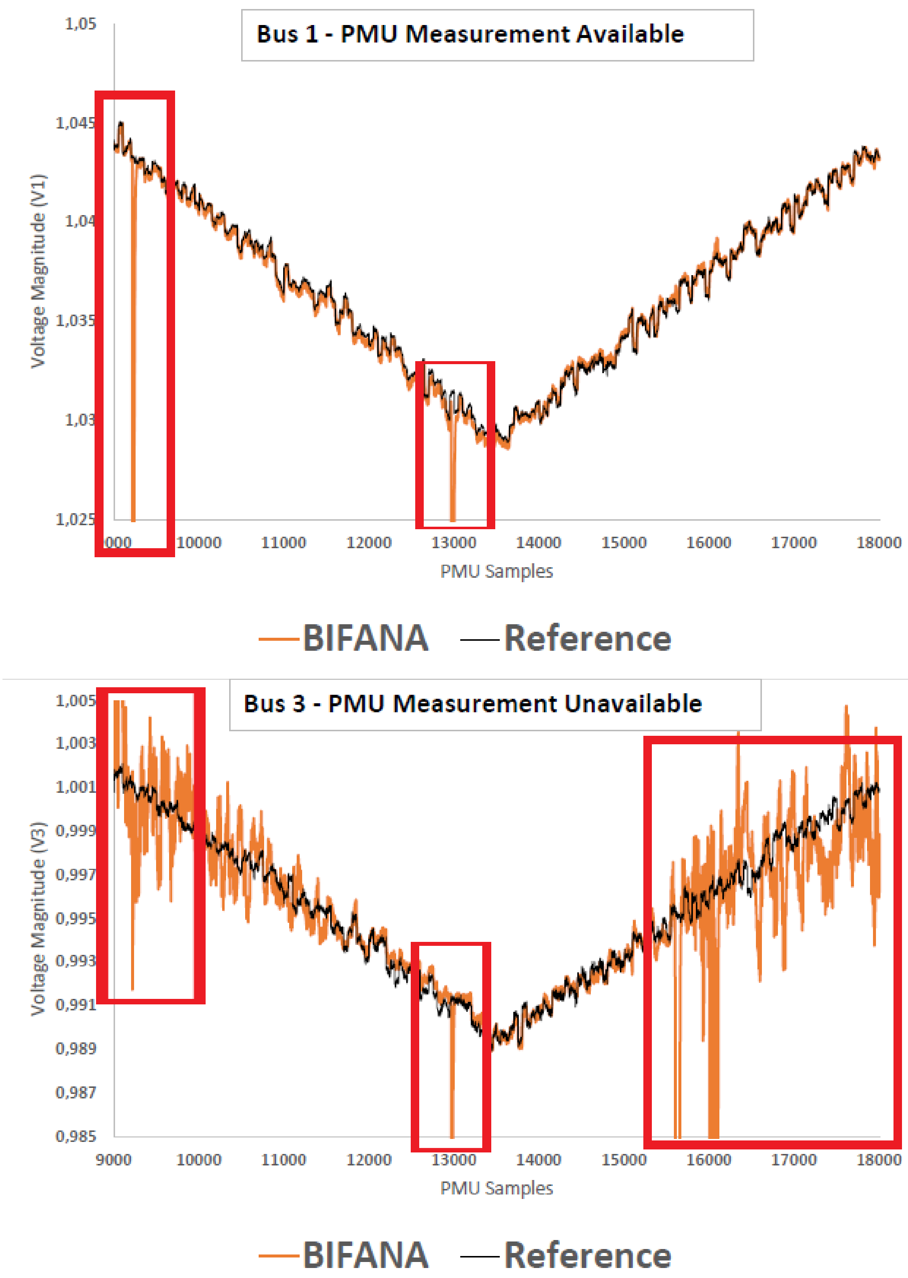

Figure 5.19: Effect of gross errors in a PMU available measurement bus (above) and unavailable measurement (below).

5.6 Discussion

In the present chapter the proposed algorithm's response to different operating scenarios was analyzed demonstrating a clear improvement of the estimation procedure with its adoption.

Regarding the tuning simulation procedure, results revealed a beneficial impact of the PMU related prior broadening. This extension was responsible for the enhancement of the overall accuracy and stability of the estimator both in a stationary operating point and when responding to a transient event. On the other hand, the enlargement of the SCADA related prior proved to be inefficient in enhancing the estimation procedure. The timespan between SCADA samples, due to its low sampling rate, reveals inconsequential value to the extension of its related prior. Therefore, it was maintained as only considering the latest SCADA estimate.

The BIFANA algorithm's reported response to the designed 3-bus system and reference scenario demonstrates a significant improvement in the estimation accuracy of bus voltage magnitudes when compared to Powertech, a state of the art estimator. The previously referred trade-off between stability and accuracy is emphasized by the illustrated time series evolution. Voltage phase angle estimation results revealed insignificant statistical differences between the two. Therefore, it is expected that the BIFANA estimator is able to effectively capture the system's dynamics without compromising the stability of the monitoring and control operations of power networks. However, it must be taken into consideration the limitations and restrictions of the defined simulation environment. The designed 3-bus system revealed to be an interesting starting point to inquire the algorithm's benefits. Nevertheless, simulations in larger scale systems with more complex behaviors and different metering combinations/architectures must be thoroughly executed to profound the extent of the above stated benefits and quantify the influence of other factors.

Finally, the robustness of the algorithm was briefly addressed. As expected, and commonly to other estimators of its kind, the BIFANA method is extremely sensitive to gross errors in the measurement sets. However, and in PMU metered locations, it is exceptionally fast at recovering stability and enhanced accuracy due to its limited prior time window consideration. The above stated conclusions highlight the need for a measurement bad data processing stage in this methodology.

Chapter 6

Conclusion & Contributions

This Master's thesis proposed a novel real-time advanced Bayesian fusion hybrid estimation framework. This new approach is an evolution from the method published in [1], designated as *Powertech* in the present document. The described solution relies on Bayesian principles to incorporate multiple historical and recent data in the *a priori* distribution of a MAP-based fusion estimator, enhancing its accuracy. This new development is an actual contribution to the progress of the state-of-the-art. The improvement resulted from the extension of the prior distribution to a larger historical data set. The work proved that this enlargement is beneficial. As such, with the help of some confirmation in tests with larger systems, it has a strong potential of publication in one major international journal.

The work primarily addressed two important considerations. First and foremost, the need to develop a mechanism that ensures the processing of PMU measurements with extremely high sampling rates in the state estimation framework. Secondly, it identified the potential benefits of broadening the consideration of past information to both recent PMU data and historical SCADA data.

Besides the theoretical background development of the proposed method, this research work also resulted in the following contributions:

- Implementation of a SCADA and PMU measurements transformation based on the Jacobian method, enabling the consideration of a linear model. The proposed methodology addresses the lack of consideration for a proper transformation method that is often encountered in other fusion based estimators. Therefore, the transformation procedure grants statistical consistency between estimation stages.

- Description of a practical simulation procedure considering real power systems' generation and load diagrams and PMU measurement data from EPFL's database.

- Impact analysis of different prior compositions in the estimator response to stationary and transient events.

- Primary assessment of the proposed estimator's sensitivity to gross errors. Commonly to other hybrid state estimators, the BIFANA algorithm proved to be extremely sensitive to outliers in the measurement sets. Nevertheless, with the integration of BD processing functions (a research hot topic in the recent years) this vulnerability is overcome.

The obtained results demonstrate the successful fulfillment of the proposed objectives of this thesis, pointing out the scientific contribution of a novel Bayesian fusion state estimation framework for advanced network assessment.

The broadening of the estimation prior to a certain extent, including data from multiple recent estimates, revealed a beneficial impact in the accuracy of the estimation. Furthermore, it resulted in a less variable estimation output, increasing the method's value in terms of stability for future integration with other EMS applications. On the other hand, the integration of multiple historical SCADA estimates did not contribute to a significant enhancement of the estimation accuracy. This is due to the different PMU and SCADA sampling rates and it became evident in the parameter tuning procedure.

Therefore, and after comparing the estimation results from the BIFANA, Powertech and Kalman filter estimators, the balanced trade-off between an accurate response to state transitions while maintaining an overall stability, illustrates the proposed method's improvement in the state estimation procedure.

Concluding, the BIFANA estimator proved to be an effective tool in resiliently capturing the system's dynamics. Due to the designed framework, its implementation in the conventional state estimation architecture will require significantly less structural changes. Therefore, it ultimately stands as an economically competitive solution to accommodate the inevitable modernization of power systems infrastructure.

6.1 Further Research and Concept Exploration

The scope of the state estimation context is of such dimension that for any new proposed methodology, numerous challenges, possibilities and future works emerge. Throughout the development of this thesis the following research opportunities were identified, motivating future works related to the proposed solution:

- Exhaustive testing of the proposed solution on bigger scaled and more complex simulation environments as well as in adverse conditions/restrictions such as: faults, contingencies, intermittent scenarios and energy market dynamics.
- Employment of kernel density estimation to build the prior distributions, increasing statistical robustness and consistency.
- Implementation of bad data processing functions to enhance the algorithm's robustness to outliers.
- Exploration of the Bayesian inference concepts to a wider selection of parameters determining, for example: the optimal selection and tuning of prior distributions in the presence of adverse events or different probability distribution models.

- Interpretation of the estimation results aided by advanced Artificial Intelligence (AI) such as Deep Neural Networks (DNN) to evaluate the current system state and its dynamic evolution with pattern recognition techniques.
- Integration of forecasting methods to enhance the prior information.

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Appendix A

SCADA in Power Systems

Balancing the power generation and consumption of large-scale power systems, whilst maintaining its operation reliable, uninterrupted and within tight parameters brings a challenge that can only be addressed with accurate monitoring and control automation.

A.1 Scada Concepts

Supervisory control and data acquisition (SCADA) systems are commonly implemented in scenarios where the processes to be monitored and controlled are geographically spread. These systems are characterized by a numerous assembly of interacting components that yield information and execute control tasks on different equipment [104]. The yielded information is provided to the system operator in a distant location (usually a control center) and the control tasks are either sent back to the equipment or automatically executed through local predefined control functions.

As its name points out, a SCADA system, applied to a power network, is divided in two different operating purposes: to monitor the grid, acquiring and storing a large amount of data, and to control the monitored processes.

The monitoring process begins with the collection of data from multiple devices deployed on the field. The data is then converted, coded and transmitted through specific channels. Arriving to the control center, the information is decoded and displayed to the system operator through the *human machine interface (HMI)* using display functions standardized in [105].

Once the information is analyzed, the system operator can decide if a control action must take place. If so, the operator begins the control process by sending encoded command signals through the above mentioned channels. These signals are received and decoded by the field equipment which initiate the control actions. With the continuous development of the equipment technology and processing capability, alongside with the continuous change towards a decentralized architecture, several actions can also take place automatically (without human intervention) if the system identifies certain events both locally and remotely. [105]

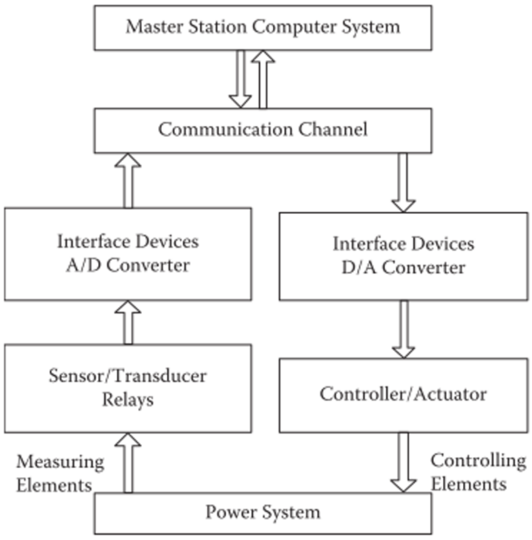

Figure A.1: SCADA Information Flowchart [104].

This remote bilateral flow of information, with standardized communication protocols, describes the typical SCADA communication scheme represented in Figure A.1, page 80.

A.2 System Components

SCADA for power systems are characterized by a collection of interrelating hardware and software with different roles and functionalities. The main hardware components are the *Master Terminal Unit* (MTU), *Remote Terminal Units* (RTUs), as well as deployed sensors and actuators. The main implemented software is the *Human Machine Interface* (HMI) with some applications using other software capable of providing a communication link between hardware and software. [106] The implementation of standardization in SCADA systems lead to a significant increase in the interoperability of equipment and versatility of the overall system. [107]

The present section aims to describe the main components and features that form a typical modern SCADA applied to power systems.

Master Station (Control Center): SCADA master station, located in control centers, is responsible for the overall command and overview of the system. It controls the system's RTUs, gathers and stores data from the grid and efficiently displays the information through the HMI for the control center operators. It is characterized by multiple computers and servers linked through an appropriate and dedicated *Local/Wide Area Network* (LAN/WAN). This connection leads to a distributed architecture of processing power, which has proven advantages in case of a single server failure as well as the overall economic cost of the system. [105].

RTU: The *Remote Terminal Unit* (RTU) or Substation gathers real-time data from network linked sensors and actuators deployed in the field, sending it to the *Master Terminal Unit* (MTU)

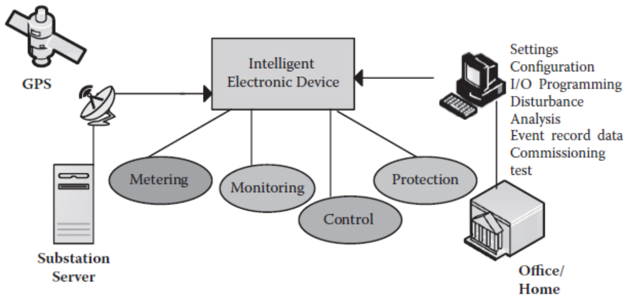

Figure A.2: IED Functionality and Integration [104]

typically upon request from the master station. Information can also be sent without higher hierarchy request in cases of critical events such as disaster (and consequent recovery) as well anomalies in measuring/actuating devices. [106]

IED: *Inteligent Electronic Device* is an instrument capable of sending and receiving data and control information from an outter source. IEDs are being intensively implemented in modern SCADA for power systems, progressively replacing the use of RTUs for their interoperability characteristics and data processing power. [104] These devices are featured with event recording functions, an important aspect for power system operation analysis, diminishing the need for additional equipment implemented for that purpose. Figure A.2 represents the integration of IEDs in SCADA power systems. Data Concentrators are devices typically implemented in substations for the collection of information from IEDs as well as from RTUs if necessary, featuring communication capabilities with systems outside of the SCADA master network.

HMI: *Human Machine Interface* also referred to as *User Interface* (UI), is an interface software between the master station and the system operators. It is responsible for the efficient display of the SCADA observable parameters controlling the operational information. Modern HMIs have multiple features that combined with the correct setup of displays and monitors facilitate the control center operator's analysis of the power system. The referred analysis can be both as a "macro" point of view, visualizing the complete grid in large screen displays (Mapboard) but also in great detail (Multi-VDU Interface) with report generation functions providing historical or real-time measurements as well as links to relevant documentation. [105]

Appendix B

PMUs

B.1 Phasor and Phasor Measurement Concepts

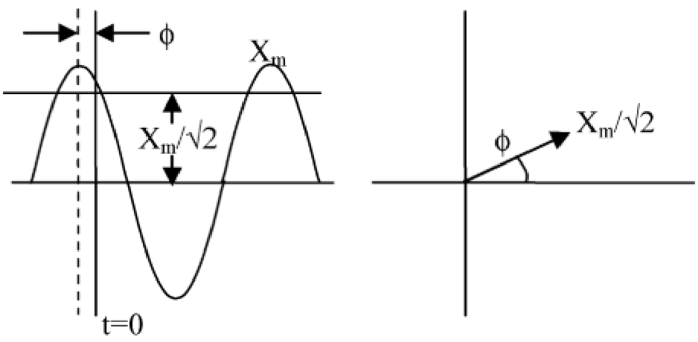

Figure B.1: Phasor representation of a sinusoidal signal. Sinusoidal signal (left) and phasor representation (right) [108]

The first definition of phasor was originally proposed by Steinmetz Charles P. Steinmetz, who suggested the use of complex numbers for the study of linear electrical networks with sinusoidal sources assuming a steady state condition [109].

Considering the classical representation of a sinusoidal signal, with a determined frequency f, expressed by its magnitude X_m and angle Φ, as follows:

$$x(t) \;=\; X_m \, cos(2\pi f t + \phi) \tag{B.1}$$

The phasor representation of this signal is expressed by:

$$X \;=\; \frac{X_m}{\sqrt{2}} \, (cos\phi + jsin\phi) \tag{B.2}$$

It is evident that the signal frequency f is not considered in the phasor representation expressed in B.1, dispite the fact that is an implicit property of it. The magnitude of the phasor is the rms value of the signal (sinusoid) and the phase angle is the same defined in B.1. The representation of a sinusoidal signal and its phasor are shown in Figure B.1.

B.2 Synchronised Measurement Technology (SMT)

A phasor measurement unit (PMU) is a measuring device that estimates multiple parameters of an input signal at its terminals/interface. The signal parameters include the magnitude, phase angle, frequency and rate of change of frequency (ROCOF). It is important to clarify that the signal's quality can be compromised by harmonics influence, noise, or system state changes [110].

The project of these devices was initially proposed in the early 1980s [108] and the first unit was invented by Prof. A Phadke and Prof. J. Thorp in 1988 [111]. Since then, the technology has undergone a deep evolving process leading to an abundance of critical applications regarding modern power systems and smart grids operation and marking future trends in this field [112][113]. Some of the referred applications, mainly regarding *Wide Area Measurement Systems* (WAMS) and *State Estimation* (SE) will be further addressed in the following sections.

A PMU resulting synchrophasor is defined as phasor estimated at a time-tagged instant [108], through captured samples of the voltage/current AC waveforms [110]. The estimation takes place by the definition of a time period for the samples to be collected. Once the time period is established, the samples are gathered and the average value is calculated. The time window definition becomes a critical factor for the estimation since variations of the waveform characteristics may take place during the sampling period. Hence, appropriate filtering must be carefully selected depending on the applications [110]. In Figure B.2, the input and output parameters of a PMU device are illustrated. It is important to note that the UTC time signal must be provided with high accuracy since it plays a key role in the correct synchronization and time-tagging of measurements [114]. Typically satellites-based systems like *Global Navigation Satellite System* (GNSS) or *Global Positioning System* (GPS) are the implemented time signal sources for their reliability and accuracy [114].

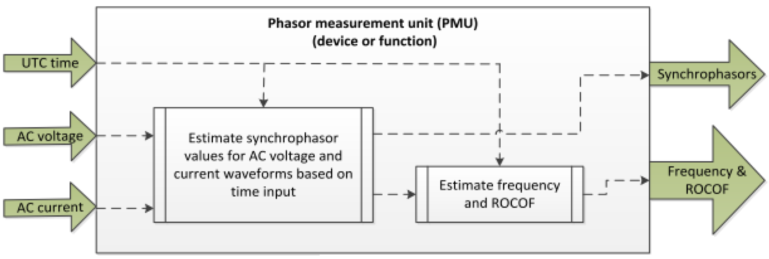

Figure B.2: Input and Output parameters of a Phasor Measurement Unit [110]

When in comparison with the conventional SCADA measurement rate, PMUs report notably faster. These devices are capable of rates from 50 to 100 Hz, approximately 100 times faster than the typical rate of SCADA systems operation [115].

As described in the introduction of this document, this feature plays a pivotal role in the real-time monitoring of modern power grids, giving a reliable display of the system dynamics to the operator.It becomes evident that the progressive SMT/PMU technology implementation is rapidly breaking down critical limitations for the reliable operation of the ever growing complex power network. Other areas may also be positively affected with improvements resulting from SMT research, such as [116]:design of advanced early warning systems, cause analysis of system blackouts, enhancement in state estimation, real-time congestion management and so on.

B.3 Wide Area Monitoring System (WAMS)

Owing to the fact that electric power systems are so geographically extent and complex, the monitoring and control of these systems has proved to be a difficult task [117]. Based of PMU technology, *Wide Area Monitoring Systems* (WAMSs) measure electrical parameters at multiple points of the grid, supplying the system operator with an unmatched real time overview of the system. Figure B.3 illustrates the integration and connection of a WAM system with the conventional SCADA monitoring system. A complete list of developed algorithms for the calculation of the above mentioned parameters in PMU/SMT is detailed in [68].

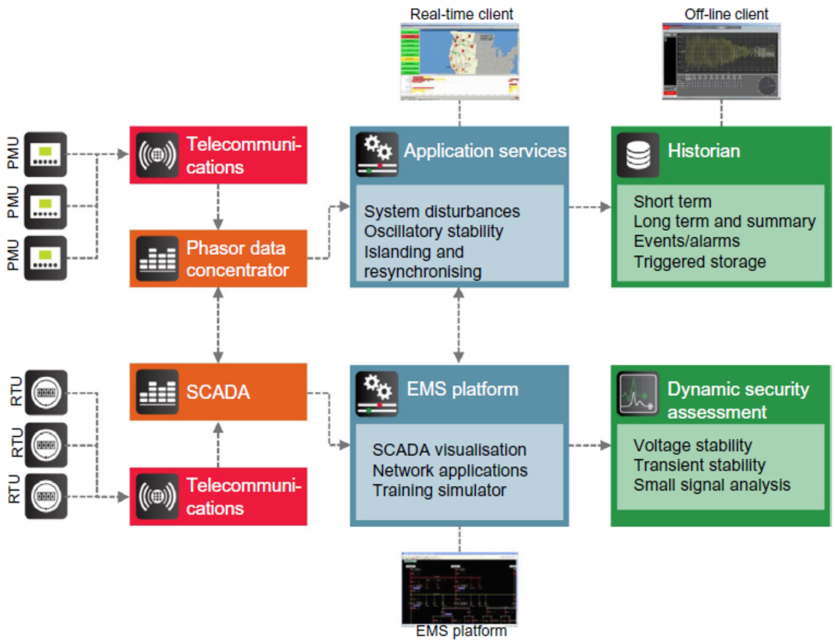

Figure B.3: Integration and connection of a WAM System with conventional SCADA monitoring [118]

Diversified real case applications of these monitoring systems [119][120][121] in various areas such as the increase of power grids' stability have proven to be of great success. With the continuous development of PMU technology and the clear benefits of its integration, the electric utilities are adopting its gradual implementation. The increasing penetration of new distributed energy sources (DEGs), mainly photovoltaic DG has also lead to a significant interest in the implementation of these devices in distribution power systems [112][15]. Since these units have a considerable cost (even though manufacturers are focusing efforts towards less expensive products), the rise of proposed Optimal PMU Placement (OPP) methodologies, maximizing multi-criteria benefits of WAMS Infrastructures, has been of great importance for the cost-restrained application of this technology today. The different proposed approaches towards OPP are described in [68].

Appendix C

Forecasting-Aided State Estimation Formulation

The forecasting-aided state estimation relies on a state space model for the state variables. Its formulation describes a measurement model as well as a forecasting model correlating the state of the system at different timestamps [70]. This methodology can be expressed according to a discrete time-variant system as follows:

$$x_t = F_{t-1}x_{t-1} + g_{t-1} + \omega_{t-1} \tag{C.1}$$

$$z_t = h(x_t) + e \tag{C.2}$$

Regarding (C.1) [70]:

- F_{t-1} - state transition matrix.
- g_{t-1} - forecasting trend.
- ω_{t-1} - forecasting error. This error is assumed to be white Gaussian noise characterized by zero mean.

And (C.2) expresses the measurement model at the moment t.

Concluding the estimation process, a *Maximum Likelihood Estimation* (MLE) based inference procedure provides the estimated state, through the minimization of the following expression:

$$min\ [z_t - h(x_t)]^T R^{-1}[z_t - h(x_t)] + [Fx_{t-1} + g_{t-1} - x_t]^T\ Q_{t-1}^{-1}[Fx_{t-1} + g_{t-1} - x_t] \tag{C.3}$$

Where:

- Q_{t-1} - covariance matrix of the forecasting error, ω_{t-1} (C.1)

Appendix D

Demonstration of the Posterior Distribution

The present section aims to provide a demonstration of the posterior distribution as previously presented in (3.24). By using the prior distribution (3.22) given by the state space model, and the likelihood (3.23) by the PMU linear measurement model, the Baye's Theorem (3.3) can be directly applied, which results in:

$$\begin{aligned} P(x_t|z_t) \propto \exp\big(-\frac{1}{2}(z_t - Hx_t)' R_{PMU}^{-1} (z_t - Hx_t)\big). \\ \exp\big(-\frac{1}{2}(x_t - F\hat{x}_{t-1})' Q_{t-1}^{-1} (x_t - F\hat{x}_{t-1})\big) \end{aligned} \tag{D.1}$$

Expanding the exponent:

$$\begin{aligned} z_t' R_{PMU}^{-1} z_t + x_t' H' R_{PMU}^{-1} H x_t - x_t' H' R_{PMU}^{-1} z_t - \\ z_t' R_{PMU}^{-1} H x_t + x_t' Q_{t-1}^{-1} x_t + \hat{x}_{t-1}' F' Q_{t-1}^{-1} F \hat{x}_{t-1} \\ -\hat{x}_{t-1}' F' Q_{t-1}^{-1} x_t - x_t' Q_{t-1}^{-1} F \hat{x}_{t-1} \end{aligned} \tag{D.2}$$

As a way of determining the posterior probability distribution, one can search for its kernel to simplify the calculations. Therefore, the constants of the above stated expression can be neglected, yielding:

$$\begin{aligned} x_t' \left(H' R_{PMU}^{-1} H + Q_{t-1}^{-1}\right) x_t - x_t' \left(H' R_{PMU}^{-1} z_t + Q_{t-1}^{-1} F \hat{x}_{t-1}\right) \\ - \left(z_t' R_{PMU}^{-1} H + \hat{x}_{t-1}' F' Q_{t-1}^{-1}\right) x_t \end{aligned} \tag{D.3}$$

The kernel of a Multivariate Normal distribution with expected value a and covariance matrix B is characterized by the following exponent structure:

$$(x-a)'B(x-a) = x'Bx - x'Ba - a'Bx - a'Ba \tag{D.4}$$

Comparing (D.3) and (D.4), the expected value and covariance matrix of the posterior distribution kernel are given by:

$$B \equiv \left(H' R_{PMU}^{-1} H + Q_{t-1}^{-1}\right) \tag{D.5}$$

$$Ba \equiv \left(H' R_{PMU}^{-1} z_t + Q_{t-1}^{-1} F \hat{x}_{t-1}\right) \tag{D.6}$$

$$a \equiv \left(H' R_{PMU}^{-1} H + Q_{t-1}^{-1}\right)^{-1} \left(H' R_{PMU}^{-1} z_t + Q_{t-1}^{-1} F \hat{x}_{t-1}\right) \tag{D.7}$$

This way, as expected, the posterior distribution is indeed a multivariate normal distribution shown in (3.24) since the inference is performed with a conjugate prior.

$$P(x_t|z_t) \propto e^{(x-a)' B (x-a)} \tag{D.8}$$

Appendix E

Influence of SCADA Historical Information - Stationary Operating Point

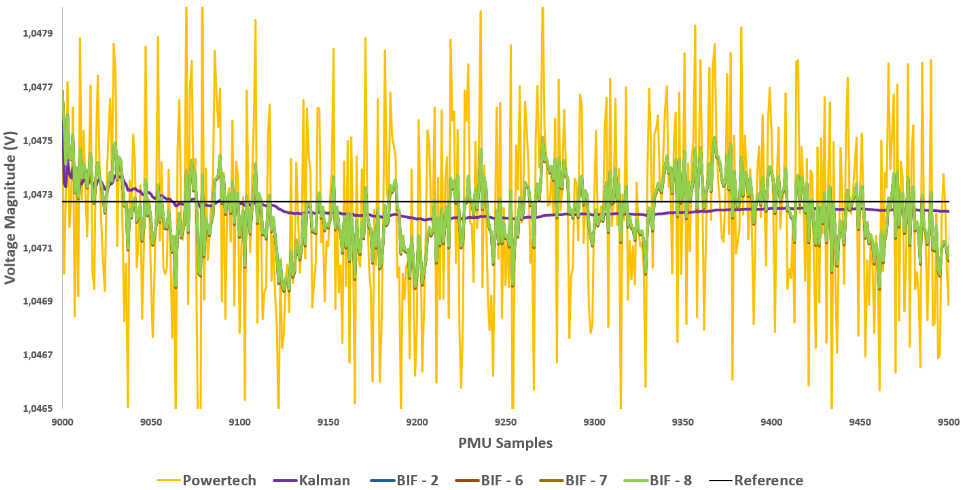

Figure E.1: Response to a stationary operating condition between the tested algorithms.

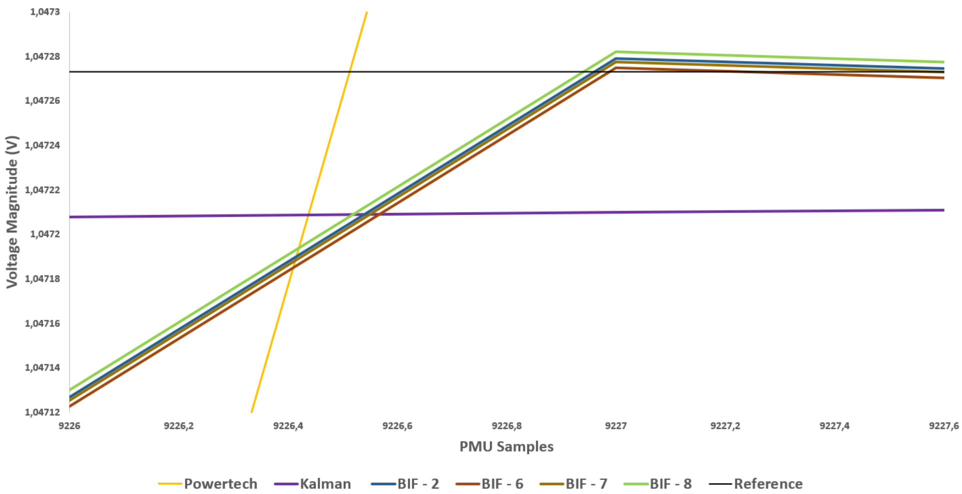

Figure E.2: Response to a stationary operating condition between the tested algorithms.

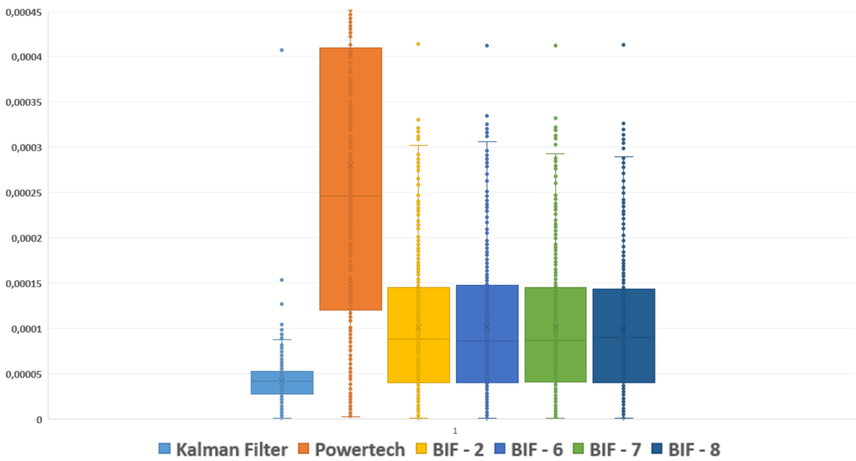

Figure E.3: Error distribution of the tested algorithms.

Appendix F

Complementary Simulation Results

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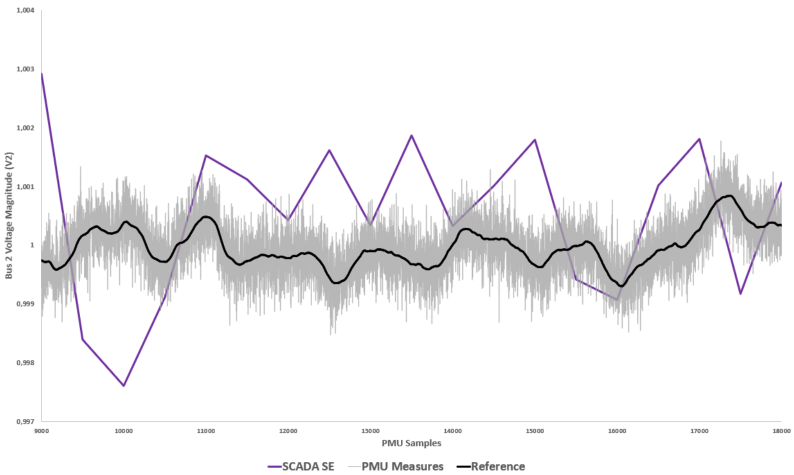

Figure F.1: Reference scenario for Bus 2 voltage magnitude.

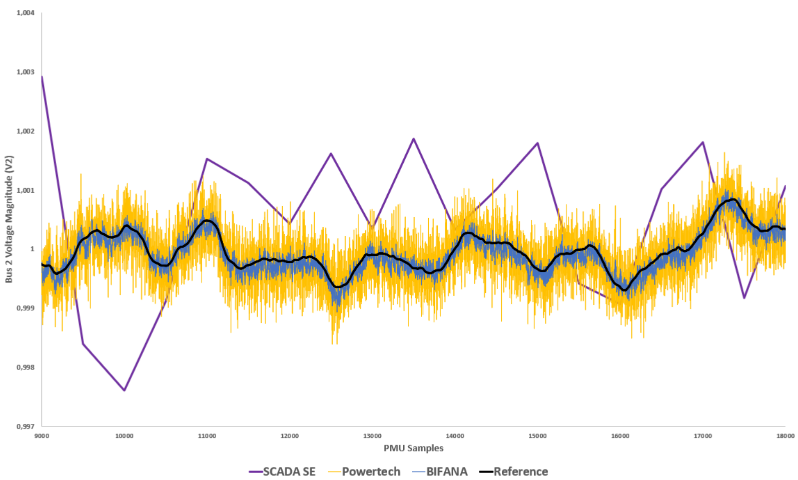

Figure F.2: Estimation comparison between the tested algorithms for Bus 2 voltage magnitude.

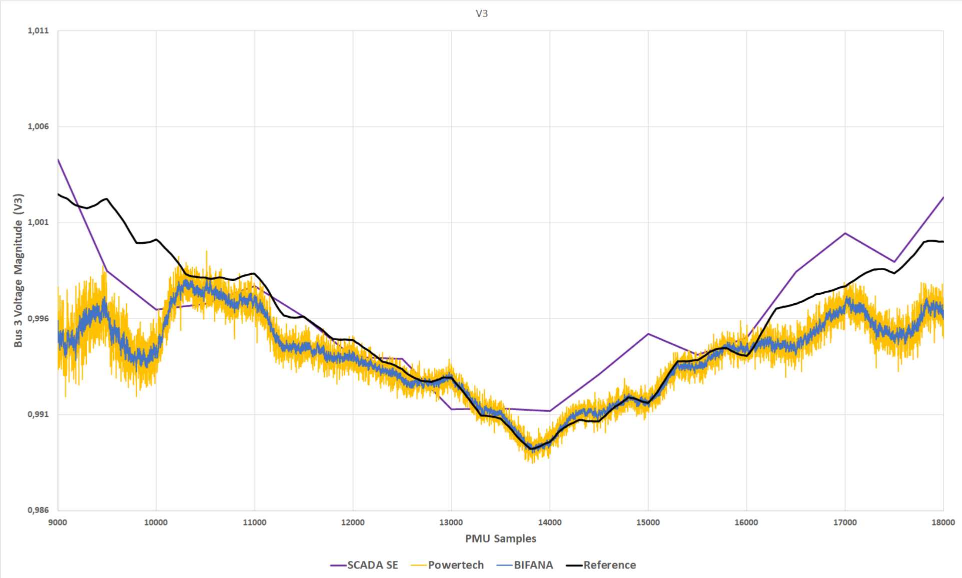

Figure F.3: Estimation comparison between the tested algorithms for Bus 3 voltage magnitude.

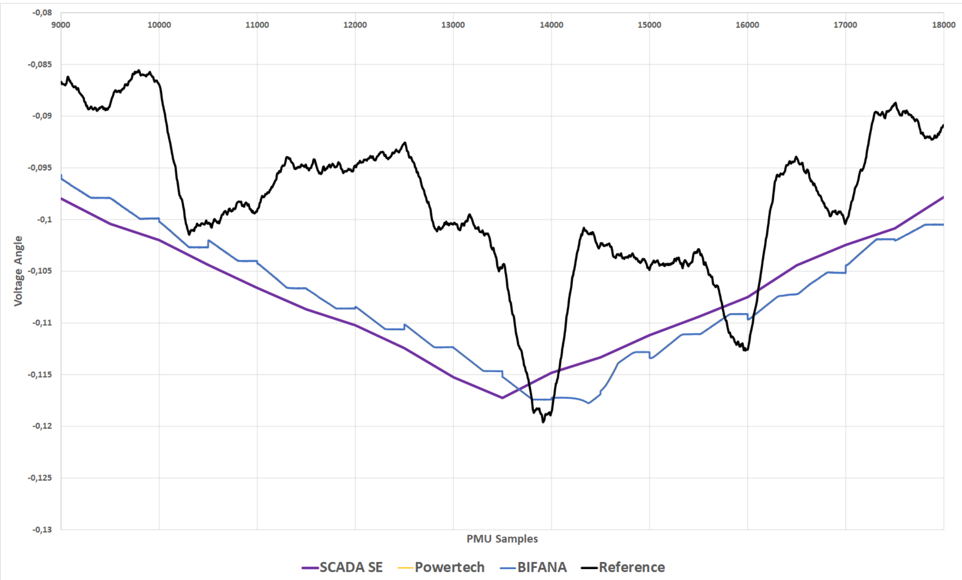

Figure F.4: Estimation comparison between the tested algorithms for Bus 3 phase angle.