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**Estimação de Parâmetros de um
Modelo Trifásico de Gerador Síncrono
Distribuído Utilizando Medições com
Ruído**

Edson Luis Geraldi Junior

**Parameter Estimation for a
Three-Phase Distributed Synchronous
Generator Model Using Noisy
Measurements**

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Field of Research: Electric Power Systems

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*“If you can’t fly then run, if you can’t run then walk, if you can’t walk then crawl,
but whatever you do you have to keep moving forward.”*

(Martin Luther King Jr.)

Resumo

Geraldi Jr., E. L. **Estimação de Parâmetros de um Modelo Trifásico de Gerador Síncrono Distribuído Utilizando Medições com Ruído.** 171 p. Tese de doutorado – Escola de Engenharia de São Carlos, Universidade de São Paulo, 2018.

Os modelos simplificados de geradores síncronos, amplamente utilizados em estudos de estabilidade de grandes sistemas elétricos de potência, não são completamente adequados para a análise de estabilidade e projetos de controladores dos geradores síncronos distribuídos, geralmente conectados a sistemas tipicamente desequilibrados. Para que os sistemas com geração distribuída possam ser analisados mais fidedignamente, é necessária a utilização de um modelo de gerador síncrono que considere a variação de frequência em suas equações elétricas. Além disso, esse modelo também deve ser capaz de representar possíveis tensões trifásicas desequilibradas nos terminais do gerador. Entretanto, para que esse modelo mais detalhado possa fornecer respostas coerentes com a realidade, deve-se conhecer seus parâmetros. Dessa forma, este trabalho avalia a influência dos parâmetros nas respostas de um modelo de gerador síncrono mais detalhado, adequado para representar operações desbalanceadas, e propõe uma abordagem para a estimação de seus parâmetros mais importantes. Nessa estrutura, inicialmente empregam-se as Funções de Sensibilidade de Trajetória para avaliar a dependência das respostas desse modelo em relação aos seus parâmetros e, a partir disso, ordená-los conforme sua importância. Em seguida, aplica-se um processo de estimação que utiliza o Filtro de Kalman *Unscented* com o auxílio de um algoritmo genético para estimar os principais parâmetros desse modelo de gerador síncrono em condições de desbalanço. Para a obtenção dos resultados e consequente avaliação da abordagem de estimação proposta, utiliza-se um sistema composto por um gerador síncrono conectado a uma carga trifásica desbalanceada. Além da operação desbalanceada desse sistema teste, também são considerados ruídos devidos ao constante chaveamento de cargas, típicos de sistemas de distribuição. As estimações realizadas para três condições de operação do gerador foram bem satisfatórias, indicando

a eficiência da abordagem proposta na obtenção de modelos adequados para descrever a operação de geradores síncronos em condições de desbalanço.

Palavras-chave: Geração distribuída. Gerador síncrono. Operação desbalanceada. Filtro de Kalman *Unscented*. Funções de Sensibilidade de Trajetória. Estimação de Parâmetros.

Abstract

Geraldi Jr., E. L. **Parameter Estimation for a Three-Phase Distributed Synchronous Generator Model Using Noisy Measurements.** 171 p. Ph.D. Thesis – São Carlos School of Engineering, University of São Paulo, 2018.

The simplified models of synchronous generators, widely used in stability studies of large electric power systems, are not completely suitable for the stability analysis and the design of controllers of distributed synchronous generators, generally connected to typically unbalanced branches. To more accurately analyze the systems with distributed generation, it is necessary to utilize synchronous generator models that consider frequency variation in their electrical equations. Furthermore, this model must represent possible unbalanced three-phase voltages at the generator terminals as well. Nonetheless, to provide reliable responses, the parameters of this more detailed model should be known. Thus, this work assesses the influence of the parameters on the responses of a detailed synchronous generator model, suitable to depict unbalanced operating conditions, and proposes an approach for the estimation of its most important parameters. In the proposed structure, we first employ Trajectory Sensitivity Functions to evaluate the dependency of the responses of this model with respect to its parameters and, from that, we rank them according to their importance. Subsequently, we apply an estimation process that utilizes the Unscented Kalman Filter with the aid of a genetic algorithm to estimate the main parameters of this synchronous generator model under unbalanced operating conditions. To obtain the results and, therefore, assess the proposed estimation approach, we make use of a system which comprises a synchronous generator connected to a three-phase unbalanced load. In addition to the unbalanced operation of the test system, we also consider noises due to the constant load switching, typical of distribution systems. The estimations performed for three operating conditions of the generator were very satisfactory, which demonstrates the efficiency of the proposed approach to obtain adequate models for the description of synchronous generator operation under unbalanced

operating conditions.

Keywords: Distributed Generation. Synchronous Generator. Unbalanced Operation. Unscented Kalman Filter. Trajectory Sensitivity Functions. Parameter Estimation.

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Acronyms

BC Balanced Case

DG Distributed Generation

DSG Distributed Synchronous Generator

EKF Extended Kalman Filter

EPS Electric Power Systems

GA Genetic Algorithm

IF Imbalance Factor

ONS The Brazilian Interconnected Transmission System Operator

PMU Phasor Measurement Unit

SG Synchronous Generator

TSF Trajectory Sensitivity Functions

UKF Unscented Kalman Filter

UT Unscented Transformation

UC1 Unbalanced Case 1

UC2 Unbalanced Case 2

UC3 Unbalanced Case 3

Nomenclature

α	parameter of the Unscented Transformation (UT) which determines the spread of sigma points
α_m	constant angle equal to $\pi/2$
β	parameter of the UT used to include information about a statistical distribution
χ	Jacobian matrix of the output vector y with respect to the parameter vector p
λ_{0dq}	flux linkage vector composed by λ_0 , λ_d and λ_q
λ_{abc}	flux linkage vector composed by λ_a , λ_b and λ_c
λ_{FDQ}	flux linkage vector composed by λ_F , λ_D and λ_Q
C	cross-covariance matrix between the states and measurements
$f(\cdot)$	vector of nonlinear functions
$h(\cdot)$	vector functions of the measured outputs
i_{0dq}	current vector composed by i_0 , i_d and i_q
i_{abc}	current vector composed by i_a , i_b and i_c
i_{FDQ}	current vector composed by i_F , i_D and i_Q
K	Kalman gain matrix
n_{0dq}	neutral voltage vector in the $0dq$ frame of reference
p^*	vector of parameters which minimizes $J(p)$
p_{ref}	reference value of the vector p

$\mathbf{p}_{UKF}$	vector of parameters necessary for the application of the UKF
$\mathbf{P}$	error covariance matrix
$\mathbf{p}$	vector of parameters of the model
$\mathbf{q}^{par}$	vector of noise of the parameters
$\mathbf{Q}$	process covariance matrix
$\mathbf{q}$	process noise vector
$\mathbf{R}$	measurement covariance matrix
$\mathbf{r}$	measurement noise vector
$\mathbf{S}$	covariance matrix of the measurements
$\mathbf{u}$	vector of inputs of the model
$\mathbf{v}_n$	neutral voltage vector
$\mathbf{v}_{0dq}$	current vector composed by v_0 , v_d and v_q
$\mathbf{v}_{abc}$	voltage vector composed by v_a , v_b and v_c
$\mathbf{v}_{FDQ}$	current vector composed by v_F , v_D and v_Q
$\mathbf{x}$	vector of state variables of the model
$\mathbf{y}_m$	vector of measured outputs of the model
$\mathbf{y}$	vector of outputs of the model
χ	sensitivity function of the output y with respect to the parameter p_i
δ	torque angle of the machine
δ_e	electrical angle of the machine
δ_m	mechanical angle of the rotor
ϵ	parameter used to obtain the initial value of the error covariance matrix $\mathbf{P}$
λ_0	flux linkage for the stationary winding
λ_a	flux linkage for the phase- a winding
λ_b	flux linkage for the phase- b winding
λ_c	flux linkage for the phase- c winding

λ_D	flux linkage for the damper winding D
λ_d	flux linkage for the direct-axis winding
λ_F	flux linkage for the field winding
λ_Q	flux linkage for the damper winding Q
λ_q	flux linkage for the quadrature-axis winding
$\mathcal{S}$	set of sigma points
Z_x	impedance of the load of phase x , $x = \{a, b, c\}$
ω_e, ω	angular velocity of the revolving magnetic field
ω_m	shaft angular velocity
ω_R	synchronous angular frequency
ω_{m_R}	rotor angular speed when the revolving magnetic field rotates with frequency ω_R
ψ_p	parameter used to obtain the process covariance matrix $\mathbf{Q}$
ψ_s	parameter used to obtain the process covariance matrix $\mathbf{Q}$
θ	rotor angle
v	parameter of the UT used to reduce the higher order errors of the mean and covariance approximations
ζ	parameter used to obtain the measurement covariance matrix $\mathbf{R}$
D	damping constant
E_{FD}	direct axis electromotive force which corresponds to a field voltage v_F
$E_{p_i}^{y_j}$	quadratic function employed to assess the influence of the parameter p_i on the output y_j
H	inertia constant
h_i	one of the hypothesis of the population
i_0	stationary current
i_a	stator phase a current
i_b	stator phase b current

i_c	stator phase c current
i_D	damper winding D current
i_d	direct-axis current
i_F	field current
i_Q	damper winding Q current
i_q	quadrature-axis current
I_{agline}	value of the field current for 1 p.u. armature voltage
J	error functional employed as fitness function of the estimation process
J_M	moment of inertia
J_{i_d}	error functional considering only i_d
J_{i_F}	error functional considering only i_F
J_{i_q}	error functional considering only i_q
k_c	constant equal to $\sqrt{3/2}$
L_0	stationary inductance
L_D	damper winding D self-inductance
L_d	direct-axis inductance
L_F	field self-inductance
L_m	amplitude of variation of the phase self-inductance and of the mutual inductance between two phases
L_n	neutral inductance
L_Q	damper winding Q self-inductance
L_q	quadrature-axis inductance
L_s	average inductance of the phase self-inductance
M_D	maximum mutual inductance between the damper winding D and each phase winding
M_F	maximum mutual inductance between the field winding and the winding of each one of the stator phases

M_Q	maximum mutual inductance between the damper winding Q and each phase winding
M_R	mutual inductance between the field winding and damper winding D
M_s	average value of the mutual inductance between two phases
MR	probability of applying the mutation operator to an individual of the population
n	sum of the number of states plus the number of parameters of the model ($n_s + n_p$)
n_i	number of inputs of the model
n_o	number of outputs of the model
n_p	number of estimated of the model
n_s	number of state variables of the model
N_{eli}	number of individuals in the elite of the population
N_{pop}	number of individuals in the population
N_w	number of samples in the window used for parameter estimation
p	number of poles of the machine
p_i	the i -th element of the vector $\mathbf{p}$
P_m	mechanical power on the machine shaft
P_v	output of the speed control
P_{inj}	generator active power injection
p_{out}	total output three-phase electrical power of the machine
P_{T_e}	part of the generator electrical power responsible for the electrical torque
Q_{inj}	generator reactive power injection
r	armature resistance
r_a	phase- a stator resistance
r_b	phase- b stator resistance
r_c	phase- c stator resistance

r_D	damper winding D resistance
r_F	field resistance
r_n	neutral resistance
r_Q	damper winding Q resistance
R_{noise}	random value of the load resistance of phases a , b , and c
$R_{xL_{Fix}}$	fixed value of the load resistance of phase x , $x = \{a, b, c\}$
R_{xL}	value of the load resistance of phase x , $x = \{a, b, c\}$
REF	reference of the speed governor
S_B	rated three-phase power of the machine
$S_{1\phi}$	single-phase apparent power of the load
S_{dl}	apparent power of the decreased load
S_{il}	apparent power of the increased load
S_{ul}	apparent power of the unbalanced load
T_a	resulting accelerating torque on the machine shaft
T_d	viscous friction torque
T_e	electrical torque
T_m	mechanical torque on the machine shaft
v_0	stationary voltage
v_a	stator phase a voltage
V_B	rated line voltage of generator stator
v_b	stator phase b voltage
v_c	stator phase c voltage
v_D	damper winding D voltage
v_d	direct-axis voltage
v_F	field voltage
v_Q	damper winding Q voltage

v_q	quadrature-axis voltage
V_t	terminal voltage of the synchronous machine
V_+	positive sequence voltage
V_-	negative sequence voltage
V_{IMB}	voltage imbalance index
V_{REF}	reference voltage of the automatic voltage regulator
$v_{x_{RMS}}$	root mean square value of stator voltage v_x , $x = \{a, b, c\}$
W_k	kinetic energy stored in the machine rotor when it rotates with angular speed ω_{m_R}
y_j	the j -th element of the vector $\mathbf{y}$

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Introduction

One of the biggest challenges of modern society is the acquisition of energy from renewable sources that do not cause a significant environmental impact. Presently, clean sources generate a significant amount of electric power, propelling the economic development of many countries. These clean sources are often located close to large consumer blocks, resulting in a deconcentration of electric power production and in changes to paradigms of Electric Power Systems (EPS) operation. These systems expanded since 1950 based on a centralized structure, in which large central generators produce electric power and high voltage transmission lines transfer it to great consumer centers (JENKINS et al., 2000).

The efficiency of this structure was enhanced over the years with the development of equipment which improved the power generation performance and the appearance of new transmission technologies. Despite the efficacy of the centralized structures, the search for environmentally friendly sources near the large load centers puts in evidence a type of generation known as Distributed Generation (DG) (JENKINS et al., 2000). Furthermore, the utilization of these resources has a great economic importance since it increases the energy supply without the need to build new transmission lines or hydroelectric and thermoelectric plants, which normally require substantial investments.

The concept of DG is not new. Before the introduction of electric power as a commercial alternative, all the energy was generated close to the equipment and services that consumed it. In mid-1880 in the United States, there were small electric power plants in the cities, which had their energy generation limited by the direct-current transmission technology. Each power plant was able to supply only the loads within the distance of one mile and so there were several isolated systems in a city. Nevertheless, at the end of the 1920s, with the transition of the transmission systems to alternate current, the electric energy transport over large distances began and the interconnection of electric systems started, resulting in technical and economic benefits (BORBELY; KREIDER, 2001). From then on, large-sized power plants were built close to places with greater potential for exploration of primary energy sources, but far from the big consumer centers. This centralized architecture, responsible for the major part of the energy consumed until now,

started being modified in mid-1990 when the DG began to be implemented again.

Decentralized small-sized power plants, directly connected to the distribution or sub-transmission systems, are usually called DG. However, there are divergences in the definition of DG in the technical literature. These divergences appear in terms of the installed capacity, the location, the employed technologies and the environmental impact caused by the power plants. Nevertheless, DG is generally defined as the production of electric power from small-sized generators located near the loads. These generators can be connected to distribution grids or directly to the final consumer (ACKERMANN; ANDERSSON; SÖDER, 2001; JENKINS et al., 2000). This proximity between the generator and the load may lead the former to supply unbalanced distribution branches. In this case, the generator is subject to three-phase unbalanced voltages and, therefore, its operation is different from the case when it is connected to long transmission lines (SALIM, 2011).

Although the photovoltaic solar sources (which have shown an expressive growth in recent years), for instance, achieved in 2015 the electric power production of 20 GWh in Brazil, this level is still practically negligible when compared to the 49.3 TWh coming from biomass, which represents 8.0% of the total production of electric power in the country (EPE, 2016). This data confirms that, although the worldwide trend is the connection of primary sources of energy to the distribution grids through frequency inverters, in Brazil the cogeneration power plants which utilize synchronous generators prevail, especially in the State of Sao Paulo where the energy production from sugar cane bagasse is common.

The use of synchronous generators is convenient from the facility perspective since it does not require inverters, which are costly. Besides, different from the asynchronous generators, which generally need a source to supply reactive power, the synchronous generators do not have this requirement (JENKINS et al., 2000). Nonetheless, the presence of generation sources directly connected to subtransmission and distribution grids turns these systems into active circuits (as opposed to the previous ones, which had predominantly passive characteristics).

Given that there is energy generation derived from the conversion of rotating kinetic energy into electricity, problems of angular stability appear in these systems. Stability studies conducted in systems with one Distributed Synchronous Generator (DSG) or more show that underdamped electromechanical oscillations can appear in these systems (KUIAVA et al., 2008). Therefore, in order to expand the cogeneration systems that use synchronous machines, it is necessary to acquire a broader knowledge of the synchronous generators and their control and protection systems when connected to unbalanced grids.

From the point of view of large EPS, it is important to highlight that the presence of a considerable number of DG plants can interfere in the stability studies. Nowadays in Brazil, the power generated by the DG plants is taken into account in the load estimation for the planning and the stability studies performed by the The Brazilian Interconnected Transmission System Operator (ONS). However, the dynamics of these plants is not

considered in these analyses. With the increase in the number of DG enterprises, such as biomass cogeneration and small hydroelectric plants, for example, neglecting the dynamics of the DSGs may lead to inaccurate results (CUTSEM et al., 2017). The ONS considers adopting more models for the distributed generators in order to employ more realistic stability studies. Nevertheless, it is necessary to emphasize that the models adopted for the DSGs do not need to be as detailed as the one employed for the stability and protection studies and assessment of the power quality in distribution grids.

Most of the works which address stability studies for distributed generation systems, of which (FREITAS et al., 2006; ABDEL-AKHER, 2013; ELIZONDO; TUFFNER; SCHNEIDER, 2016) are examples, take into account their inherent imbalance. Protection studies, e.g. (CHOI et al., 2004; SALIM et al., 2009), and power quality analyses, such as (EAJAL; EL-HAWARY, 2010; DASH; PADHEE; BARIK, 2012), also consider the typical characteristics of these systems and fault location is usually more complex than in transmission systems (BRAHMA, 2011). In (NASR-AZADANI et al., 2014), a detailed study of the dynamic and steady-state behavior of distribution systems with synchronous and doubly fed induction generators is carried out and it shows that imbalance may significantly affect the dynamics of a system. Salim (2011) assesses the operation of synchronous generators at the subtransmission and distribution levels, showing the influence of the grid imbalance on the electromechanical oscillations that may be present in distribution systems.

To precisely analyze a system with DG, it is necessary to represent the loads and the distribution lines in detail, as well as to assign a model suitable for unbalanced systems to the synchronous generator. Different from transmission systems, the voltage imbalance between phases are common and the impact of the frequency variation on the line reactances cannot be neglected in systems with DG (KERSTING, 2002). That way, simplified models of synchronous generators, such as the one-axis and two-axis models (ANDERSON; FOUAD, 2002), are not adequate to represent distributed generators since they neglect the transformatory voltages, consider nominal frequency in the stator electrical equations and assume there is an equilibrium between phases. An appropriate modeling for the distributed generator must take into account the frequency variation and unbalanced three-phase voltages in its equations.

The parameters of a complete synchronous generator model, which can be reliably used in stability studies and in the assessment of the power quality of a distribution system, need to be satisfactorily estimated (GHOMI; SAREM, 2007). Although the generator manufacturers provide some of them, mechanical wear, temperature changes during the operation, magnetic saturation and even possible construction flaws may affect the value of these parameters. Besides, the values of the parameters shown in generator datasheets are often adequate for simplified models, but not for detailed models. It is also worth mentioning that in detailed models the number of parameters is greater than in simplified models and this fact undermines their correct estimation due to numerical and

computational difficulties.

In order to have a better assessment of the importance of a correct estimation of the parameters in a general sense, in the United States the policy adopted by the Western Electricity Coordinating Council (WECC) and several other grid-operating entities is the revalidation of the models of power plants connected to the transmission system every five years or when changes are made to relevant facility equipment (OVERHOLT et al., 2014).

On account of the relatively high number of parameters in detailed models of synchronous generators, finding a method that precisely estimates them is a big challenge. In most cases, the correct estimation of all the parameters of a model requires the measurement of several quantities of the generator. However, the measurement of some quantities is infeasible due to technical and/or economic reasons, making the estimation of all the parameters almost impossible to be performed in practice. A good alternative, on the other hand, is to find the parameters that have the largest impact in the generator responses and to estimate them in order to minimize the error between the measured quantities and the simulated curves. The parameters which do not significantly affect the generator responses do not need to be precisely estimated since they do not interfere with stability studies or with the design of generator speed and voltage controllers.

Several works in the technical literature employ estimation methods to obtain values of parameters of generator models and their controllers. In (HUANG; LI; YAN, 2010), for example, a square-root unscented Kalman filter is used to estimate the state variable and electrical and mechanical parameters of a third-order synchronous generator model. Aghamolki et al. (2015) employ the UKF to estimate parameters of a simplified model of synchronous generator, which is represented by a constant voltage source behind an impedance. Furthermore, parameters of the turbine-governor and the primary and secondary frequency control block models are also estimated in this work. The UKF is generally employed when nonlinear models are taken into account. In (KARRARI; MALIK, 2004), the relations of the Heffron-Phillips parameters with the physical parameters and an identification technique of linear time-invariant system are used to estimate electrical and mechanical parameters of a synchronous generator model. All the aforementioned works utilize simplified synchronous generator models which are not adequate for the representation of DSGs.

It must be mentioned that there are other works which estimate parameters of more detailed models of synchronous generators. Cisneros-Gonzalez et al. (2013) draws on the time-domain *chirp* signal excitation to obtain the dq axis parameters of a fifth-order synchronous machine model (a hybrid optimization technique composed by a genetic and a quasi-Newton algorithm is employed to estimate the electrical parameters of the generator model). Kyriakides, Heydt and Vittal (2004) use a method based on least squares estimation to obtain the electrical parameters of a seventh-order synchronous generator model (the method uses the measurements at the terminals of the machine

and an observer for estimation of synchronous generator damper currents). Although the aforementioned works present detailed models in terms of the electric part of the machine, they do not consider the generator mechanical equations. In (VALVERDE et al., 2011), a complete model of a synchronous generator is considered, including the mechanical equations. The employed methodology, which is based on unscented Kalman filter, can be applied without interrupting the normal operation of the generator, avoiding financial losses and keeping the system reliability. However, the method estimates just the electrical parameters of the model.

Therefore, to the best knowledge of the author, there is no work in the technical literature which estimates electrical and mechanical parameters of a three-phase synchronous generator model by using measurements obtained under unbalanced operating conditions, typical of DSGs. Having this in mind, the aim of this work is to propose an algorithm capable of estimating electrical and mechanical parameters of a synchronous generator model suitable for the representation of DSGs by using measurements obtained from an unbalanced operating point. The synchronous generator model adopted in this work is based on consolidated models used in the technical literature, as for example in (ANDERSON; FOUAD, 2002), which takes into account the generator frequency to calculate the elements of the grid and the typical imbalance of distribution systems.

Before estimating the parameters of the synchronous generator model, the parameters which have the biggest impact on the responses of this model are found in this work. Note that these parameters can be more easily estimated (HISKENS; PAI, 2002). Trajectory sensitivity functions (FRANK, 1978) are highly efficient to perform this evaluation and have been used in several applications in the area of power systems, e.g. (BENCHLUCH; CHOW, 1993; HISKENS; PAI, 2000; CARI et al., 2005; TANG; MCCALLEY, 2013). Thus, these functions are employed in this work to assess the importance of the electrical and mechanical parameters for the model responses as well as to examine their observability in a specific sampling window.

After analyzing the importance and the observability of the parameters, we apply an estimation technique to a set of sampled measurements in order to obtain the values the most relevant electrical and mechanical parameters. There are several techniques used in the literature to estimate parameters of synchronous generators. Genetic algorithms (ARJONA et al., 2012; CISNEROS-GONZALEZ et al., 2013), trajectory sensitivity methods (CARI et al., 2005; CARI, 2009), particle swarm optimization (HAN; WU; MA, 2011), least square methods (KYRIAKIDES; HEYDT; VITTAL, 2004; OTEAFY; CHIASSON; AHMED-ZAID, 2016; GHAREMANI; KARRARI; MALIK, 2008) and Kalman filter based methods (HUANG; LI; YAN, 2010; AGHAMOLKI et al., 2015; VALVERDE et al., 2011) can be cited as examples. In this work, the unscented Kalman filter is employed because of its ability to deal with the nonlinear equations and its superior performance in the application to certain parameter estimation problems when compared to the extended Kalman filter (WAN; MERWE, 2000;

JULIER; UHLMANN, 2004).

Although the UKF is widely employed for online estimation of states and parameters, in the case of this work the three-phase synchronous generator model is utilized for stability, protection and power quality studies. Hence, the model is not used for real-time applications and the performance of the method in terms of time is not an issue. The focus of this work is an adequate estimation of the model parameters by only using measured generator quantities. In other words, there is no need to measure voltages and currents beyond the generator terminal bus or to have any knowledge of the grid parameters.

1.1 Objectives and Expected Contributions

Based on the importance that the DSG models will have in the future for the stability studies of EPS with a high level of DG penetration and on the difficulty of estimating parameters of models which adequately represent the behavior of DSG, we define the main contribution of this thesis:

- Estimation of parameters of a synchronous generator model adequate for the representation of a DSG inserted into an unbalanced system.

To reach this contribution, we must pursue the following objectives:

- Evaluate the influence of the parameters on the responses of a synchronous generator model suitable for unbalanced operations;
- Develop an approach which correctly estimates the main parameters of the synchronous generator model;
- Define a strategy to verify whether the parameters were correctly estimated;
- Assess the influence of imbalance and noise on the estimation approach.

1.2 Thesis Outline

This thesis is organized to present the necessary elements for the comprehension of the problem shown in this chapter. The remaining of this thesis is structured as follows:

- **Chapter 2** presents the synchronous generator model utilized in this thesis and whose parameters are estimated using the proposed approach. It also depicts details about the modeling of the synchronous generator and its voltage and speed controls.

- **Chapter 3** shows the general structure of the proposed approach employed for parameter estimation. The features and importance of Trajectory Sensitivity Functions, Unscented Kalman Filter and Genetic Algorithm employed in the estimation approach are explained in this chapter.
- **Chapter 4** makes use of the estimation approach shown in Chapter 3 to estimate the main parameters of the synchronous generator model described in Chapter 2. The results show the efficiency of the proposed approach under noisy measurements and the differences to estimate the parameters under balanced and unbalanced operating conditions.
- **Chapter 5** summarizes the thesis content and presents the main conclusions, contributions and future work resulting from this research.

Before finalizing this chapter, it is important to highlight that we decided not to gather the literature review in only one chapter, but to distribute it throughout the thesis.

Synchronous Generator Model Suitable for Unbalanced Operating Conditions

There are several mathematical models that can describe the dynamics of a SG, some of them being more simplified and others being more complex. The selection of the SG model depends on the type of study to be performed. In order to represent large-sized generation plants directly connected to transmission systems in stability studies of large-sized EPS, simplified models such as E'_q , E'' , one-axis and two-axis models (KUNDUR, 1994; ANDERSON; FOUAD, 2002) are usually adequate for phasor-based simulations. Nonetheless, on stability studies or analyses to assess the power quality of systems with distributed synchronous generation, where the loads are close to the generators, the models must take into account the voltage imbalance and the frequency due to the asymmetrical lines and unbalanced loads of distribution systems (SALIM, 2011).

The main objective of this chapter is to present a model of SG that can be used to describe the behavior of a synchronous machine when operating under unbalanced conditions. The set of equations used in this work to represent the dynamics of a SG connected to subtransmission or distribution systems is based on a consolidated model available in the technical literature, shown in (ANDERSON; FOUAD, 2002). The presentation of the set of parameters that compose the adopted SG model is another objective of this chapter.

The first section of this chapter presents Park's transformation, which is used to simplify the electrical equations of the SG model. After that, three different set of equations generally employed to model a SG are shown: flux linkage, voltage, and current equations. Then, the mechanical equations of the generator are presented. In the last section, we highlight the quantities necessary to estimate the parameters of the current formulation (the model used in this work) without further knowledge of the generator controllers, the loads, and lines of the distribution system connected to the SG. We also emphasize the importance of the synchronous torque angle to transform voltages and currents from the reference frame in which they are measured to the one used in the adopted model.

2.1 Park's Transformation

Great simplification of the equations that describe the behavior of a synchronous machine can be obtained with variable transformations. The transformation normally employed to synchronous machine models is the Park's transformation, which defines a new set of stator variables, such as currents, voltages or flux linkages in terms of the actual winding variables (ANDERSON; FOUAD, 2002).

After applying this transformation there is a change of reference frame from abc to $0dq$. The new quantities are obtained by projecting the actual variables on three axes: the first one lined up with the rotor field winding, called direct axis (d axis); a second axis perpendicular to the direct axis, known as quadrature axis (q axis); and the third one on a stationary axis. The d axis of the rotor is defined at some instant of time to be at an angle θ (in radians) with respect to a fixed position. As can be seen in Fig. 1, the axis of phase a is chosen to be the fixed reference position, preventing an angle of displacement appears between the a axis and the supposed arbitrary reference. By defining the stator phase currents i_a , i_b and i_c leaving the generator terminals, the corresponding currents in d and q axes of the rotor are:

Figure 1: A simplified representation of a synchronous machine. (Adapted from (ANDERSON; FOUAD, 2002))

$$\begin{aligned} i_d &= \frac{2}{3} \left[i_a \cos \theta + i_b \cos \left(\theta - \frac{2\pi}{3} \right) + i_c \cos \left(\theta + \frac{2\pi}{3} \right) \right] \\ i_q &= \frac{2}{3} \left[i_a \sin \theta + i_b \sin \left(\theta - \frac{2\pi}{3} \right) + i_c \sin \left(\theta + \frac{2\pi}{3} \right) \right] \end{aligned} \quad (1)$$

The main objective of Park's transformation is basically to convert all the quantities of phases a , b and c to variables that move together with the rotor. Three new quantities come from the application of this transformation to currents i_a , i_b and i_c : the d axis current (i_d), the q axis current (i_q) and a stationary current (i_0), which is proportional to the zero-sequence current. Thus by definition

$$\mathbf{i}_{0dq} = P\mathbf{i}_{abc} \quad (2)$$

where the current vectors are

$$\mathbf{i}_{0dq} = \begin{bmatrix} i_0 \\ i_d \\ i_q \end{bmatrix} \quad \mathbf{i}_{abc} = \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} \quad (3)$$

and the Park's transformation matrix is defined as

$$P = \sqrt{\frac{2}{3}} \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} & 1/\sqrt{2} \\ \cos \theta & \cos(\theta - \frac{2\pi}{3}) & \cos(\theta + \frac{2\pi}{3}) \\ \sin \theta & \sin(\theta - \frac{2\pi}{3}) & \sin(\theta + \frac{2\pi}{3}) \end{bmatrix}. \quad (4)$$

The main field-winding flux is along the direction of the d axis of the rotor. This flux produces an electromotive force that lags the field-winding flux by 90° . Hence, the electromotive force (E) is aligned with the rotor q axis. Taking into account that the machine has a constant terminal voltage V and it is operating in generator mode, the phasor $\overline{E}$ should be leading the phasor $\overline{V}$. The angle between $\overline{E}$ and $\overline{V}$ is defined as the torque angle δ of the machine if the phasor $\overline{V}$ is in the direction of the reference phase (phase a in the case of this work) (ANDERSON; FOUAD, 2002).

At the instant of time $t = 0$ the phasor $\overline{V}$ is aligned with the reference axis of the synchronous machine representation of Fig. 1, i.e, the phase a . At this instant, the q axis is located at an angle δ and the d axis is located at $\theta = \delta + \pi/2$. At $t > 0$, the reference axis is located at an angle $\omega_R t$ with respect to the axis of phase a . Therefore, the d axis of the rotor is located at

$$\theta = \omega_R t + \delta + \frac{\pi}{2} \quad (5)$$

where ω_R (in rad/s) is the synchronous angular frequency and δ (in electrical radians) is the synchronous torque angle¹.

Expressions similar to (2) may also be written for voltages or flux linkages:

$$\mathbf{v}_{0dq} = P\mathbf{v}_{abc} \quad \boldsymbol{\lambda}_{0dq} = P\boldsymbol{\lambda}_{abc} \quad (6)$$

¹The picture of Fig. 1 illustrates a two-pole machine. In this case, the electrical angle (θ_e) is equal to the mechanical angle (θ_m). When the number of poles is bigger, there is a mathematical relationship between these two quantities, given in function of the number of poles (p) of the machine, which is $\theta_e = p/2 \cdot \theta_m$

Since the matrix P is nonsingular, the inverse transformation P^{-1} also exists and, therefore:

$$\mathbf{i}_{abc} = P^{-1} \mathbf{i}_{0dq} \quad (7)$$

where

$$P^{-1} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1/\sqrt{2} & \cos \theta & \sin \theta \\ 1/\sqrt{2} & \cos(\theta - \frac{2\pi}{3}) & \sin(\theta - \frac{2\pi}{3}) \\ 1/\sqrt{2} & \cos(\theta + \frac{2\pi}{3}) & \sin(\theta + \frac{2\pi}{3}) \end{bmatrix}. \quad (8)$$

We can note that the matrix P is orthogonal, i.e., $P^{-1} = P^t$. Due to this characteristic, the transformation P is power invariant, which means the power in references abc and $0dq$ are the same, as demonstrated in (9):

$$\begin{aligned} p_{out} &= v_a i_a + v_b i_b + v_c i_c = \mathbf{v}_{abc}^t \mathbf{i}_{abc} = (P^{-1} \mathbf{v}_{0dq})^t (P^{-1} \mathbf{i}_{0dq}) \\ &= \mathbf{v}_{0dq}^t (P^{-1})^t P^{-1} \mathbf{i}_{0dq} = \mathbf{v}_{0dq}^t P P^{-1} \mathbf{i}_{0dq} = \mathbf{v}_{0dq}^t \mathbf{i}_{0dq} = v_0 i_0 + v_d i_d + v_q i_q \end{aligned} \quad (9)$$

2.1.1 Flux Linkage Equations

We can observe six mutually coupled coils from Fig. 1. Three of them are in the stator, the phase windings a - a' , b - b' and c - c' , while the other three are in the rotor, the field winding F - F' and the damper windings D - D' and Q - Q' . Because of the magnetic coupling, there exist flux linkages among them, given by:

$$\begin{bmatrix} \lambda_a \\ \lambda_b \\ \lambda_c \\ \lambda_F \\ \lambda_D \\ \lambda_Q \end{bmatrix} = \begin{bmatrix} L_{aa} & L_{ab} & L_{ac} & L_{aF} & L_{aD} & L_{aQ} \\ L_{ba} & L_{bb} & L_{bc} & L_{bF} & L_{bD} & L_{bQ} \\ L_{ca} & L_{cb} & L_{cc} & L_{cF} & L_{cD} & L_{cQ} \\ L_{Fa} & L_{Fb} & L_{Fc} & L_{FF} & L_{FD} & L_{FQ} \\ L_{Da} & L_{Db} & L_{Dc} & L_{DF} & L_{DD} & L_{DQ} \\ L_{Qa} & L_{Qb} & L_{Qc} & L_{QF} & L_{QD} & L_{QQ} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \\ i_F \\ i_D \\ i_Q \end{bmatrix} \quad [\text{Wb} \cdot \text{turns}] \quad (10)$$

where L_{jk} is the winding self-inductance when $j = k$. If $j \neq k$, then L_{jk} represents the mutual inductance between two coils. The inductance matrix is symmetric, i.e., the inductances L_{jk} are equal to L_{kj} . Note that the lowercase subscripts refer to stator quantities while the uppercase subscripts are used for rotor quantities. Most of the inductances shown in (10) are not constant. This occurs due to the variation of the magnetic permeability of the coils with respect to the rotor position angle θ (PRENTICE, 1937).

The self-inductances of the stator phase windings are given by (ANDERSON; FOUAD, 2002; KUNDUR, 1994)

$$\begin{aligned} L_{aa} &= L_s + L_m \cos 2\theta & [\text{H}] \\ L_{bb} &= L_s + L_m \cos \left[2\left(\theta - \frac{2\pi}{3}\right) \right] & [\text{H}] \\ L_{cc} &= L_s + L_m \cos \left[2\left(\theta + \frac{2\pi}{3}\right) \right] & [\text{H}] \end{aligned} \quad (11)$$

where $L_s > L_m$ and both inductances are constants. L_s is the average inductance and L_m is the amplitude of variation of the phase self-inductance. The self-inductance of a phase winding is maximum when the d axis is lined up with the magnetic axis of the phase and minimum when the q axis is in line with it.

Since saturation and slot effect are neglected, all rotor self-inductances are also constants and given by (ANDERSON; FOUAD, 2002; KUNDUR, 1994)

$$L_{FF} = L_F [\text{H}] \quad L_{DD} = L_D [\text{H}] \quad L_{QQ} = L_Q [\text{H}] \quad (12)$$

The mutual inductances between each two phases are functions of θ and symmetric (ANDERSON; FOUAD, 2002; KUNDUR, 1994):

$$\begin{aligned} L_{ab} &= L_{ba} = -M_s - L_m \cos \left[2\left(\theta + \frac{\pi}{6}\right) \right] & [\text{H}] \\ L_{bc} &= L_{cb} = -M_s - L_m \cos \left[2\left(\theta - \frac{\pi}{2}\right) \right] & [\text{H}] \\ L_{ca} &= L_{ac} = -M_s - L_m \cos \left[2\left(\theta + \frac{5\pi}{6}\right) \right] & [\text{H}] \end{aligned} \quad (13)$$

where $|M_s| > L_m$. The signs of mutual inductance terms depend upon assumed current directions and coil orientations. M_s is the average value of the mutual inductance between phases and L_m is the amplitude of pulsation of the mutual inductance. Note that the inductance L_m is the same as used in (11).

The mutual inductance between windings F and D is constant. This occurs because these windings are always lined up, independent of the rotor angle θ . The coefficient of coupling between the d and q axes is zero since they have a 90° displacement. Therefore, we have

$$\begin{aligned} L_{FD} &= L_{DF} = M_R [\text{H}] \\ L_{FQ} &= L_{QF} = 0 & [\text{H}] \\ L_{DQ} &= L_{QD} = 0 & [\text{H}] \end{aligned} \quad (14)$$

The mutual inductances between stator and rotor windings are also functions of the rotor angle θ , as shown in (15). In these expressions, the signs of the mutual terms depend upon assumed current directions and coil orientation.

$$\begin{aligned}
L_{aF} &= L_{Fa} = M_F \cos \theta & [\text{H}] \\
L_{bF} &= L_{Fb} = M_F \cos \left(\theta - \frac{2\pi}{3} \right) & [\text{H}] \\
L_{cF} &= L_{Fc} = M_F \cos \left(\theta + \frac{2\pi}{3} \right) & [\text{H}] \\
L_{aD} &= L_{Da} = M_D \cos \theta & [\text{H}] \\
L_{bD} &= L_{Db} = M_D \cos \left(\theta - \frac{2\pi}{3} \right) & [\text{H}] \\
L_{cD} &= L_{Dc} = M_D \cos \left(\theta + \frac{2\pi}{3} \right) & [\text{H}] \\
L_{aQ} &= L_{Qa} = M_Q \sin \theta & [\text{H}] \\
L_{bQ} &= L_{Qb} = M_Q \sin \left(\theta - \frac{2\pi}{3} \right) & [\text{H}] \\
L_{cQ} &= L_{Qc} = M_Q \sin \left(\theta + \frac{2\pi}{3} \right) & [\text{H}]
\end{aligned} \tag{15}$$

2.1.1.1 Transformation of inductances

From the description of the inductances in the matrix of equation (10), we note that almost all terms of this matrix are functions of the angle θ , which varies with time, as shown in (5). Only four of the elements out of the diagonal are zeros, as it can be observed in (14). That way, in voltage equations the $\dot{\lambda}$ term cannot simply be represented by $L\dot{i}$ but must be calculated as $\dot{\lambda} = L\dot{i} + \dot{L}i$.

Therefore, when the equations are in the abc frame of reference we have time-varying inductances and, as a consequence, a complex formulation. However, the application of Park's transformation to (10) eliminates these time-varying elements and the formulation becomes simpler. This transformation is applied in the following way:

$$\begin{bmatrix} P & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} \lambda_{\text{abc}} \\ \lambda_{\text{FDQ}} \end{bmatrix} = \begin{bmatrix} P & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} L_{ss} & L_{sR} \\ L_{Rs} & L_{RR} \end{bmatrix} \begin{bmatrix} P^{-1} & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} P & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} \mathbf{i}_{\text{abc}} \\ \mathbf{i}_{\text{FDQ}} \end{bmatrix} \tag{16}$$

where P is Park's transformation defined in (4), L_{ss} are stator inductances, L_{sR} and L_{Rs} are mutual inductances between stator and rotor, and L_{RR} are rotor inductances.

Simplifying (16), we obtain:

$$\begin{bmatrix} \lambda_0 \\ \lambda_d \\ \lambda_q \\ \lambda_F \\ \lambda_D \\ \lambda_Q \end{bmatrix} = \begin{bmatrix} L_0 & 0 & 0 & 0 & 0 & 0 \\ 0 & L_d & 0 & k_c M_F & k_c M_D & 0 \\ 0 & 0 & L_q & 0 & 0 & k_c M_Q \\ \hline 0 & k_c M_F & 0 & L_F & M_R & 0 \\ 0 & k_c M_D & 0 & M_R & L_D & 0 \\ 0 & 0 & k_c M_Q & 0 & 0 & L_Q \end{bmatrix} \begin{bmatrix} i_0 \\ i_d \\ i_q \\ i_F \\ i_D \\ i_Q \end{bmatrix} \quad (17)$$

where

$$\begin{aligned} L_d &= L_s + M_s + \frac{3}{2}L_m & [H] \\ L_q &= L_s + M_s - \frac{3}{2}L_m & [H] \\ L_0 &= L_s - 2M_s & [H] \end{aligned} \quad (18)$$

and $k_c = \sqrt{3/2}$.

In (17) λ_d is the flux linkage in a circuit moving with the rotor and lined up with d axis. Similarly, the flux linkage λ_q is centered on the q axis. Flux linkage λ_0 is completely uncoupled from the other circuits, since the first row and column of the matrix in (17) have only a diagonal term. It is important to highlight that all the inductances of the matrix in (17) are constants, different from the inductances in (10).

2.1.2 Voltage Equations

The voltage equations that represent a synchronous generator can be derived from Fig. 2, where the coils represent the same circuits as in Fig. 1, including coil terminations. Mutual inductances are omitted from the circuits of Fig. 2 in order to simplify the picture, however they are assumed present with the values given previously. The direction of the stator currents is flowing out of the machine terminals, since the machine is a generator. Taking into account the former conditions, we obtain the following matrix equation:

$$\begin{bmatrix} v_a \\ v_b \\ v_c \\ -v_F \\ 0 \\ 0 \end{bmatrix} = - \begin{bmatrix} r_a & 0 & 0 & 0 & 0 & 0 \\ 0 & r_b & 0 & 0 & 0 & 0 \\ 0 & 0 & r_c & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & r_F & 0 & 0 \\ 0 & 0 & 0 & 0 & r_D & 0 \\ 0 & 0 & 0 & 0 & 0 & r_Q \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \\ i_F \\ i_D \\ i_Q \end{bmatrix} - \begin{bmatrix} \dot{\lambda}_a \\ \dot{\lambda}_b \\ \dot{\lambda}_c \\ \dot{\lambda}_F \\ \dot{\lambda}_D \\ \dot{\lambda}_Q \end{bmatrix} + \begin{bmatrix} \mathbf{v}_n \\ \mathbf{0} \end{bmatrix} \quad [\text{V}] \quad (19)$$

Figure 2: Circuits of a synchronous machine. (Adapted from (ANDERSON; FOUAD, 2002))

where the neutral voltage v_n is given by

$$\mathbf{v}_n = - \begin{bmatrix} r_n & r_n & r_n \\ r_n & r_n & r_n \\ r_n & r_n & r_n \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} - \begin{bmatrix} L_n & L_n & L_n \\ L_n & L_n & L_n \\ L_n & L_n & L_n \end{bmatrix} \begin{bmatrix} \dot{i}_a \\ \dot{i}_b \\ \dot{i}_c \end{bmatrix} \quad [\text{V}] \quad (20)$$

and r_n and L_n are the neutral resistance and inductance of the generator grounding system, respectively.

Assuming the phase winding resistances are equal ($r_a = r_b = r_c = r$), as is usually the case, we define

$$\mathbf{R}_{abc} = r \mathbf{I}_3 \quad (21)$$

where $\mathbf{I}_3$ is the 3×3 unit matrix. Then, the equation (19) can be written in partitioned form as follows:

$$\begin{bmatrix} \mathbf{v}_{abc} \\ \mathbf{v}_{FDQ} \end{bmatrix} = - \begin{bmatrix} \mathbf{R}_{abc} & 0 \\ 0 & \mathbf{R}_{FDQ} \end{bmatrix} \begin{bmatrix} \mathbf{i}_{abc} \\ \mathbf{i}_{FDQ} \end{bmatrix} - \begin{bmatrix} \dot{\boldsymbol{\lambda}}_{abc} \\ \dot{\boldsymbol{\lambda}}_{FDQ} \end{bmatrix} + \begin{bmatrix} \mathbf{v}_n \\ \mathbf{0} \end{bmatrix} \quad [\text{V}] \quad (22)$$

where

$$\mathbf{v}_{FDQ} = \begin{bmatrix} -v_F \\ 0 \\ 0 \end{bmatrix} \quad \mathbf{i}_{FDQ} = \begin{bmatrix} i_F \\ i_D \\ i_Q \end{bmatrix} \quad \boldsymbol{\lambda}_{FDQ} = \begin{bmatrix} \lambda_F \\ \lambda_D \\ \lambda_Q \end{bmatrix} \quad (23)$$

Equation (22) is complex since there are time-varying coefficients in the $\dot{\lambda}$ term. Nonetheless, it is possible to eliminate these terms by applying Park's transformation to the partition of the matrix related to the stator terms. Thus both sides of (22) must be premultiplied by the matrix

$$\begin{bmatrix} P & 0 \\ 0 & I_3 \end{bmatrix}. \quad (24)$$

Applying the matrix above to the left side of (22) and making use of (6), we have

$$\begin{bmatrix} P & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} \mathbf{v}_{abc} \\ \mathbf{v}_{FDQ} \end{bmatrix} = \begin{bmatrix} \mathbf{v}_{0dq} \\ \mathbf{v}_{FDQ} \end{bmatrix} \quad (25)$$

Pre-multiplying the matrix (24) to the resistance voltage drop term in (22), we obtain

$$\begin{aligned} \begin{bmatrix} P & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} R_{abc} & 0 \\ 0 & R_{FDQ} \end{bmatrix} \begin{bmatrix} \mathbf{i}_{abc} \\ \mathbf{i}_{FDQ} \end{bmatrix} &= \begin{bmatrix} P & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} R_{abc} & 0 \\ 0 & R_{FDQ} \end{bmatrix} \begin{bmatrix} P^{-1} & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} P & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} \mathbf{i}_{abc} \\ \mathbf{i}_{FDQ} \end{bmatrix} \\ &= \begin{bmatrix} PR_{abc}P^{-1} & 0 \\ 0 & R_{FDQ} \end{bmatrix} \begin{bmatrix} \mathbf{i}_{0dq} \\ \mathbf{i}_{FDQ} \end{bmatrix} = \begin{bmatrix} R_{abc} & 0 \\ 0 & R_{FDQ} \end{bmatrix} \begin{bmatrix} \mathbf{i}_{0dq} \\ \mathbf{i}_{FDQ} \end{bmatrix} \end{aligned} \quad (26)$$

since R_{abc} is a diagonal matrix and $PR_{abc}P^{-1} = PP^{-1}R_{abc} = R_{abc}$.

The matrix (24) is also applied to the second term on the right side of (22), which is transformed as

$$\begin{bmatrix} P & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} \dot{\lambda}_{abc} \\ \dot{\lambda}_{FDQ} \end{bmatrix} = \begin{bmatrix} P\dot{\lambda}_{abc} \\ \dot{\lambda}_{FDQ} \end{bmatrix} \quad (27)$$

From (6) we know that $\lambda_{0dq} = P\lambda_{abc}$ and therefore

$$\dot{\lambda}_{0dq} = P\dot{\lambda}_{abc} + \dot{P}\lambda_{abc}$$

thus

$$P\dot{\lambda}_{abc} = \dot{\lambda}_{0dq} - \dot{P}\lambda_{abc} = \dot{\lambda}_{0dq} - \dot{P}P^{-1}\lambda_{0dq} \quad (28)$$

The term $\dot{P}P^{-1}\lambda_{0dq}$ given by (29) is the speed voltage term. We can note that the voltage given by this term depends on the speed of the machine and it is zero when the machine is at a stanstill position.

$$\dot{P}P^{-1}\lambda_{0dq} = \omega \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \lambda_0 \\ \lambda_d \\ \lambda_q \end{bmatrix} = \begin{bmatrix} 0 \\ -\omega\lambda_q \\ \omega\lambda_d \end{bmatrix} \quad (29)$$

Finally, matrix (24) is applied to the third term on the right side of (22):

$$\begin{bmatrix} P & 0 \\ 0 & I_3 \end{bmatrix} \begin{bmatrix} \mathbf{v}_n \\ \mathbf{0} \end{bmatrix} = \begin{bmatrix} P\mathbf{v}_n \\ \mathbf{0} \end{bmatrix} = \begin{bmatrix} \mathbf{n}_{0dq} \\ \mathbf{0} \end{bmatrix} \quad [\text{V}] \quad (30)$$

where by definition $\mathbf{n}_{0dq}$ is the drop voltage from neutral to ground in the $0dq$ frame of reference. By using (20) we obtain (31), which demonstrates that the voltage drop occurs only in the zero sequence.

$$\begin{aligned} \mathbf{n}_{0dq} &= P\mathbf{v}_n = -PR_nP^{-1}P\mathbf{i}_{abc} - PL_nP^{-1}P\dot{\mathbf{i}}_{abc} \\ &= -PR_nP^{-1}\mathbf{i}_{0dq} - PL_nP^{-1}\dot{\mathbf{i}}_{0dq} = - \begin{bmatrix} 3r_n i_0 \\ 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 3L_n \dot{i}_0 \\ 0 \\ 0 \end{bmatrix} \quad [\text{V}] \end{aligned} \quad (31)$$

The substitution of (25)-(28) and (30) into (22) leads to

$$\begin{bmatrix} v_{0dq} \\ \mathbf{v}_{FDQ} \end{bmatrix} = - \begin{bmatrix} R_{abc} & 0 \\ 0 & R_{FDQ} \end{bmatrix} \begin{bmatrix} \mathbf{i}_{0dq} \\ \mathbf{i}_{FDQ} \end{bmatrix} - \begin{bmatrix} \dot{\lambda}_{0dq} \\ \dot{\lambda}_{FDQ} \end{bmatrix} + \begin{bmatrix} \dot{P}P^{-1}\lambda_{0dq} \\ \mathbf{0} \end{bmatrix} + \begin{bmatrix} \mathbf{n}_{0dq} \\ \mathbf{0} \end{bmatrix} \quad [\text{V}] \quad (32)$$

All the terms in (32) are known. By writing this equation in a detailed way, we have the final voltage equations:

$$\begin{bmatrix} v_0 \\ v_d \\ v_q \\ v_F \\ v_D \\ v_Q \end{bmatrix} = - \begin{bmatrix} r & 0 & 0 & 0 & 0 & 0 \\ 0 & r & 0 & 0 & 0 & 0 \\ 0 & 0 & r & 0 & 0 & 0 \\ 0 & 0 & 0 & r_F & 0 & 0 \\ 0 & 0 & 0 & 0 & r_D & 0 \\ 0 & 0 & 0 & 0 & 0 & r_Q \end{bmatrix} \begin{bmatrix} i_0 \\ i_d \\ i_q \\ i_F \\ i_D \\ i_Q \end{bmatrix} - \begin{bmatrix} \dot{\lambda}_0 \\ \dot{\lambda}_d \\ \dot{\lambda}_q \\ \dot{\lambda}_F \\ \dot{\lambda}_D \\ \dot{\lambda}_Q \end{bmatrix} + \begin{bmatrix} 0 \\ -\omega\lambda_q \\ \omega\lambda_d \\ 0 \\ 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 3r_n i_0 + 3L_n \dot{i}_0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad [\text{V}] \quad (33)$$

2.1.3 Current Equations

In order to obtain a model where the currents are the state variables, we must replace the terms λ_{0dq} , $\dot{\lambda}_{0dq}$ and $\dot{\lambda}_{FDQ}$ in (32). For this purpose, consider (17) rearranged in the following partitioned form:

$$\begin{bmatrix} \lambda_{0dq} \\ \lambda_{FDQ} \end{bmatrix} = \begin{bmatrix} L_{0dq} & L_M \\ L_M^t & L_{FDQ} \end{bmatrix} \begin{bmatrix} i_{0dq} \\ i_{FDQ} \end{bmatrix} \quad [\text{Wb} \cdot \text{turns}] \quad (34)$$

where L_M^t is the transpose of L_M . Since the inductance matrix is constant, we may write $\dot{\lambda} = L\dot{i}$. Substituting this expression into (32) and rearranging the equation, we have

$$\begin{bmatrix} v_0 \\ v_d \\ -v_F \\ v_D = 0 \\ v_q \\ v_Q = 0 \end{bmatrix} = - \begin{bmatrix} r + 3r_n & 0 & 0 & 0 & 0 & 0 \\ 0 & r & 0 & 0 & \omega L_q & \omega k_c M_Q \\ 0 & 0 & r_F & 0 & 0 & 0 \\ 0 & 0 & 0 & r_D & 0 & 0 \\ 0 & -\omega L_d & -\omega k_c M_F & -\omega k_c M_D & r & 0 \\ 0 & 0 & 0 & 0 & 0 & r_Q \end{bmatrix} \begin{bmatrix} \dot{i}_0 \\ \dot{i}_d \\ \dot{i}_F \\ \dot{i}_D \\ \dot{i}_q \\ \dot{i}_Q \end{bmatrix} - \begin{bmatrix} L_0 + 3L_n & 0 & 0 & 0 & 0 & 0 \\ 0 & L_d & k_c M_F & k_c M_D & 0 & 0 \\ 0 & k_c M_F & L_F & M_R & 0 & 0 \\ 0 & k_c M_D & M_R & L_D & 0 & 0 \\ 0 & 0 & 0 & 0 & L_q & k_c M_Q \\ 0 & 0 & 0 & 0 & k_c M_Q & L_Q \end{bmatrix} \begin{bmatrix} \dot{i}_0 \\ \dot{i}_d \\ \dot{i}_F \\ \dot{i}_D \\ \dot{i}_q \\ \dot{i}_Q \end{bmatrix} \quad [V] \quad (35)$$

Placing the current derivatives of (35) into the right side of the equation, we obtain

$$\begin{bmatrix} \dot{i}_0 \\ \dot{i}_d \\ \dot{i}_F \\ \dot{i}_D \\ \dot{i}_q \\ \dot{i}_Q \end{bmatrix} = -A' \begin{bmatrix} r + 3r_n & 0 & 0 & 0 & 0 & 0 \\ 0 & r & 0 & 0 & \omega L_q & \omega k_c M_Q \\ 0 & 0 & r_F & 0 & 0 & 0 \\ 0 & 0 & 0 & r_D & 0 & 0 \\ 0 & -\omega L_d & -\omega k_c M_F & -\omega k_c M_D & r & 0 \\ 0 & 0 & 0 & 0 & 0 & r_Q \end{bmatrix} \begin{bmatrix} \dot{i}_0 \\ \dot{i}_d \\ \dot{i}_F \\ \dot{i}_D \\ \dot{i}_q \\ \dot{i}_Q \end{bmatrix} - A' \begin{bmatrix} v_0 \\ v_d \\ -v_F \\ 0 \\ v_q \\ 0 \end{bmatrix} \quad (36)$$

where

$$A' = \begin{bmatrix} L_0 + 3L_n & 0 & 0 & 0 & 0 & 0 \\ 0 & L_d & k_c M_F & k_c M_D & 0 & 0 \\ 0 & k_c M_F & L_F & M_R & 0 & 0 \\ 0 & k_c M_D & M_R & L_D & 0 & 0 \\ 0 & 0 & 0 & 0 & L_q & k_c M_Q \\ 0 & 0 & 0 & 0 & k_c M_Q & L_Q \end{bmatrix}^{-1} \quad (37)$$

We can note from (36) that the currents are the state variables and the voltages v_0 , v_d , v_F and v_q are the model inputs. This formulation has the advantage of offering simple relations between the voltages v_0 , v_d and v_q and the state variables. The stationary voltage v_0 only depends upon the stationary current i_0 and its derivative $\dot{i}_0$. Thus the first line of (36) can be solved independently since the initial condition for i_0 is available.

All the terms in the coefficient matrix are constants, except those where the speed ω is present. Since we can not assume that the generator speed is constant when it is connected to distribution systems, the equation (36) is nonlinear. The model described in (36) together with the mechanical equations of the synchronous machine shown in the sequence describe the behavior of synchronous generators connected to distribution systems.

2.1.4 Swing Equation

The swing equation, which is based on Newton's second law for the circular movement, governs the motion of the machine rotor relating the inertia torque to the resultant of the mechanical and electrical torques on the rotor, as follows (ANDERSON; FOUAD, 2002)

$$J_M \ddot{\theta} = T_a \quad (38)$$

where J_M is the moment of inertia (in $kg \cdot m^2$) of all rotating masses attached to the shaft, θ is the mechanical angle of the shaft (in rad) with respect to a fixed reference, and T_a is the resulting accelerating torque (in $N \cdot m$) on the shaft. The focus of this work is to handle the machine as a generator and, hence, the mechanical torque T_m is the driving torque produced by the primary machine (generally a thermal or hydraulic machine) and the electrical torque T_e is the retarding or load torque. Therefore a positive T_m accelerates the shaft, whereas a positive T_e is a decelerating torque. Thus we have

$$T_a = T_m - T_e \quad [N \cdot m] \quad (39)$$

The angular reference moves with the same angular speed ω_R of the machine, i.e.,

$$\theta = \omega_R t + \alpha_m + \delta_m \quad [rad] \quad (40)$$

where α_m is a constant angle necessary if δ_m is measured from an axis different from the angular reference frame, as explained in section 2.1. For instance, we have $\alpha_m = \pi/2$ in Fig. 1 and, as a consequence, $\theta = \omega_R t + \pi/2 + \delta_m$. From (40), we can note that $\ddot{\theta} = \ddot{\delta}_m$ and then

$$J_M \ddot{\delta}_m = J_M \dot{\omega}_m = T_m - T_e \quad (41)$$

where ω_m is the shaft angular velocity (in rad/s).

Taking into account the network connected to the machine, it is more useful to write (41) in terms of an electrical angle that can be conveniently related to the position of the rotor. This is the torque angle δ , which is the angle between the field magnetomotive force and the resultant magnetomotive force in the air gap, both rotating at synchronous speed. It is also the electrical angle between the generated electromotive force and the resultant stator voltage phasors (ANDERSON; FOUAD, 2002).

The torque angle δ , which is the same as the electrical angle δ_e , is related to the rotor mechanical angle δ_m by

$$\delta = \delta_e = \frac{p}{2}\delta_m \quad (42)$$

where p is the number of poles of the machine. For simplicity, from this point on, the electrical angle is just represented as δ . From (42), we may also define the angular velocity of the revolving magnetic field as

$$\omega_e = \dot{\delta}_e = \frac{p}{2}\dot{\delta}_m = \frac{p}{2}\omega_m \quad (43)$$

From (41) and (43) we have

$$\frac{2J_M}{p}\dot{\omega}_e = T_m - T_e \quad (44)$$

which relates the machine accelerating torque to the angular velocity of the revolving magnetic field ω_e ². In practice, there is a fundamental difficulty to utilize (44), since the moment of inertia J_M is not a parameter commonly provided by the manufacturers. In general, the manufacturers of synchronous machines provide the inertia constant H (in s). This constant is defined as the kinetic energy W_k (in Joules) stored in the rotor when it rotates with angular speed ω_{mR} divided by the rated three-phase power S_B of the machine, i.e.,

$$H = \frac{W_k}{S_B} = \frac{J_M\omega_{mR}^2}{2S_B} \quad (45)$$

where ω_{mR} is the rotor angular speed when the revolving magnetic field rotates with synchronous speed ω_R , i.e.,

$$\omega_{mR} = \frac{2}{p}\omega_R \quad (46)$$

From (44), (45) and (46), we have the swing equation considering the parameter H :

$$\frac{pHS_B}{\omega_R^2}\dot{\omega} = T_m - T_e \quad (47)$$

In this work, we assume a synchronous machine with two poles ($p = 2$) in order to simplify the model equations³. That way, the above equation becomes:

$$\frac{2HS_B}{\omega_R^2}\dot{\omega} = T_m - T_e \quad (48)$$

²For simplicity, from this point on, the angular velocity of the revolving magnetic field ω_e is simply represented by ω .

³This simplification does not cause loss of generality of the model and does not reduce the complexity in the estimation of synchronous machine parameters.

For a detailed representation of (48), it is necessary to define the electrical torque T_e . To do that, consider the total output three-phase electrical power p_{out} of a synchronous machine, which according to (9) is given by

$$p_{out} = v_a i_a + v_b i_b + v_c i_c = v_d i_d + v_q i_q + v_0 i_0 \quad [\text{V} \cdot \text{A}] \quad (49)$$

Substituting v_d , v_q and v_0 in (49) by the equations in (33), we obtain

$$p_{out} = -r(i_d^2 + i_q^2 + i_0^2) - (\dot{\lambda}_d i_d + \dot{\lambda}_q i_q + \dot{\lambda}_0 i_0) + \omega(\lambda_d i_q - \lambda_q i_d) - 3r_n i_0^2 - 3L_n \dot{i}_0 i_0 \quad (50)$$

The only term in (50) that contributes to the electrical torque T_e is $\omega(\lambda_d i_q - \lambda_q i_d)$, which is the power transferred across the air gap (ANDERSON; FOUAD, 2002). Considering that the flux linkages are functions of the currents, as previously shown in (17):

$$\lambda_d = L_d i_d + k_c M_F i_F + k_c M_D i_D \quad [\text{V} \cdot \text{s}] \quad \lambda_q = L_q i_q + k_c M_Q i_Q \quad [\text{V} \cdot \text{s}]$$

we obtain the portion of the generator electrical power P_{T_e} that actually contributes to the electrical torque

$$P_{T_e} = (L_d i_q i_d + k_c M_F i_q i_F + k_c M_D i_q i_D - L_q i_d i_q - k_c M_Q i_d i_Q) \omega \quad [\text{V} \cdot \text{A}] \quad (51)$$

Knowing that the electrical torque can be written as

$$T_e = \frac{P_{T_e}}{\omega_m} \quad (52)$$

and having in mind that $p = 2$, in other words, $\omega_m = \omega$, we have

$$T_e = L_d i_q i_d + k_c M_F i_q i_F + k_c M_D i_q i_D - L_q i_d i_q - k_c M_Q i_d i_Q \quad (53)$$

Consequently, we obtain the following swing equation:

$$\dot{\omega} = \frac{\omega_R^2}{2HS_B} (T_m - L_d i_q i_d - k_c M_F i_q i_F - k_c M_D i_q i_D + L_q i_d i_q + k_c M_Q i_d i_Q) \quad (54)$$

Considering the viscous friction in the machine, it is desirable to insert an additional term in (54):

$$T_d = D\omega_m \quad (55)$$

where T_d (in $N \cdot m$) is the torque due to viscous friction and D (in $N \cdot m \cdot s$) is a damping constant.

Recalling that $\omega_m = \omega$, we have a final expression for the swing equation:

$$\dot{\omega} = \frac{\omega_R^2}{2HS_B} (T_m - L_d i_q i_d - k_c M_F i_q i_F - k_c M_D i_q i_D + L_q i_d i_q + k_c M_Q i_d i_Q - D\omega) \quad (56)$$

After obtaining an equation for the electrical speed variation of the machine, we may also write an equation for the electrical angle variation. From (40) and recalling that $\delta = \delta_m$, we have

$$\dot{\delta} = \omega - \omega_R \quad (57)$$

In the next section, we use (56) and (57) and the current formulation presented in section 2.1.3 to obtain a state-space model for the synchronous machine.

2.2 Synchronous generator model used in this work

From (36), (56) and (57), it is possible to obtain an eighth-order model to describe the behavior of a DSG, as follows

$$\begin{bmatrix} \dot{i}_0 \\ \dot{i}_d \\ \dot{i}_F \\ \dot{i}_D \\ \dot{i}_q \\ \dot{i}_Q \end{bmatrix} = -A' \begin{bmatrix} r + 3r_n & 0 & 0 & 0 & 0 & 0 \\ 0 & r & 0 & 0 & \omega L_q & \omega k_c M_Q \\ 0 & 0 & r_F & 0 & 0 & 0 \\ 0 & 0 & 0 & r_D & 0 & 0 \\ 0 & -\omega L_d & -\omega k_c M_F & -\omega k_c M_D & r & 0 \\ 0 & 0 & 0 & 0 & 0 & r_Q \end{bmatrix} \begin{bmatrix} i_0 \\ i_d \\ i_F \\ i_D \\ i_q \\ i_Q \end{bmatrix} - A' \begin{bmatrix} v_0 \\ v_d \\ -v_F \\ 0 \\ v_q \\ 0 \end{bmatrix}$$

$$\dot{\delta} = \omega - \omega_R$$

$$\dot{\omega} = \frac{\omega_R^2}{2HS_B} (T_m - L_d \dot{i}_q i_d - k_c M_F \dot{i}_q i_F - k_c M_D \dot{i}_q i_D + L_q \dot{i}_d i_q + k_c M_Q \dot{i}_d i_Q - D\omega) \quad (58)$$

In the set of differential equations above, we can note that the state variables are the currents i_0 , i_d , i_F , i_D , i_q , i_Q , the torque angle δ and the rotor speed ω . The inputs of the model are the voltages v_0 , v_d , v_q , v_F and the mechanical torque T_m applied to the synchronous machine shaft. In cases where the generator has voltage and speed controllers, the inputs v_F and T_m are substituted for the respective outputs of these controllers. Furthermore, simplifications can be applied to the model shown in (58) as for instance neglecting the damper windings.

Ignoring the damper windings D and Q in the synchronous generator model does not significantly impact the stability studies. However, these windings must be considered in protection studies, where the subtransient period is important. In stability studies, the subtransient period has little relevance when compared to the transient period (KUNDUR, 1994). For that reason, and also to facilitate the parameter estimation, these windings are not considered in this work⁴ and the differential equations shown in (59) are used to

⁴Parameters M_D and M_Q are not present in the model when the damper windings are neglected. In addition, reducing the order of the model implies a better efficiency of the estimation methods.

represent DSGs.

$$\begin{bmatrix} \dot{i}_0 \\ \dot{i}_d \\ \dot{i}_F \\ \dot{i}_q \end{bmatrix} = - \begin{bmatrix} \frac{r+3r_n}{L_0+3L_n} & 0 & 0 & 0 \\ 0 & \frac{rL_F}{L_dL_F-k_c^2M_F^2} & -\frac{k_cr_FM_F}{L_dL_F-k_c^2M_F^2} & \frac{\omega L_qL_F}{L_dL_F-k_c^2M_F^2} \\ 0 & -\frac{k_cr_FM_F}{L_dL_F-k_c^2M_F^2} & \frac{r_FL_d}{L_dL_F-k_c^2M_F^2} & -\frac{k_c\omega L_qM_F}{L_dL_F-k_c^2M_F^2} \\ 0 & -\frac{\omega L_d}{L_q} & -\frac{k_c\omega M_F}{L_q} & \frac{r}{L_q} \end{bmatrix} \begin{bmatrix} i_0 \\ i_d \\ i_F \\ i_q \end{bmatrix} - \begin{bmatrix} \frac{1}{L_0+3L_n} & 0 & 0 & 0 \\ 0 & \frac{L_F}{L_dL_F-k_c^2M_F^2} & -\frac{k_cM_F}{L_dL_F-k_c^2M_F^2} & 0 \\ 0 & -\frac{k_cM_F}{L_dL_F-k_c^2M_F^2} & \frac{L_d}{L_dL_F-k_c^2M_F^2} & 0 \\ 0 & 0 & 0 & \frac{1}{L_q} \end{bmatrix} \begin{bmatrix} v_0 \\ v_d \\ -v_F \\ v_q \end{bmatrix} \quad (59)$$

$$\dot{\delta} = \omega - \omega_R$$

$$\dot{\omega} = \frac{\omega_R^2}{2HS_B} (T_m - L_d i_q i_d - k_c M_F i_q i_F + L_q i_d i_q - D\omega)$$

Rearranging (59) and focusing on the coefficients of the state variables, we obtain

$$\dot{i}_d = a_{11}i_d + a_{12}i_F + a_{13}\omega i_q + b_{11}v_d + b_{12}v_F \quad (60)$$

$$\dot{i}_F = a_{21}i_d + a_{22}i_F + a_{23}\omega i_q + b_{21}v_d + b_{22}v_F \quad (61)$$

$$\dot{i}_q = a_{31}\omega i_d + a_{32}\omega i_F + a_{33}i_q + b_{33}v_q \quad (62)$$

$$\dot{i}_0 = a_{41}i_0 + b_{41}v_0 \quad (63)$$

$$\dot{\delta} = \omega - \omega_R \quad (64)$$

$$\dot{\omega} = \frac{\omega_R^2}{2HS_B} (T_m + a_{61}i_d i_q + a_{62}i_F i_q - D\omega) \quad (65)$$

where the coefficients are given by

$$a_{11} = -\frac{rL_F}{L_dL_F - k_c^2M_F^2} \quad a_{12} = \frac{k_cr_FM_F}{L_dL_F - k_c^2M_F^2} \quad a_{13} = -\frac{L_qL_F}{L_dL_F - k_c^2M_F^2} \quad (66)$$

$$a_{21} = \frac{k_cr_FM_F}{L_dL_F - k_c^2M_F^2} \quad a_{22} = -\frac{r_FL_d}{L_dL_F - k_c^2M_F^2} \quad a_{23} = \frac{k_cL_qM_F}{L_dL_F - k_c^2M_F^2} \quad (67)$$

$$a_{31} = \frac{L_d}{L_q} \quad a_{32} = \frac{k_cM_F}{L_q} \quad a_{33} = -\frac{r}{L_q} \quad (68)$$

$$a_{41} = -\frac{r+3r_n}{L_0+3L_n} \quad a_{61} = L_q - L_d \quad a_{62} = -k_cM_F \quad (69)$$

$$b_{11} = -\frac{L_F}{L_dL_F - k_c^2M_F^2} \quad b_{12} = -\frac{k_cM_F}{L_dL_F - k_c^2M_F^2} \quad b_{21} = \frac{k_cM_F}{L_dL_F - k_c^2M_F^2} \quad (70)$$

$$b_{22} = \frac{L_d}{L_dL_F - k_c^2M_F^2} \quad b_{33} = -\frac{1}{L_q} \quad b_{41} = -\frac{1}{L_0+3L_n} \quad (71)$$

We may note from (60)-(65) and (66)-(71) that the parameters present in the synchronous generator model are:

- r : armature resistance;
- r_F : field resistance;
- L_F : field self-inductance;
- L_d : d -axis self-inductance;
- L_q : q -axis self-inductance;
- L_0 : zero-sequence self-inductance;
- H : inertia constant;
- D : damping constant;
- r_n : neutral resistance;
- L_n : neutral inductance;
- M_F : maximum mutual inductance between the field winding and the winding of each one of the stator phases;
- ω_R : rated synchronous speed of the generator;
- S_B : rated three-phase power of the generator.

The generator datasheet generally indicates the values of the parameters ω_R and S_B , which are defined by the manufacturer and whose values do not change with machine operation. The parameter M_F is defined according to

$$M_F = \frac{V_B}{k_c \cdot \omega_R \cdot I_{agline}} \quad (72)$$

where V_B is the rated line voltage of generator stator and I_{agline} is the field current for 1 p.u. armature voltage. Since V_B and I_{agline} are also provided by the generator manufacturer, the parameter can be easily obtained. Thus the values of the parameters ω_R , S_B and M_F are known and it is not necessary to estimate them. Although the parameters r_n and L_n are present in the synchronous generator model, it is important to highlight that they are part of the generator grounding system and their values depend on the type of adopted grounding strategy (IEEE, 2001). Since these parameters are related to static components and are generally provided in the generator grounding design, we assume that their values are usually known and do not change during the time.

In order to estimate the other parameters of the model, it is necessary to obtain some measurements to decouple the synchronous generator model from its controllers and the grid. Fig. 3 highlights in red the set of measurements that makes it possible to estimate the SG parameters without any knowledge of the terminal load, the parameters of the

grid and controllers. The terminal voltage V_t is calculated from the voltages v_a , v_b and v_c . The voltage E_{FD} is not part of the SG model represented by (60)-(65), however we can calculate v_F by using the following equation (ANDERSON; FOUAD, 2002):

$$v_F = \frac{r_F}{M_F} \frac{E_{FD}}{\omega} \quad (73)$$

Furthermore, the mechanical torque T_m in (65) is not the output of the speed control, since the output provided by this controller is generally the mechanical power P_m . However, we may obtain the mechanical torque T_m from the following relation:

$$T_m = \frac{P_m}{\omega} \quad (74)$$

Figure 3: Necessary measurements to decoupled the SG model.

The field current i_F is not necessary to decouple the SG model. However, we can assume that this current is available since it can be measured without significant additional difficulties. This quantity is important because it provides significant information to estimate the field resistance and inductance and also the other parameters, given that it is present in (60)-(62) and (65).

As can be seen in Fig. 3, the output of the speed control (P_v) is a quantity that regulates the position of the turbine valve (KUNDUR, 1994; ANDERSON; FOUAD, 2002). In this work, we neglect the dynamics of the turbine since it is slow when compared to dynamics of terminal currents and voltages of the SG. Therefore, assuming that the static gain of the turbine is known, it is possible to obtain the mechanical power provided by the turbine to the shaft of the generator through the value of the quantity P_v .

Examining (60)-(65), we can see that the voltages and currents of this model are in $0dq$ frame of reference. In practice, however, these three-phase quantities are measured in abc frame of reference. The transformation of voltages and currents from abc to $0dq$ reference frame can be done by using (2) and (6). Nevertheless, the application of Park's transformation requires the rotor angle θ , which depends on the torque angle δ , as can be seen from (5). To estimate the torque angle, the angular speed ω must be available. Since this quantity is difficult to measure (KUNDUR et al., 2003), the torque angle cannot be

precisely estimated from the angular speed and, consequently, this imprecision is reflected on the rotor angle θ . Having this in mind, in this work we estimate the torque angle δ without measuring or estimating the angular speed to overcome the mentioned difficulty.

2.3 Final Remarks

This chapter presents the theoretical background necessary for understanding the SG model adopted in this work. Besides, we also exhibit the measurements required to decouple this model from its controllers and the grid and the importance of the synchronous torque angle. We must highlight that even without measuring or estimating the SG angular speed, the torque angle and electrical and mechanical parameters can be estimated by the procedures proposed in this work.

Proposed Approach for Parameter Estimation

After defining the model of synchronous generator employed in this work, we propose an approach to estimate its parameters. Having this in mind, we present in the first section of this chapter a general mathematical formulation for the problem of estimating the parameters of the SG model shown in the previous chapter, pointing out some difficulties in it related to nonlinear optimization. The schematics of the approach utilized to estimate the model parameters are exhibited after the first section, in order to present a general idea of the importance of the Trajectory Sensitivity Functions (TSF), UKF and Genetic Algorithm (GA) for the estimation process. A short description of each stage of the proposed approach is also presented in this section.

Since the TSF are important to identify the parameters which can be estimated and the ones which do not significantly impact the model response (thus being difficult to be estimated from it), there is a section specially dedicated to explaining their formulation and application in this work. The UKF is the central part of the estimation approach and, therefore, we explain in this chapter how this method works and the importance of some elements of this filter in the estimation process, such as the covariance matrices, for example. After showing the mathematical formulation of the UKF, a brief introduction to GAs is presented in this chapter to better understand its use to determine the initial values of the UKF parameters. Once the theories of TSF, UKF and GA are introduced, it is possible to describe the proposed estimation approach in detail, including the process of analysis of the results and validation of the obtained model.

This chapter also addresses the differences between the operation of the synchronous generator under balanced and unbalanced conditions, focusing on the differences between the SG responses in each case. The main objective of presenting these differences is to show the increase in complexity when the parameters are estimated by using measurements obtained from an unbalanced operation, which may lead to the estimation of a smaller number of parameters.

3.1 General Mathematical Formulation

In Chapter 2 we present the nonlinear model which is used in this work to describe the behavior of a DSG. This section focuses on presenting a general mathematical formulation that explains how optimization methods obtain the estimation of parameters of nonlinear models, which include the SG model studied in this thesis.

The nonlinear model presented in (62)-(65) has n_s state variables, n_i inputs and n_o outputs, which are used to estimate the value of n_p parameters of this model. Thus, let $\mathbf{p} \in \mathbb{R}^{n_p}$ be the vector of parameters of the model, $\mathbf{x} \in \mathbb{R}^{n_s}$ be the state variable vector, $\mathbf{u} \in \mathbb{R}^{n_i}$ be the input vector and $\mathbf{y} \in \mathbb{R}^{n_o}$ be the output vector of the model. Also, let $\mathbf{f} : \mathbb{R}^{n_s} \times \mathbb{R}^{n_i} \times \mathbb{R}^{n_p} \rightarrow \mathbb{R}^{n_s}$ and $\mathbf{h} : \mathbb{R}^{n_s} \times \mathbb{R}^{n_p} \rightarrow \mathbb{R}^{n_o}$ be the vector functions of the system and of the measured outputs, respectively. Therefore, we have

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}, \mathbf{p}) \quad (75)$$

$$\mathbf{y} = \mathbf{h}(\mathbf{x}, \mathbf{p}) \quad (76)$$

Let $\mathbf{y}_m \in \mathbb{R}^{n_o}$ be the vector of measurements obtained from the real system. Then, we can define the functional

$$J(\mathbf{p}) = \int_{t_0}^{t_f} [\mathbf{y}(t) - \mathbf{y}_m(t)]^T \cdot [\mathbf{y}(t) - \mathbf{y}_m(t)] dt. \quad (77)$$

That way, the process of estimating the parameters of the nonlinear model consists in finding a vector of parameters $\mathbf{p}^*$ such that

$$\mathbf{p}^* = \arg \min J(\mathbf{p}). \quad (78)$$

It is important to highlight that since the model is nonlinear, there are several local minimum points that can be found by estimation methods. However, some of these points are not in a feasible region from the physical point of view and cannot be used as parameters of the model. Hence, the main objective of this work is to propose an estimation process that can find local minima belonging to a feasible region, i.e., a vector of parameters that physically makes sense and produces a SG model whose responses are compatible with the ones obtained from the real system.

In the course of this thesis, with the presentation of the estimation approach, we verify that the correct estimation of the SG model parameters depends on the right selection of some parameters of the estimation method.

3.2 Schematics of the Proposed Approach

In this section, we briefly explain the steps of the proposed approach. That way, the main goals of each stage are highlighted in the next subsections to facilitate the comprehension of the estimation approach. As a whole, the five main steps of the approach are exhibited in the schematics of Fig. 4, where we can note in which part each method is applied.

Figure 4: Schematics of the proposed approach

Basically, the main tool of the approach is the UKF, which is responsible for the parameter estimation. Since the UKF composes the core of the approach, some parameters of this filter significantly interfere in the estimation process. For this reason, we make use of a GA to set some important parameters of the UKF and, consequently, to obtain better estimates. Although UKF is very effective to estimate parameters of nonlinear models, there are some parameters whose estimation is not simple since they almost do not affect the outputs of the model. Having this in mind, we apply the TSF to analyze the influence of the parameters in the SG model and to select the ones which really need to have their values estimated.

Because of the importance of UKF, GA and TSF, we separately explain these tools in the next sections. In this section, we just present an overview of the proposed approach. Section 3.6 shows a detailed description of the estimation approach.

3.2.1 Analysis of the influence of the parameters in the model

This step of the approach is important to identify the parameters that have significant influence on the outputs of the SG model. The variation in the value of some parameters almost do not change the outputs of the model and, therefore, these parameters are not so significant for the model. However, others are very important since small variations in their values can substantially impact the outputs of the model.

Consider the vector of outputs $\mathbf{y}$ in (76) and the vector of parameters $\mathbf{p}$ of the model. The TSF of $\mathbf{y}$ with respect to p_i , which is i -th element of $\mathbf{p}$, depends on the following

partial derivative (FRANK, 1978):

$$\left. \frac{\partial \mathbf{y}}{\partial p_i} \right|_{\mathbf{p}_{ref}} \quad (79)$$

where $\mathbf{p}_{ref}$ corresponds to the reference value of the vector $\mathbf{p}$. The partial derivative in (79) is the basis for the calculation of the TSF, which is fundamental for the assessment of the parameter influence on the responses of the SG model. Analyzing the variation of the outputs provided by TSF, it is possible to order the most important parameters of the model, as will be shown in Section 3.3.

3.2.2 Selection of the parameters for estimation

This stage of the proposed approach is important to select the parameters whose estimation is possible since estimating all the parameters of the model is very difficult. This difficulty is due to few outputs provided to the estimation method when compared to the number of parameters to be estimated. Thus, the classification of the most important parameters of the model, which can be more easily estimated, is possible by using a quadratic functional based on the TSF.

The order of importance of the parameters depends on the type of disturbance applied to the system, on the operational conditions, and also on the values of the parameters themselves. However, some parameters present high values for the proposed quadratic functional in most situations, which indicates that they are important for the model. Therefore, the main goal of this step is to identify and to select the most important parameters for their subsequent estimation.

3.2.3 Parameter estimation from a set of measurements

In this step, we apply the methods for parameter estimation itself to obtain a set of parameter values that minimize the functional in (77). The main method of this stage is the UKF, which is applied to a sampling window usually containing a disturbance. The UKF is applied in this work since it has a good performance when employed in nonlinear models. As shown in Fig. 5, this filter has three main stages: calculation of sigma points, prediction stage and correction stage.

Assuming that we know the value of the state vector $\mathbf{x}$ at the instant $k - 1$, the UKF estimates the value of this vector at the instant k . However, this estimation depends on the matrices $\mathbf{P}$, $\mathbf{Q}$ and $\mathbf{R}$, which are the error, process, and measurement covariance matrices, respectively. Fig. 5 shows that the vector of measurements $\mathbf{y}_m$ and the covariance matrix $\mathbf{R}$ are used in the correction stage, which calculates the value of the state vector $\mathbf{x}$. Besides updating $\mathbf{x}$, the correction stage also calculates a new error covariance matrix

P that is used in the next iteration. Section 3.4 explains better the importance of the covariance matrices and the operation of each stage of the UKF.

Despite its desirable performance when applied to nonlinear systems, the UKF depends on the tuning of some covariance matrices (SCARDUA; CRUZ, 2016). Therefore, an auxiliary method is necessary to define these covariance matrices. In this work, we apply a GA to obtain a set of matrices that produce acceptable estimation for the parameters. Section 3.5 presents more details about this genetic algorithm.

Figure 5: Main stages of the UKF

3.2.4 Analysis of the results

Once the UKF obtains a set of parameter values, it is necessary to verify whether the resulting SG model produces satisfactory responses when compared to the measurements of the real system. In this work, we utilize the functional in (77) to assess the quality of the estimated parameters, although there are other functions which can also be used for that purpose.

It is important to stress out that at this stage we only use the measurements employed as outputs of the UKF to analyze the estimated parameters. This is done to facilitate the procedure since the assessment of the obtained model for several events would be a cumbersome process.

3.2.5 Validation of the obtained model

This stage consists of assessing the SG model obtained with the best set of estimated parameters. Different from the previous step, where we only utilize a sampling window, several sampling windows can be employed to assess the final SG model. In order to validate the model, its responses must be satisfactorily close to the measured signals obtained from the real system. It is important to remark that the sampling windows used in this step must contain the responses to different events so that the SG model can be considered validated.

3.3 Trajectory Sensitivity Functions (TSF)

Trajectory sensitivity is a powerful technique utilized for analysis of dynamic behavior of power systems (TANG; MCCALLEY, 2013). This method linearizes the trajectory of a system to complement time domain simulation in the analysis of the responses to large disturbance (HISKENS; PAI, 2002). By using this technique, it is possible to obtain relevant information about the influence of the parameters in the dynamics of the model. Besides, properties which are not easily observed in time domain responses become evident through sensitivity analysis (HISKENS; PAI, 2000).

According to Tang and McCalley (2013), the applications of trajectory sensitivity technique to EPS began in the 1980s and, since then, trajectory sensitivities have been widely explored and applied to them for a variety of purposes, including system monitoring, security assessment, control design, and planning. Within the context of refinement and validation of models, divergences between measured data and the responses of a simulated model are common (FERNANDES, 2017). In order to diminish these differences, some parameters of the model must have their values modified. However, choosing the parameters to be changed is normally a difficult task (HISKENS, 2001).

The different applications of trajectory sensitivity technique are justified by the large amount of information about the dynamic behavior of a system which can be obtained from its utilization. In this work, the trajectory sensitivity functions are employed to assist the estimation of electrical and mechanical parameters of the DSG model presented in the previous chapter. Knowing these parameters is fundamental to a correct assessment of the stability of a DG system.

The trajectory sensitivity technique may also be used to estimate the parameters of simplified SG models by using measurements obtained without the need to disconnect the generator from the system where it operates (CARI, 2005). This method allows to quantify the influence of each parameter on the behavior of the system model through the sensitivity functions and adjusts the parameter value as an attempt to reduce the error between the model response and the measurement. However, as emphasized by Benchluch and Chow (1993), Hiskens and Pai (2002), it is difficult to estimate parameters that significantly affect the system dynamic behavior but which are not observable in the measurements. Hence, to use the trajectory sensitivity technique to estimate parameters, the measured data must have sufficiently rich information. Although this technique is not employed in this work to estimate parameters, the TSF are utilized to assess the importance of the parameters in the SG model.

The TSF quantify the variation of differential equation solutions with regard to their parameters. That way, the acquisition of sensitivity functions of a system provide the knowledge of the dependency of solutions of differential equations with respect to their parameters (CARI, 2005). Basically, the trajectory sensitivity function corresponds to the

partial derivative of the variables of the system with regard to a certain parameter. Let $\mathbf{y}(t, \mathbf{p})$ be the solution vector of a set of ordinary differential equations dependent on the parameter vector $\mathbf{p} = [p_1, p_2, \dots, p_r]^T$. The variation of this solution due to the change in $\mathbf{p}$ ($\Delta \mathbf{p}$) can be approximated as (FRANK, 1978):

$$\Delta \mathbf{y}(t, \mathbf{p}) \approx \sum_i^n \left. \frac{\partial \mathbf{y}}{\partial p_i} \right|_{\mathbf{p}_{ref}} \Delta p_i \quad (80)$$

where $\mathbf{p}_{ref}$ is the reference value of the parameter vector $\mathbf{p}$ and $\Delta p_i = p_i - p_{ref_i}$. Therefore, the partial derivatives in (80) are sensitivity functions, which are written as:

$$\chi_{ji}(t, \mathbf{p}_{ref}) := \left. \frac{\partial y_j}{\partial p_i} \right|_{\mathbf{p}_{ref}} \quad (81)$$

Assuming that the system consists of n outputs, we can obtain the trajectory sensitivity matrix by calculating the sensitivity function of these n outputs with respect to each one of the elements of the vector $\mathbf{p}$, which results in (FRANK, 1978):

$$\boldsymbol{\chi} = \left[\begin{array}{ccc} \frac{\partial y_1}{\partial p_1} & \dots & \frac{\partial y_1}{\partial p_r} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_n}{\partial p_1} & \dots & \frac{\partial y_n}{\partial p_r} \end{array} \right]_{\mathbf{p}_{ref}} \quad (82)$$

where $\boldsymbol{\chi}$ is the Jacobian matrix of the outputs in analysis with regard to the vector of parameters $\mathbf{p}$, calculated for the reference vector $\mathbf{p}_{ref}$.

For low-order linear models, we can obtain the sensitivity functions analytically without major problems. Nevertheless, the obtainment of sensitivity functions is quite tricky for high-order nonlinear models. Thus, the TSF can be numerically obtained with reasonable precision by evaluating the difference between the output curves of the model when we consider small changes to each parameter, keeping the other parameters in their reference values:

$$\frac{\partial y_j(t)}{\partial p_i} \approx \frac{y_j^{(1)}(t) - y_j^{(0)}(t)}{p_i^{(1)} - p_i^{(0)}} \quad (83)$$

where $y_j^{(1)}(t)$ and $y_j^{(0)}(t)$ are the output curves of the model for the parameter values $p_i^{(1)}$ and $p_i^{(0)}$, respectively.

The analysis of sensitivity functions can be utilized to identify the importance of one or more parameters in a model. A significant value of trajectory sensitivity implies that the corresponding parameter has a major influence on the analyzed output. Hence, the change in the value of this parameter causes a significant modification of the model response. On the other hand, a small value of sensitivity indicates that minor changes in

the corresponding parameter do not cause a significant change in the system trajectory (HISKENS; PAI, 2002).

The larger the value of sensitivity functions, the more easily parameters have their respective values estimated. Therefore, parameters with a negligible value of sensitivity functions have little influence in the trajectories of the system and, consequently, cannot be accurately estimated. However, in most cases, the precise estimation of the less significant parameters do not lead to a considerable enhancement of the model.

3.4 Unscented Kalman Filter (UKF)

The Kalman filter arose in the 1960s when R. E. Kalman published his famous paper describing a recursive solution to the discrete-data linear filtering problem (KALMAN, 1960). Since then, the Kalman filter has been the subject of extensive research and application, in the areas of autonomous or assisted navigation, electrical engineering, statistics, and economics. The great success of Kalman filter is due to its low computational effort, fine recursive properties and the condition of an optimal estimator for linear systems with Gaussian statistical error (ANDERSON; MOORE, 2005).

The Kalman filter is a tool that can estimate the variables of processes expressed in state-space form. In mathematical terms, it estimates the states of a linear system, minimizing the variance of the estimation error. Through the observation of some measurements, non-observable state variables can be efficiently estimated. It can be shown that of all possible filters, it is the one that minimizes the variance of the estimation error (SIMON, 2001).

Some variations of the Kalman filter are the Extended Kalman Filter (EKF) (SORENSEN, 1985) and the UKF (JULIER; UHLMANN, 2004). Since the Kalman filter was developed for applications involving linear models, these variations include modifications such that they can be applied to nonlinear systems. The EKF is probably the most widely used estimation algorithm for nonlinear systems. However, its usage over the years has shown that it is a filter difficult to implement and tune, aside from being only reliable for systems that are almost linear on the time scale of the updates. That occurs because the EKF simply linearize all the nonlinear transformations and substitutes Jacobian matrices for the linear transformations in the Kalman filter equations. However, these approximations may lead to a suboptimal performance and, sometimes, to the divergence of the filter. The UKF was developed to correct these shortcoming of the EKF (WAN; MERWE, 2000).

The UKF provides a more direct and explicit mechanism for the transformation of mean and covariance of a Gaussian variable by using the UT. Different from the EKF, which only reaches first order accuracy in mean and covariance, the UT obtains higher order information on the variable probability distribution from a small number of points,

which are deterministically obtained (JULIER; UHLMANN, 2004).

In recent years, some works that utilize the UKF for state and parameter estimation of synchronous generator models were published. Ariff, Pal and Singh (2015) estimate the parameters of a SG dynamic model employed in protection and adaptive control studies by applying the UKF in measurements obtained from Phasor Measurement Unit (PMU). Ghahremani and Kamwa (2011) also applies the UKF to data acquired from PMU for state estimation, including rotor angle and speed of a synchronous generator. In (VALVERDE et al., 2011), an approach based on UKF makes use of signals of stator and field currents and voltages for the parameter estimation of a SG model used in stability studies. The aforementioned works highlight the better performance of the UKF in comparison with the EKF, especially when noisy signals are utilized. Having this in mind, in this work, we choose to employ the UKF for the parameter estimation.

In this section, we first present the basic idea of the UT. After that, the equations of a state-space model are shown in the time domain and in discrete form. Subsequently, we describe the three first stages of the UKF utilized for the parameter and state estimation: sigma point calculation, prediction, and correction.

3.4.1 Unscented Transformation (UT)

The UT is a method employed to calculate statistical information of a random variable subject to a nonlinear function. This transformation is based on the idea that it is easier to approximate a probability distribution than an arbitrary nonlinear function or transformation (UHLMANN, 1994). Considering this concept, a set composed of a small and fixed number of points, known as sigma points, with mean $\bar{\mathbf{x}}$ and covariance $\Sigma_{\mathbf{x}}$ is deterministically chosen. Afterward, a nonlinear function is successively applied to each point, forming a set of transformed points. From the calculation of statistical information of these transformed points, we can obtain an estimate of the mean and covariance, which also have undergone the nonlinear transformation.

The set of sigma points $\mathcal{S}$ is composed by $s + 1$ vectors and their respective weights, which may be represented by $\mathcal{S} = \{\mathbf{x}^{(i)}, W^{(i)}, i = 0, 1, \dots, s\}$. The weights $W^{(i)}$ may be positive or negative. Nonetheless, for a impartial estimate these weights must satisfy the following condition (JULIER; UHLMANN, 2004):

$$\sum_{i=0}^s W^{(i)} = 1. \quad (84)$$

Considering the sigma points and the transformed points, the mean $\bar{\mathbf{z}}$ and the covariance $\Sigma_{\mathbf{z}}$ of the transformed points may be calculated according to the following equations:

$$\bar{\mathbf{z}} = \sum_{i=0}^s W^{(i)} \mathbf{z}^{(i)} \quad (85)$$

$$\Sigma_{\mathbf{z}} = \sum_{i=0}^s W^{(i)} \{\mathbf{z}^{(i)} - \bar{\mathbf{z}}\} \{\mathbf{z}^{(i)} - \bar{\mathbf{z}}\}^T \quad (86)$$

where

$$\mathbf{z}^{(i)} = \mathbf{h}_{UT}(\mathbf{x}^{(i)}) \quad (87)$$

and $\mathbf{h}_{UT}$ is the function employed to transform the sigma points.

Despite its apparent simplicity, the UT has some important properties. Among these properties, we may highlight the computational effort of the algorithm, which has the same order of magnitude as the EKF (JULIER; UHLMANN, 2004). In addition, it is possible to correctly calculate the mean and the covariance of the transformed points with a precision of second order, without the need to calculate the derivative function. The most important property of the UT for this work is the fact that the algorithm works well with a small number of points and may be used as a black box (JULIER; UHLMANN, 2004). However, for that, it is necessary to adequately define the model with the inputs and outputs, as will be shown in the following.

3.4.2 Model Definition

It is possible to represent a state-space model in time domain through the following set of equations:

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{p}(t)) \quad (88)$$

$$\mathbf{y}(t) = \mathbf{h}(\mathbf{x}(t), \mathbf{p}(t)) \quad (89)$$

where $\mathbf{x}$ is the state variable vector, $\mathbf{u}$ is the input vector, $\mathbf{p}$ is the vector of estimated parameters and $\mathbf{y}$ is the output vectors (vector of measurements) of the model. The nonlinear function vectors $\mathbf{f}$ and $\mathbf{h}$ represent the system dynamics and the measurement process, respectively. More details about the dimensions of the previous vectors and functions are shown in Section 3.1.

In order to utilize the model represented by the above equations in the UKF estimation process, which uses discrete measurements, it is necessary to depict it in a discrete way. Therefore, we approximate (88) and (89) by:

$$\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{p}_{k-1}, \mathbf{u}_k) + \mathbf{q}_{k-1} \quad (90)$$

$$\mathbf{y}_k = \mathbf{h}(\mathbf{x}_k, \mathbf{p}_k) + \mathbf{r}_k \quad (91)$$

where the subscript k refers to the values in time instant t_k . The vectors $\mathbf{q}$ and $\mathbf{r}$ represent Gaussian noise of the process and of the measurements, respectively, with zero mean and uncorrelated covariance matrices $\mathbf{Q}$ and $\mathbf{R}$.

To estimate the parameters, it is necessary to treat the vector $\mathbf{p}$ as a state variable. Therefore, the order of this augmented model becomes $n_s + n_p$ (n_s is the number of states of the original model and n_p is the number of parameters to be estimated) and we have:

$$\begin{bmatrix} \mathbf{x}_k \\ \mathbf{p}_k \end{bmatrix} = \begin{bmatrix} \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{p}_{k-1}, \mathbf{u}_k) \\ \mathbf{p}_{k-1} \end{bmatrix} + \begin{bmatrix} \mathbf{q}_{k-1} \\ \mathbf{q}_{k-1}^{par} \end{bmatrix} \quad (92)$$

Then, we define an augmented state vector $\mathbf{x}^{aug} = [\mathbf{x}^T, \mathbf{p}^T]^T$, an augmented function $\mathbf{f}^{aug} = [\mathbf{f}^T, \mathbf{p}^T]^T$ and an augmented noise vector $\mathbf{q}^{aug} = [\mathbf{q}^T, \mathbf{q}^{parT}]^T$. Consequently, (88)-(89) may be written as

$$\mathbf{x}_k^{aug} = \mathbf{f}^{aug}(\mathbf{x}_{k-1}^{aug}, \mathbf{u}_k) + \mathbf{q}_{k-1}^{aug} \quad (93)$$

$$\mathbf{y}_k = \mathbf{h}(\mathbf{x}_k^{aug}) + \mathbf{r}_k. \quad (94)$$

From this point onwards, whenever the state vector $\mathbf{x}$, the function vector $\mathbf{f}$ and the noise vector $\mathbf{q}$ are mentioned, we are in fact referring to the augmented vectors $\mathbf{x}^{aug}$, $\mathbf{f}^{aug}$ and $\mathbf{q}^{aug}$, respectively. Similarly, whenever the order of the system n is mentioned, we are in fact referring to the order $n_s + n_p$ of the augmented system.

The application of the UKF can be divided into two main stages (JULIER; UHLMANN, 2004), described in the sequel.

3.4.3 Mathematical formulation

In this subsection, we show how the UKF can be applied to the discrete model in (93)-(94). Since the UKF is not a contribution of this work, it is not demonstrated. Nonetheless, additional information about its formulation can be seen in literature (JULIER; UHLMANN, 2004; WAN; MERWE, 2000; RHUDY; GU, 2013). In this work, we utilize the information of these previous references to write the three main steps of the method: calculation of sigma points, prediction stage and correction stage.

3.4.3.1 Calculation of sigma points

Let $\mathbf{x}_{k-1}$ be the state vector of the model and $\mathbf{P}_{k-1}$ the corresponding error covariance matrix of order n . The matrix $\mathbf{X}_{k-1}$ that contains the $2n + 1$ sigma points in its columns is obtained by (WAN; MERWE, 2000):

$$\mathbf{X}_{k-1} = \begin{bmatrix} \overbrace{\mathbf{x}_{k-1} \quad \cdots \quad \mathbf{x}_{k-1}}^{2n+1} \end{bmatrix} + \sqrt{c} \begin{bmatrix} 0 & \sqrt{\mathbf{P}_{k-1}} & -\sqrt{\mathbf{P}_{k-1}} \end{bmatrix} \quad (95)$$

where $\sqrt{\mathbf{P}_{k-1}}$ is the positive-definite square root of matrix $\mathbf{P}_{k-1}$, obtained from $\mathbf{P}_{k-1} = \mathbf{L}\mathbf{L}^T$, and $\mathbf{L}$ is the lower left triangular matrix obtained from the Cholesky factorization (PRESS et al., 1992) of $\mathbf{P}_{k-1}$. The value of the scalar c is obtained from the following equations:

$$c = n + \tau \quad (96)$$

$$\tau = \alpha^2(n + v) - n \quad (97)$$

where n is the order of the model, v is a parameter that may be used to reduce the higher order errors of the mean and the covariance approximations and α is a scalar that establishes the spread of sigma points (UHLMANN, 1994; SCARDUA; CRUZ, 2016). Hence, lower values of α lead to lower dispersal of sigma points, while larger α gives a wider spread of sigma points (RHUDY; GU, 2013).

3.4.3.2 Prediction Stage

In this step, we obtain predictions of the mean and covariance of the set of sigma points transformed by the nonlinear function of the model. That way, initially, the set of sigma points calculated in the previous step are evaluated, one by one, by the nonlinear function $\mathbf{f}$, according to:

$$\hat{\mathbf{X}}_k^i = \mathbf{f}(\mathbf{X}_{k-1}^i, \mathbf{u}_k) \quad (98)$$

where $\mathbf{X}_{k-1}^i$ is the i -th column of the matrix $\mathbf{X}_{k-1}$ and $\hat{\mathbf{X}}_k^i$ is the i -th column of the matrix $\hat{\mathbf{X}}_k$, which contains the transformed sigma points.

Afterward, from the columns of the matrix $\hat{\mathbf{X}}_k$, we calculate predictions of the mean ($\mathbf{x}_k^-$) and of the error covariance matrix ($\mathbf{P}_k^-$) of the transformed sigma points:

$$\mathbf{x}_k^- = \sum_{i=0}^{2n} W_i^m \hat{\mathbf{X}}_k^i \quad (99)$$

$$\mathbf{P}_k^- = \sum_{i=0}^{2n} W_i^c \left[(\hat{\mathbf{X}}_k^i - \mathbf{x}_k^-) (\hat{\mathbf{X}}_k^i - \mathbf{x}_k^-)^T \right] + \mathbf{Q} \quad (100)$$

where the weights W_i^m and W_i^c of the above equations are given by:

$$\begin{aligned} W_0^m &= \frac{\tau}{n + \tau} & W_0^c &= \frac{\tau}{n + \tau} + 1 - \alpha^2 + \beta \\ W_i^m &= W_i^c = \frac{1}{2(n + \tau)} & i &= 1, \dots, 2n \end{aligned} \quad (101)$$

and the scaling parameter β is used to include information about a statistical distribution (RHUDY; GU, 2013).

3.4.3.3 Correction Stage

In this stage, the predictions of the mean ($\mathbf{x}_k^-$) and of the error covariance matrix ($\mathbf{P}_k^-$) of the transformed points, calculated in the previous step, are utilized to update the state vector $\mathbf{x}_k$ and the error covariance matrix $\mathbf{P}_k$.

First the vector $\mathbf{x}_k^-$ and the matrix $\mathbf{P}_k^-$ are used to calculate the matrix $\mathbf{X}_k^-$, which contains a set of sigma points:

$$\mathbf{X}_k^- = \left[\overbrace{\mathbf{x}_k^- \cdots \mathbf{x}_k^-}^{2n+1} + \sqrt{c} \begin{bmatrix} 0 & \sqrt{\mathbf{P}_k^-} & -\sqrt{\mathbf{P}_k^-} \end{bmatrix} \right] \quad (102)$$

Then, this set of sigma points is evaluated, element by element, in the nonlinear function $\mathbf{h}$ that represents the measurement process

$$\mathbf{Y}_k^{-i} = \mathbf{h}(\mathbf{X}_k^{-i}) \quad (103)$$

where $\mathbf{X}_k^{-i}$ is the i -th column of the matrix $\mathbf{X}_k^-$.

The mean vector $\boldsymbol{\mu}_k$ of these sigma points transformed by the function $\mathbf{h}$ is calculated in the following way:

$$\boldsymbol{\mu}_k = \sum_{i=0}^{2n} W_i^m \mathbf{Y}_k^{-i} \quad (104)$$

After obtaining the mean vector $\boldsymbol{\mu}_k$, the covariance matrix of the measurements ($\mathbf{S}_k$) and the cross-covariance between the states and measurements ($\mathbf{C}_k$) are calculated:

$$\mathbf{S}_k = \sum_{i=0}^{2n} W_i^c \left[(\mathbf{Y}_k^{-i} - \boldsymbol{\mu}_k) (\mathbf{Y}_k^{-i} - \boldsymbol{\mu}_k)^T \right] + \mathbf{R} \quad (105)$$

$$\mathbf{C}_k = \sum_{i=0}^{2n} W_i^c \left[(\mathbf{X}_k^{-i} - \mathbf{x}_k^-) (\mathbf{Y}_k^{-i} - \boldsymbol{\mu}_k)^T \right] \quad (106)$$

Afterward, the Kalman gain $\mathbf{K}_k$, the state vector $\mathbf{x}_k$ and the error covariance matrix $\mathbf{P}_k$ are calculated:

$$\mathbf{K}_k = \mathbf{C}_k \mathbf{S}_k^{-1} \quad (107)$$

$$\mathbf{x}_k = \mathbf{x}_k^- + \mathbf{K}_k (\mathbf{y}_{m_k} - \boldsymbol{\mu}_k) \quad (108)$$

$$\mathbf{P}_k = \mathbf{P}_k^- - \mathbf{K}_k \mathbf{S}_k \mathbf{K}_k^T \quad (109)$$

The state vector $\mathbf{x}_k$ and the error covariance matrix $\mathbf{P}_k$ calculated above are used to obtain the sigma points of the subsequent iteration. The algorithm described by the three steps shown in this section is iteratively repeated over the sampling window.

3.4.4 UKF Parameters

Throughout this section, we verify that the UKF have some parameters that need to be adequately chosen so that the estimation process works correctly. Such parameters are the scalars α , v and β , which defines the spread of sigma points, reduces the higher order errors of the mean and covariance approximations, and provide information about a statistical distribution, respectively. However, as we will see later in this work, these parameters have some usual values which are widely used in the literature.

Other parameters that need to be correctly set for a good performance of the UKF are the initial error covariance matrix $\mathbf{P}_0$, the covariance matrix of the process $\mathbf{Q}$ and the covariance matrix of the measurements $\mathbf{R}$. In this work, we initialize the matrix $\mathbf{P}_0$ as a diagonal matrix with all the diagonal elements equal, i.e.,

$$\mathbf{P}_0 = \text{diag}(\overbrace{(\epsilon, \dots, \epsilon)}^n) \quad (110)$$

The definition of the process covariance matrix is similar to the initial error covariance matrix, however it is separated in two blocks. The first block comprises the diagonal elements related to the state variables and the second one corresponds to the diagonal elements corresponding to parameters to be estimated. In this work, we define all the diagonal elements of the first block with the same value, as well the diagonal elements of the second block, although the elements of the first (ψ_s) block are not necessary equal to the ones in the second block (ψ_p), i.e.,

$$\mathbf{Q} = \text{diag}(\overbrace{(\psi_s^2, \dots, \psi_s^2)}^{n_s}, \overbrace{(\psi_p^2, \dots, \psi_p^2)}^{n_p}) \quad (111)$$

Similarly to the initial error covariance matrix, we assume only one value for the diagonal elements of the measurement covariance matrix $\mathbf{R}$. Hence, we have

$$\mathbf{R} = \text{diag}(\overbrace{(\zeta^2, \dots, \zeta^2)}^{n_o}) \quad (112)$$

Besides the aforementioned covariance matrices, the initial values of the parameters to be estimate by the UKF also need to be defined. These initial values, as will be shown later in this work, are important for the estimation process. Given the vector of parameters $\mathbf{p} = [p_1, p_2, \dots, p_{n_p}]$ to be estimated, the initial value of parameters is $\mathbf{p}_0 = [p_{10}, p_{20}, \dots, p_{n_{p0}}]$. Therefore, the parameters that need to be initially defined for the estimation process are

$$\mathbf{p}_{UKF} = [\epsilon, \psi_s, \psi_p, \zeta, p_{10}, p_{20}, \dots, p_{n_{p0}}] \quad (113)$$

In the next section, we will present an introduction to genetic algorithms, which are used in this work to search the vector of parameters $\mathbf{p}_{UKF}$ employed in the UKF.

3.5 Genetic Algorithms

Genetic Algorithms (GAs) are search algorithms based loosely on simulated evolution. These algorithms have been developed by John Holland, his colleagues, and students at the University of Michigan. The main objectives of their research were to abstract and explain the adaptive processes of natural systems, and to design artificial systems software that retains the important mechanisms of natural systems (GOLDBERG, 1989; HOLLAND, 1975).

The GA generates successor hypotheses by repeatedly mutating and recombining parts of the best currently known hypothesis instead of searching for general-to-specific hypotheses. At each step, the current population, which is a collection of hypotheses or individuals, is updated by substituting a fraction of it by offspring of the fittest current hypotheses. This procedure generates and tests a set of hypotheses, in which variants of the best current hypothesis are most likely to be considered next (MITCHELL, 1997).

Although there are different implementations of genetic algorithms, they usually have the same structure. The algorithm operates by iteratively updating the population, which is a set of hypothesis. On each iteration, all members of the population are evaluated for the problem at hand according to a predefined numerical measure, called fitness function. Then, a new population is generated by probabilistically selecting the fittest individuals from the current population. Some of these selected individuals are carried forward into the next generation population without modifications. Others are used as the basis for creating new offspring individuals by applying genetic operations. The two common operators are crossover and mutation (MITCHELL, 1997).

The iterative process of renovating the individuals of the current generation by applying genetic operations, and therefore creating a new population, comes to an end. The GA finalizes the search and returns the fittest individual when a stop criterion is achieved. The choice of the stop criterion usually depends on the strategy adopted in each algorithm. Among the most utilized stop criteria, we may highlight the ones based on the value of fitness function and on the number of generations (AYTUG; KOEHLER, 1996; AYTUG; KOEHLER, 2000).

It is important to highlight that before we can begin evolving solutions, we must have an initial population of solutions which we can evolve. The hypotheses of the initial population are randomly created and, then, we evaluate the fitness function for each hypothesis. After that, the cyclical process consisting of the selection of a set of hypotheses that will be used to create the new population and the evaluation of the individuals in this new population is repeated until the stop criterion is achieved. When that occurs, the genetic algorithm returns the hypothesis with the best fitness.

The selection of the individuals, the crossover and mutation operators generally follow fixed structures. The most common frameworks for each of these steps are shown in the following subsections.

3.5.1 Selection

Each generation must produce new solutions from the current population of solutions. The selection step defines the number of hypotheses in the current population used to generate new solutions. Besides, it also sets which hypotheses should be used to generate the next population and which individuals of the current population should be erased to make room for the new solutions. Some types of selection are (CHAMBERS, 1998; MITCHELL, 1997)

- **Roulette wheel selection:** the probability that a hypothesis will be selected is given by the ratio of its fitness to the fitness of other members of the current population, according to

$$Pr(h_i) = \frac{Fitness(h_i)}{\sum_{j=1}^{n_h} Fitness(h_j)} \quad (114)$$

where $Pr(h_i)$ is the probability of selecting the hypothesis h_i and n_h is the number of hypotheses in the current population. It is important to point out that each solution in the population has a slice of a roulette wheel. Better solutions have proportionately larger sections of the wheel and therefore there is a greater chance they will be selected.

- **Tournament selection:** two hypotheses are first chosen at random from the current population. With some predefined probability pr the more fit of these two is then selected, and with probability $1 - pr$ the less fit hypothesis is selected (MITCHELL, 1997). Tournament selection often yields a more diverse population than roulette wheel selection (GOLDBERG; DEB, 1991).
- **Rank selection:** first the hypotheses in the current population are sorted by fitness. Then, a hypothesis is selected with a probability proportional to its rank in this sorted list, rather than its fitness. Rank selection reduces the potentially dominating effects of comparatively high-fitness hypotheses in the population by establishing a predictable, limited amount of selection pressure in favor of such hypotheses (KOZA, 1992).

3.5.2 Crossover Operators

After selecting the hypotheses, we need a technique or techniques of combining these hypotheses such that will produce new offspring. These are known as recombination or crossover operators. The crossover operator creates variation in the population by producing new offspring that consist of parts taken from each parent. In other words, it

produces two new offspring from two parent strings by copying selected bits from each parent. The bit at position i in each offspring is copied from the bit at position i in one of the two parents. The choice of which parent contributes to the bit of position i is determined by an additional string called the crossover mask (KOZA, 1992; MITCHELL, 1997; CHAMBERS, 1998).

The common forms of crossover are one-point, two-point and uniform crossover (Fig. 6):

- **One-point crossover:** offspring are created by combining a segment that comprises the first bits of one parent string with a segment composed of the last bits of the other parent. In the one-point crossover, the crossover mask is always constructed so that it begins with a string containing n_1 contiguous ones, followed by the necessary number of zeros to complete the string.
- **Two-point crossover:** offspring are created by substituting intermediate segments of one parent into the middle of the second parent string. The crossover mask is a string beginning with n_0 zeros, followed by a contiguous string of n_1 ones, followed by the necessary number of zeros to complete the string.
- **Uniform crossover:** offspring are created by combining bits sampled uniformly from the two parents. In this case, the crossover mask is generated as a random bit string with each bit chosen at random and independent of the others.

Figure 6: Different types of crossover (Adapted from Mitchell (1997)).

3.5.3 Mutation Operators

After the crossover operator produces offspring by combining parts of two parents, the mutation operator introduces random changes in offspring string. In conventional

genetic algorithms, the mutation operation can be beneficial in reintroducing diversity in a population that may be tending to converge prematurely (KOZA, 1992). Although the mutation operation may occasionally have beneficial results, it is a relatively unimportant secondary operation in the conventional genetic algorithm (HOLLAND, 1975; GOLDBERG, 1989).

The mutation operator produces small random changes to the bit string by choosing a single bit at random and changing its value, as shown in Fig. 7:

$$\begin{array}{lcl} 1011\underline{1}001 & \longrightarrow & 1011\underline{0}001 \\ 001101\underline{0}00 & \longrightarrow & 001101\underline{1}00 \end{array}$$

Figure 7: Examples of mutation.

3.6 Detailed Description of the Method

In Section 3.2, in order to have an overview of the proposed estimation approach, we present its schematics and the tools that we use to estimate the parameters of the SG model. The most important tools employed in the proposed approach are TSF, UKF and GA, explained in previous sections.

The main goal of this section is to describe how the tools previously explained are assembled to obtain the method used to estimate the parameters. Fig. 8 presents the flowchart of the proposed estimation method. In the sequence, we explain in detail the blocks of the flowchart.

3.6.1 Influence of Parameters in the Model

As mentioned before in Subsection 3.2.1, this step of the estimation method is important to identify the parameters that have the highest influence on the outputs of the SG model. It provides a ranking list according to the impact of the parameters in the outputs of the model.

It is important to highlight that the influence of the parameters on the outputs generally does not significantly change for a given model. However, there are some situations in which some parameters may interfere more than in others. Therefore, we must have in mind the following points when ordering the parameters of the model according to their influence in the outputs of the model:

Figure 8: Flowchart of the Proposed Method.

- The influence of a parameter on a model output may depend on the condition of operation. That way, the order of importance of the parameters for a given output may change for different operating conditions. For instance, the ranking list obtained for a balanced operation may be different from the one obtained for an unbalanced condition;
- The parameters do not impact all the outputs of the model in the same way. Consequently, to generate the ranking list we must take into account a specific or a set of outputs. The strategy adopted in this work is to consider the model quantities which are used as outputs of the UKF;
- The value of the parameters may interfere with the calculation of the TSF. That can be seen from (80), where the sensitivity functions depend on the reference value of the parameter vector.

Although the three points above show that the generation of the ranking list is not trivial, the order of the parameters in this list normally does not substantially change. Hence, it can be used as a good indicator of which parameters should be estimated. The following quadratic function is employed in this work to sort the most important parameters:

$$E_{p_i}^{y_j} = \sum_{k=1}^{N_w} \left[\frac{\partial y_j(k)}{\partial p_i} \right]^2 \quad (115)$$

The above function makes use of the same sampling window (with N_w samples) which is used in the estimation process. It takes into account the sensitivity function of the output y_j with respect to the parameter p_i . Through the quadratic function in (115), it is possible to identify the parameters which almost do not change the outputs of the model and are not significant for the model. On the other hand, the value of this quadratic function also indicates the parameters which substantially impact the outputs of the model and must have their values estimated.

We must point out that the analysis of the influence of the parameters in the model is a pre-stage that does not depend on a specific sampling window. As previously mentioned, we can obtain the ranking list from an extensive study which involves several operating conditions and sampling windows. That way, this stage can be defined as an analysis prior to the estimation method and, hence, is highlighted in Fig. 8.

3.6.2 Choice of Parameters for Estimation

After calculating the quadratic function of all the model outputs that may be used in the UKF with respect to the parameters that may be estimated, the next step is determining the parameters which actually need to be estimated. This decision is important

since it is difficult to estimate parameters with great difference in the respective values of their quadratic functions. For instance, consider two parameters with a large difference in the value of the quadratic function for the same output. When using this variable as an output of UKF to estimate these parameters, the first one with the biggest value of the quadratic function is generally estimated with a good accuracy. However, the one with the lowest value, for example, may not be correctly estimated in the majority of cases.

In fact, estimating the parameters with the lowest values of the quadratic function in the situation described above is normally not necessary since that does not add considerable improvements of the model. In short, striving for the estimation of a parameter by using an output which is not significantly affected by this parameter is an unnecessary effort.

Deciding which parameters we should estimate by analyzing their respective quadratic function is a simple task when there is a great difference between them. Nonetheless, there are situations in which the difference between the highest and the lowest quadratic function values is not so high. In other cases, there is a group of parameters with large quadratic function values, a group of parameters with intermediate values and another one with small values of quadratic functions. In these cases, identifying the parameters that should be estimated is not a straightforward task.

As far as we know, there is no formulae or well-established algorithm that can be employed to select the parameters that should be estimated. In these situations, a prior knowledge of the model and some experience in parameter estimation are necessary requirements for a good decision on which parameters to estimate. Although it is not easy to decide which parameters with intermediate values of quadratic functions should be estimated, it is important to stress out that the ones with the highest values of this function need to be estimated for the construction of an accurate model.

In this thesis, the approach employed to define a list of parameters that should be estimated (called estimation list) takes into account the value of the quadratic function and the performance of the estimation process for a certain case where the values of the parameters are already known. At first, we sort the parameters according to the descending order of quadratic function and separate them in up to three groups. As seen in Fig. 9, the first group includes the n_{fg} parameters with the highest values of quadratic functions, the second one comprises the n_{sg} parameters with intermediate values of quadratic functions and the third one comprehends the n_{tg} parameters with the smallest values of quadratic functions. We must highlight that depending on the values of the quadratic functions the second group may not exist, i.e, there is no parameter with intermediate value for the quadratic function.

After this initial classification, we estimate the parameters with the highest values of quadratic functions and then include, one by one, the parameters with intermediate values of quadratic functions. In order to decide which parameters of the intermediate

group should be estimated, we compare the error between the measured output and the one generated by the model obtained with the estimated parameters. The increase of the error with the addition of a parameter of the intermediate group indicates that this parameter should not be estimated, as well as the ones with smaller values of the quadratic function. As shown in Fig. 9, the parameters of the third group are never estimated.

Figure 9: Algorithm employed to obtain the estimation list.

3.6.3 Creation of Initial Population

After obtaining the list of parameters that will be estimated, it is necessary to create an initial population to start the estimation process. This first generation is initialized by utilizing a probability distribution. Each individual or hypothesis of the population is a vector of parameters, shown in (113) and repeated here:

$$\mathbf{p}_{UKF} = [\epsilon, \psi_s, \psi_p, \zeta, p_{10}, p_{20}, \dots, p_{n_{p0}}]$$

The values $p_{10}, p_{20}, \dots, p_{n_{p0}}$ are the initial values of the parameters of the SG model whose values are estimated by the UKF, whereas the scalars ϵ, ψ_s, ψ_p and ζ compose the initial error covariance matrix $\mathbf{P}_0$, the process covariance matrix $\mathbf{Q}$ and the measurement covariance matrix $\mathbf{R}$.

Let N_{pop} be the number of individuals in the population. That way, we initially generate N_{pop} different vectors $\mathbf{p}_{UKF}$. Each element of each vector is picked randomly according to the intervals defined below:

$$\begin{aligned} \epsilon_{min} &\leq \epsilon \leq \epsilon_{max} \\ \psi_{smin} &\leq \psi_s \leq \psi_{smax} \\ \psi_{pmin} &\leq \psi_p \leq \psi_{pmax} \\ \zeta_{min} &\leq \zeta \leq \zeta_{max} \\ p_{10min} &\leq p_{10} \leq p_{10max} \\ p_{20min} &\leq p_{20} \leq p_{20max} \\ &\vdots \\ p_{n_{pmin}} &\leq p_{n_p} \leq p_{n_{pmax}} \end{aligned} \tag{116}$$

where the minimum and maximum values of each element depends on prior information about the state variables, the measurements and the parameters of the SG model which are estimated.

Once the elements of all the N_{pop} individuals are generated by using a probability distribution function, we obtain the initial population which is used for the calculation of the fitness function throughout the estimation process by applying the UKF.

3.6.4 Application of UKF and fitness function calculation

In this subsection, we explain how to apply the UKF to estimate the parameters of the SG model and how to calculate the fitness function for each individual of the population. That way, given a window with N_w samples, we apply the UKF in this window for each of the N_{pop} vectors $\mathbf{p}_{UKF}$, i.e., at the end of this stage there are N_{pop} available sets of estimated parameters.

As shown in the flowchart of Fig. 10, before the application of UKF it is necessary to obtain the initial error covariance matrix $\mathbf{P}_0$, the process covariance matrix $\mathbf{Q}$, the

covariance matrix $\mathbf{R}$, and the initial values for the SG model parameters $p_1, p_2, \dots, p_{n_p}$. All these parameters are obtained from the individual $\mathbf{p}_{UKF}$. It is important to point out that the matrices $\mathbf{Q}$ and $\mathbf{R}$ do not vary for the whole sampling window. However, the initial error covariance matrix $\mathbf{P}_0$ and the values $p_{1_0}, p_{2_0}, \dots, p_{n_{p_0}}$ are only used for the first sample of the window.

Figure 10: Flowchart for the application of UKF and calculation of the fitness function.

After obtaining the parameters necessary for the application of UKF, the next step

is the attainment of the initial states of the SG model from the available measurements. Once we have the initial values of the states and of the SG model parameters, we have the vector $\mathbf{x}_0$ and UKF can be applied.

As previously shown in Section 3.4, the application of UKF consists of the three following steps: calculation of sigma points, prediction stage and correction stage. For each sample of the window, we apply these three steps and update the error covariance matrix $\mathbf{P}_k$ and the state vector $\mathbf{x}_k$ for the next iteration.

Once we apply the UKF for all the N_w samples of the window, we have the final value of the parameters and, consequently, the SG model. Then, we simulate the obtained model to generate the same outputs used to estimate the parameters. After that, we calculate the fitness function J according to the following equation:

$$J(\mathbf{p}) = \sum_{k=1}^{N_w} [\mathbf{y}(k) - \mathbf{y}_m(k)]^T [\mathbf{y}(k) - \mathbf{y}_m(k)] \quad (117)$$

where $\mathbf{y}$ is the vector of outputs obtained from the SG model and $\mathbf{y}_m$ is the corresponding measurement vector employed in the UKF. Note that the fitness function J depends on all the same N_w samples of the window used to estimate the parameters. We can verify that (117) is obtained from the discretization of (77).

The process of estimating the parameters and calculating the fitness function is repeated for the whole population. After calculating the fitness function for each individual, we order the population according to the lowest value of these functions and apply the crossover and mutation operators to obtain a new set of hypotheses, as shown in the next subsection.

3.6.5 Population Updating

Before explaining how we update the population to obtain new individuals and a new generation, it is important to highlight that we only apply this step if the stopping criteria are not achieved, as can be seen in Fig. 8. These criteria, which take into account the number of the last generation and the best fitness function of the population, are better explained in the next chapter.

The type of selection employed to obtain the individuals of the elite is the roulette wheel, explained in Subsection 3.5.1. The elite individuals move to the next population without modifications. They are the parents of the new population and, therefore, responsible to generate the new offspring. Assuming that N_{eli} is the number of elite individuals and that the population has N_{pop} individuals, these hypotheses produce the new $N_{pop} - N_{eli}$ individuals of the next generation.

As shown in the flowchart of Fig. 11, the first step to update the population is to calculate the inverse of fitness function of each hypothesis in the current population. That is done since the higher the value of the fitness function the bigger the error between the

measured and the simulated outputs. Therefore, the fitness of the hypothesis h_i in (114) is given by

$$Fitness(h_i) = \frac{1}{J(\mathbf{p}_{h_i})} \quad (118)$$

where $\mathbf{p}_{h_i}$ is the vector of parameters estimated for the hypothesis h_i .

To explain the probability of selecting an individual to be part of the elite by applying the roulette wheel selection, we consider a hypothetical population of five individuals with fictitious functions $J(\mathbf{p}_{h_i})$ and construct Table 1. We can note that although the probability of selecting the hypothesis h_5 is the highest, there is also a small probability that the hypothesis h_4 is selected as a part of the elite.

Figure 11: Flowchart to update the population.

After the N_{eli} individuals of the elite are selected by the roulette wheel, the next step is to produce the offspring from these hypotheses. The parents are randomly chosen from the elite and the crossover operator is applied to obtain the offspring, as shown in Fig. 6. In this thesis, we adopt the one-point crossover with a floating mask which changes for each pair of parents selected.

It should be highlighted that once the parents are selected, the offspring parameters are obtained by applying different crossover masks. For instance, consider the parameters $\epsilon^{(P1)}$, $\zeta^{(P1)}$, $\epsilon^{(P2)}$ and $\zeta^{(P2)}$ of the parents P1 and P2, and the parameters $\epsilon^{(O1)}$, $\zeta^{(O1)}$, $\epsilon^{(O2)}$ and $\zeta^{(O2)}$ of the offspring O1 and O2. The parameters $\epsilon^{(O1)}$ and $\epsilon^{(O2)}$ are generated by applying a crossover mask different from the one applied to $\zeta^{(P1)}$ and $\zeta^{(P2)}$ to obtain the parameters $\zeta^{(O1)}$ and $\zeta^{(O2)}$.

Table 1: Probability of a hypothesis be part of the elite

Hypothesis	$J(\mathbf{p}_{h_i})$	$Fitness(h_i)$	$Pr(h_i)(\%)$
h_1	20	0.05	12.05
h_2	10	0.10	24.10
h_3	25	0.04	9.64
h_4	40	0.025	6.02
h_5	5	0.20	48.19

After the elite individuals generate the offspring, we apply the mutation operator to the $N_{pop} - N_{eli}$ hypotheses which do not belong to the elite. The mutation mask is also randomly chosen similarly to the crossover one. Therefore, we select a different mask for each parameter of each hypothesis. However, the mutation operator is not applied to all the hypothesis since the occurrence of a mutation in a hypothesis h_i depends on the mutation rate MR .

Although not shown in Fig. 11, in this thesis we apply the crossover and mutation operators to binary numbers. Since the parameters of the vector $\mathbf{p}_{UKF}$ are real numbers, we first convert them to binary and then apply the operators. After applying the mutation operator, we convert the parameters from binary to real numbers and the updated population is ready for the application of UKF and calculation of the fitness function. From the second generation onwards, it is not necessary to apply the UKF and calculate the fitness function for the elite individuals since it has already been calculated in the previous generation.

It is important to emphasize that we did not perform a detailed study to verify the impact of the crossover and mutation operations on the estimation method.

3.6.6 Validation Process

As shown in Fig. 8, when the stopping criteria are fulfilled, we apply the process of validation to the obtained model. This stage consists in verifying whether the SG model with the best set of estimated parameters is capable of representing the behavior of a SG for a set of disturbances different from the one employed to estimate the parameters. Of course, this process depends on the availability of measurements acquired under different

circumstances. Hence, the application of the validation process is subject to the existence of these measurements.

It is important to point out that the criterion to decide whether the model is validated or not depends on the application of the SG model. In some situations, the stator currents are more important than the field current and, in others, the angular speed of the rotor requires a higher accuracy, for example. The validation process may take into account a maximum error between the measured and simulated curves. This error between the curves can be calculated using the error functional in (77) or another one which takes into account different performance indices.

3.6.7 Selection of Another Sampling Window

Observing the flowchart in Fig. 8, we note that if the model is not validated, another sampling window must be selected and the estimation process must be repeated. Similarly to the validation process, the execution of this stage depends on the availability of this sampling window. This new sampling window may contain a different disturbance from the one present in the previously used window, although that is not necessary. For example, the following modifications can be applied to the not well-succeeded sampling window:

- to increase the size of the window, including the steady-state period before or after the response to the disturbance vanishes. For example, the windows W2 or W3 can be used instead of the window W1 (Fig. 12), which does not contain the steady-state period of the response. Sometimes, we can increase the length of the window without including a steady-state period, as for example the window W4 in Fig. 12. The mere consideration of a window containing a greater portion of the response to the disturbance is sometimes enough to solve the estimation problem.
- to reduce the size of the window since it may contain responses to two or more disturbances, which may interfere with the estimation of some parameters. For example, in Fig. 13, the estimation method may have a better performance by using the window W6 instead of W5.

This stage of the proposed estimation approach can be considered the most empirical part since it relies on the experience of the engineer in parameter estimation. Nevertheless, that does not diminish the importance of the proposed approach since the application of a parameter estimation technique involves some calibration adjustments, which requires a decision on the part of the engineer.

Figure 12: Selection of a wider sampling window.

3.7 Particular Features of Balanced Operation

In Section 3.6, we describe the method applied in this thesis to estimate the parameters of the SG model. The proposed estimation approach works for balanced and unbalanced operations. However, estimating the parameters by using measurements from unbalanced systems is not as simple as by utilizing signals from balanced conditions. The aim of this section is to show the main differences between the estimation in these two situations.

To better understand why the estimation for balanced cases is simpler, we present a comparison of the SG responses for both cases. Salim (2011) addresses the dynamic equilibrium of power systems when operating under load imbalance. In this case, the angular speed of the SGs exhibits a sustained oscillation in the steady state due to the effect of negative sequence currents in the winding circuits of the machine. Thus, a state variable of the dynamic system has a sinusoidal steady state, which indicates that the system does not operate in a stable equilibrium point, but in an elliptic orbit (SASTRY, 1999).

Salim (2011) proposes an Imbalance Factor (IF) to analyze the operation of SG under unbalanced conditions. This IF represents the level of variation of apparent power in two phases of the system, keeping the load of the third phase with a constant value. The load variation in one of the phases is increased, while there is a load decrease in the other phase. This definition of imbalance factor keeps the three-phase apparent power constant which allows a comparison among operating points with the same apparent power but with different levels of imbalance. That way, the calculation of the apparent power of the

Figure 13: Selection of a narrower sampling window.

loads is given by

$$S_{il} = (1 + IF) \cdot S_{1\phi} \quad (119)$$

$$S_{dl} = (1 - IF) \cdot S_{1\phi} \quad (120)$$

$$S_{ul} = S_{1\phi} \quad (121)$$

where $S_{1\phi}$ is the single-phase apparent power of the load in balanced case, and S_{il} , S_{dl} and S_{ul} are the apparent power of increased, decreased and unchanged load, respectively.

Fernandes et al. (2017) employs this IF to assess the impact of three-phase unbalanced conditions on modal estimation in distributed synchronous generation systems. Salim (2011) and Fernandes et al. (2017) show that the bigger the IF, the larger the elliptic orbit of operation. That can be seen in the phase plane of Fig. 14, where we have the plot of the variation of the angular position of the rotor ($\Delta\delta$) versus the variation of the angular speed of a synchronous generator ($\Delta\omega$) for different operating conditions. These same conditions are shown in the graph of Fig. 15, where we can note that the higher the imbalance of the system, the larger the amplitude of the sinusoidal oscillation in the response of the angular speed of the generator. As subsequently shown in this work, this oscillation is also present in other quantities of the SG, as field and stator currents.

The studies performed in Salim (2011) and Fernandes et al. (2017) show that the sustained oscillation in the steady-state operation of SGs connected to unbalanced systems may affect the estimation of underdamped electromechanical oscillations (KUNDUR et al., 2004). These unbalanced conditions can be considered a continuous excitation to the

dynamic model of SG and, therefore, the parameters of the model in (59) interfere more significantly in the responses of the generator.

The impact of the parameters in balanced and unbalanced operating conditions and the greater complexity to estimate them under the last circumstances is better evidenced by presenting the results in the next chapter. However, it is important to point out that the difficulty to estimate the parameters under unbalanced conditions increases due to the fact that they constantly influence the outputs of the model. When the generator is operating in a balanced condition, we can clearly separate the parameters into two sets. The first comprises the parameters that affect the generator responses only during the occurrence of a disturbance, whereas the second is composed by the parameters that influence the outputs of the model during a disturbance but also the steady-state operation.

Figure 14: Phase plane for different imbalance factors (adapted from Fernandes (2017)).

Under unbalanced operation, carrying out the previous classification is not possible since the parameters of the first set now affect the outputs of the generator during the sinusoidal steady-state operation of the rotor angle and speed. As shown later in this work, the number of parameters which can be correctly estimated in these situations is smaller than when using measurements obtained from balanced conditions. Despite the differences between the SG responses under balanced and unbalanced conditions, which affect the process of parameter estimation, all the steps of the proposed approach explained in this chapter are applied for both cases.

Figure 15: Rotor angular speed variation for different imbalance factors (adapted from Fernandes (2017)).

3.8 Final Remarks

The central part of the estimation approach described in this chapter is the UKF. Nevertheless, the TSF are important since it is normally not possible to estimate the parameters without a previous knowledge of their influence in the model. Besides, the GA plays an important role in the method since it defines the covariance matrices of the UKF and the initial values of the parameters, which are important for an accurate estimation of the parameters. Basically, the GA searches for a vector $\mathbf{p}_{UKF}$ that makes the UKF converge to an acceptable set of SG model parameters.

Tests and Results

This chapter presents the tests employed to assess the performance of the proposed approach in Chapter 3 to estimate the parameters of the SG model shown in Chapter 2. The evaluation of the estimation method is carried out through the analysis of the results obtained for different situations. Although we consider several operating conditions to test the approach, all of them are related to the same test system, detailed in Section 4.1.

The presentation of the results takes into account two major sets of operating conditions. That way, Section 4.2 showcases the results obtained for a balanced case, while Section 4.3 exhibits the results achieved for some unbalanced cases. We follow this structure to emphasize the particular features of balanced operation presented in Section 3.7. Besides, from the results of Section 4.2, we can verify the impact of the parameter initial values and of the covariance matrices on the UKF. At the end of this chapter, we present an analysis of the obtained results for the balanced and unbalanced cases.

4.1 Test System

The test system utilized in this work comprises a synchronous generator connected to a three-phase bus through a symmetrical distribution line, as shown in Fig. 16. There is also a three-phase load connected to the terminal bus of the SG. The voltage and speed controls are not shown in Fig. 16, however Figs. 17 and 18 exhibit their corresponding block diagrams. The test system is simulated by using the software EMTP-RV (HYDRO-QUÉBEC, 2014). In the next sections, whenever we refer to a measurement signal, we are in fact considering the corresponding simulated output provided by this software.

The block diagram of the automatic voltage regulator and speed governor connected to the SG are exhibited in Figs. 17 and 18, respectively. The parameters of the three-phase synchronous generator model used to simulate the test system (called reference parameters in this work), as well the parameters and setpoints of the voltage and speed controller are exhibited in Appendix A. The variable $\Delta\omega$ is equal to $\omega - \omega_R$. Appendix

A also presents the loads connected to the buses GB_a , GB_b and GB_c , the parameters of the distribution line and the voltage of the buses IB_a , IB_b and IB_c .

Figure 16: Test system used in this thesis.

Figure 17: Block diagram of the automatic voltage regulator.

Figure 18: Block diagram of the speed governor.

The terminal voltage V_t shown in the block diagram of Fig. 17 can be defined in different ways when the SG three-phase stator voltages are unbalanced. In this work, we utilize a generic expression for V_t that does not take into account which phase has the highest or lowest load, as shown in (122). This formulation only considers the level of imbalance between the phases (SALIM, 2011).

$$V_t = \frac{v_{aRMS} + v_{bRMS} + v_{cRMS}}{3} \quad (122)$$

Since in this thesis the measurements are in fact simulated outputs acquired from the software EMTP-RV, we know the reference value of the generator model parameters, shown in Appendix A. Hence, it is possible to assess the error between reference values and

the estimated values of the parameters. That way, in this work we represent the estimated parameters as a percentage of the reference values. For instance, if the estimation process calculates the value of 95% for a parameter, that means this value is 5% lower than the reference value. When using measurements of a SG whose parameters are completely unknown, these reference values are not available and this parameter error analysis is not feasible. Nonetheless, this analysis is not the central part of the proposed estimation approach, and the lack of this assessment does not affect the estimation process.

Basically, this test system produces four sets of measurements, which are utilized to estimate the SG parameters. We obtain the first set of measurements assuming that the loads connected to the generator terminals are balanced. The other three sets are obtained assuming that the loads Z_a , Z_b and Z_c are unbalanced. The value of the load parameters and the setpoints of the voltage regulator and speed governor for each one of these cases are shown in Appendix A. Since one of the objectives of this thesis is demonstrating that the estimation approach works for different operating conditions, we present in Table 2 the levels of imbalance, and generator active and reactive power injection for the tested cases, V_{IMB} , P_{inj} , and Q_{inj} , respectively. The voltage imbalance index V_{IMB} used in this work to quantify the level of imbalance is given by

$$V_{IMB} = \frac{V_-}{V_+} \quad (123)$$

where V_- and V_+ are the negative and positive sequence components, respectively, of the SG terminal voltage. The index V_{IMB} is adopted in several standards for power quality analyses and other types of system studies. Fernandes et al. (2017) compares the index V_{IMB} and the imbalance factor IF defined in Salim (2011) (shown in Section 3.7) for a system similar to the one adopted in this thesis. Acceptable values for the index V_{IMB} are smaller than 2.0% (IEEE, 2009).

Table 2: Operating conditions of the test system used in this thesis

Condition	V_+ (p.u.)	V_{IMB} (%)	P_{inj} (p.u.)	Q_{inj} (p.u.)
Balanced Case (BC)	1.0000	0.0	1.0	0.286
Unbalanced Case 1 (UC1)	1.0064	1.626	1.0	0.288
Unbalanced Case 2 (UC2)	1.0063	2.599	1.0	0.288
Unbalanced Case 3 (UC3)	1.0016	1.377	0.9	0.236

4.2 Balanced Case (BC)

This section presents the adopted procedures to estimate the SG parameters under the balanced operating condition shown in Table 2. Its main objective is to demonstrate that the proposed method estimates a larger number of parameters by using measurements obtained from a balanced condition in comparison with the case where the estimation makes use of signals acquired from an unbalanced operation, as discussed in Section 3.7. To do that, we use two different sampling windows: the first contains the steady-state output of the SG while the second one comprises the response to a disturbance. Another important goal is to show the impact of the initial values of the parameters and of the covariance matrices $\mathbf{Q}$ and $\mathbf{R}$ on the estimation accuracy.

Having in mind the previous aims, we must highlight that the assessment of the impact of the torque angle (δ) estimate on the SG parameter estimation process is not held for this case. Thus, we assume that the measurements i_d , i_q , i_0 , v_d , v_q and v_0 are available. In the next section, we treat the torque angle as an additional parameter and obtain the previously mentioned measurements considering the available *abc* quantities and by using (4).

Since the goal of this section is not to evaluate the estimation approach as a whole, we do not apply all steps of the flowchart in Fig. 8. For example, we do not use a GA to create an initial population containing a set of vectors $\mathbf{p}_{UKF}$. Besides, the blocks that select the parameters for estimation and the validation process are not applied to the balanced case. Although we do not use the block that selects the parameters for estimation, the separation of the SG parameters into subgroups is carried out. As presented in the next subsection, this is an important auxiliary step to identify the parameters which practically do not affect the steady-state responses of the SG.

To better comprehend the application of the estimation method for the balanced case, we relate the SG inputs and state variables of the model in (60)-(65) to the formulation (75)-(76):

- the input vector $\mathbf{u}$ is given by $[v_0, v_d, v_q, v_F, T_m]^T$;
- the output vector $\mathbf{y}$ is equal to $[i_d, i_F, i_q]^T$;
- the vector of the system state variables $\mathbf{x}$ is $[i_d, i_F, i_q, i_0, \delta, \omega]^T$;
- the vector of nonlinear functions $\mathbf{f} = [f_1, \dots, f_6]^T$ is represented by the discretization of the equations (60)-(65);
- the vector of measurements $\mathbf{h}$ is given by $[i_d, i_F, i_q]^T$.

In this subsection, we calculate four fitness functions to analyze the error between the measurements and the outputs of the obtained model. Firstly, we individually calculate

the fitness function for each of the measurements i_d , i_F and i_q and obtain the functions J_{i_d} , J_{i_F} and J_{i_q} , respectively. Then, we calculate the total error J by using (117) and taking into account the measurement vector $\mathbf{y}_m = [i_d, i_F, i_q]^T$.

4.2.1 Separation of the parameters into subgroups

This subsection shows how the selection of windows and the application of TSF are combined to obtain a classification of the parameters. The main objective of this classification is to relate each subgroup of parameters to a certain window. The choice of the set of windows used to estimate the parameters is based on the values of the quadratic function $E_{p_i}^{y^j}$, considering the outputs i_d , i_F and i_q used in the UKF and the parameters r , r_F , L_F , L_d , L_q , D and H . The parameter L_0 is not considered in this case since it does not influence the outputs of the model in balanced conditions.

It is important to point out that to obtain the sensitivity functions shown in (83), which are used to calculate the quadratic function $E_{p_i}^{y^j}$ in (115), we set $p_i^{(1)}$ and $p_i^{(0)}$ to 100.0% and 99.9% of the reference value of p_i , respectively. However, the other parameters p_l , $l \neq i$, are kept to their reference values. We apply this strategy for the calculation of all the quadratic functions $E_{p_i}^{y^j}$ in this work. Besides, we do not consider any type of noise in the sampling windows to calculate the quadratic function.

The first chosen sampling window contains the time interval between 8.0 and 9.5 s, which contemplates a steady-state condition, as shown in Fig. 19. We must highlight that the sampling rate is equal to 0.02 ms for all the experiments in this work. According to Table 3, the parameters L_q , D and L_d are the ones which influence the chosen outputs under steady-state operation. The value of the quadratic functions obtained for the parameters L_F , r_F , H and r are too small, which means they do not affect the generator responses in steady-state condition and cannot be estimated by using the first selected window.

That way, to estimate the parameters which do not affect the curves in steady-state operation, we selected the second sampling window of Fig. 19. This window extends from 9.9 to 13 s and captures the generator response to a disturbance of +5% at the reference of the voltage control (V_{REF}) during 50 ms. The values of the quadratic functions obtained for the parameters L_F , r_F , H and r considering the second sampling window are much higher than when we use the first one. That can be seen by comparing Tables 3 and 4.

Therefore, in the second sampling window, the influence of the parameters L_F , r_F , H and r in the outputs of the UKF is greater, which facilitate their estimation. It is important to highlight that the value of the parameters used to obtain the quadratic function $E_{p_i}^{y^j}$ is equal to the reference values. Depending on the reference values of the parameters and the generator point of operation, the values of the quadratic functions in Tables 3 and 4 may change. However, we could note from several tests that the quadratic

Table 3: Values of the Quadratic Functions of TSF for the First Window

p_i	$E_{p_i}^{i_d}$	$E_{p_i}^{i_F}$	$E_{p_i}^{i_q}$
L_q	$1.04 \cdot 10^{-2}$	$1.83 \cdot 10^{-6}$	$3.13 \cdot 10^{-2}$
D	$2.82 \cdot 10^{-2}$	$1.14 \cdot 10^{-1}$	$4.65 \cdot 10^{-1}$
L_d	$1.30 \cdot 10^{-2}$	$4.63 \cdot 10^{-2}$	$6.68 \cdot 10^{-3}$
L_F	$3.62 \cdot 10^{-11}$	$1.96 \cdot 10^{-10}$	$1.09 \cdot 10^{-10}$
r_F	$1.63 \cdot 10^{-11}$	$8.08 \cdot 10^{-11}$	$4.10 \cdot 10^{-11}$
H	$2.68 \cdot 10^{-13}$	$2.40 \cdot 10^{-12}$	$1.81 \cdot 10^{-12}$
r	$2.97 \cdot 10^{-7}$	$3.23 \cdot 10^{-7}$	$7.25 \cdot 10^{-8}$

Table 4: Values of the Quadratic Functions of TSF for the Second Window

p_i	$E_{p_i}^{i_d}$	$E_{p_i}^{i_F}$	$E_{p_i}^{i_q}$
L_q	$2.12 \cdot 10^{-2}$	$4.65 \cdot 10^{-6}$	$6.43 \cdot 10^{-2}$
D	$5.22 \cdot 10^{-2}$	$2.43 \cdot 10^{-1}$	$9.60 \cdot 10^{-1}$
L_d	$2.78 \cdot 10^{-2}$	$9.54 \cdot 10^{-2}$	$1.39 \cdot 10^{-2}$
L_F	$3.14 \cdot 10^{-5}$	$2.39 \cdot 10^{-5}$	$1.16 \cdot 10^{-5}$
r_F	$8.26 \cdot 10^{-6}$	$9.16 \cdot 10^{-6}$	$4.05 \cdot 10^{-6}$
H	$2.52 \cdot 10^{-5}$	$4.45 \cdot 10^{-6}$	$2.15 \cdot 10^{-5}$
r	$5.90 \cdot 10^{-7}$	$6.81 \cdot 10^{-7}$	$1.51 \cdot 10^{-7}$

functions for the parameters L_q , D and L_d continue to be much greater than for the parameters L_F , r_F , H and r in steady-state conditions.

Figure 19: Sampling windows used to estimate the parameters.

Although the second sampling window provides more information for the estimation of the parameters, there is a limitation of the UKF to estimate them all together. Besides,

even in the second window, the values of the quadratic functions for the parameters L_q , D and L_d are much larger than the ones for the parameters L_F , r_F , H and r . Thus, we use the first sampling window to estimate the three parameters with the greatest quadratic function values, which compose the first subgroup of parameters, whereas the second sampling window is employed to estimate the other four parameters of the second subgroup, with the smallest quadratic function values.

4.2.2 Application of UKF and evaluation of the estimation

After relating each subgroup of parameters to a sampling window, the UKF estimates their values. Nonetheless, there are some UKF parameters which need to be set before its application. These parameters are α , β , ν , shown in (97) and (100), and the matrices $\mathbf{P}_0$, $\mathbf{Q}$ and $\mathbf{R}$. We set α taking into account a recommendation made in (VALVERDE et al., 2011). The estimation results are not affected by α when its value is 0.1. The parameter β is set to 2 considering that the state variables have a Gaussian distribution. According to (VALVERDE et al., 2011) and also some performed tests, we could realize that the value of the parameter ν does not significantly affect the estimation results and we set it to zero.

The value of the covariance matrices $\mathbf{Q}$ and $\mathbf{R}$ are defined according to a combination of values. We fix the initial value of the error covariance matrix $\mathbf{P}_0$ ($\epsilon = 10^{-3}$) for all the situations tested in the balanced case. Besides, we also assume the parameters ψ_s and ψ_p in (111) are equal ($\psi_s = \psi_p = \psi$). The values of ψ and ζ are changed to obtain a set of generator parameter values that minimize the total error J .

Once we set the UKF parameters, the next step is estimating the first subgroup of parameters by using the first sampling window. During the estimation process of these parameters, we fix the values of the second subgroup parameters. In this work, we know the parameter values and, hence, we can fix the second subgroup of parameters to their reference values. However, in real situations, precise information about the parameters may not be available. For this reason, we carry out three different estimations, one of them considering the reference values for the non-estimated parameters (Case BC1) and other two in which the values of these parameters are fixed to 110% (Case BC2) and 90% (Case BC3) of their reference values. The initial values of the parameters D , L_q and L_d are set to 122.287%, 109.627% and 121.765% of their reference values, respectively. These values are randomly chosen in the range [70%, 130%].

Tables 5, 6 and 7 exhibit the estimated parameters in the three cases described above, as well the errors J_{i_d} , J_{i_F} , J_{i_q} and J . The best set of estimated parameters is highlighted in each table and, we can observe that the smallest error in each table occurs for $\psi = 10^{-8}$ and $\zeta = 10^{-4}$. Besides, the smallest error is very similar in these three cases, which confirms that the values of the parameters L_F , r_F , H and r do not strongly influence the

estimation of the parameters D , L_q and L_d by using a window containing a steady-state response.

Table 5: Parameters estimated in the first window for Case BC1

ψ	ζ	$L_d(\%)$	$D(\%)$	$L_q(\%)$	J_{i_d}	J_{i_F}	J_{i_q}	J
10^{-4}	10^{-4}	99.279	104.121	101.223	$1.58 \cdot 10^{-3}$	$8.91 \cdot 10^{-4}$	$2.69 \cdot 10^{-4}$	$2.74 \cdot 10^{-3}$
10^{-4}	10^{-5}	99.275	104.117	101.231	$1.59 \cdot 10^{-3}$	$8.91 \cdot 10^{-4}$	$2.70 \cdot 10^{-4}$	$2.75 \cdot 10^{-3}$
10^{-4}	10^{-6}	99.275	104.117	101.231	$1.59 \cdot 10^{-3}$	$8.91 \cdot 10^{-4}$	$2.70 \cdot 10^{-4}$	$2.75 \cdot 10^{-3}$
10^{-4}	10^{-7}	99.275	104.117	101.231	$1.59 \cdot 10^{-3}$	$8.91 \cdot 10^{-4}$	$2.70 \cdot 10^{-4}$	$2.75 \cdot 10^{-3}$
10^{-4}	10^{-8}	99.275	104.117	101.231	$1.59 \cdot 10^{-3}$	$8.91 \cdot 10^{-4}$	$2.70 \cdot 10^{-4}$	$2.75 \cdot 10^{-3}$
10^{-5}	10^{-4}	99.989	100.060	100.020	$3.51 \cdot 10^{-7}$	$1.91 \cdot 10^{-7}$	$6.43 \cdot 10^{-8}$	$6.06 \cdot 10^{-7}$
10^{-5}	10^{-5}	99.993	100.007	100.014	$1.07 \cdot 10^{-7}$	$1.60 \cdot 10^{-8}$	$3.03 \cdot 10^{-8}$	$1.53 \cdot 10^{-7}$
10^{-5}	10^{-6}	99.987	100.009	100.024	$3.41 \cdot 10^{-7}$	$4.81 \cdot 10^{-8}$	$1.01 \cdot 10^{-7}$	$4.91 \cdot 10^{-7}$
10^{-5}	10^{-7}	99.987	100.009	100.024	$3.49 \cdot 10^{-7}$	$4.92 \cdot 10^{-8}$	$1.04 \cdot 10^{-7}$	$5.02 \cdot 10^{-7}$
10^{-5}	10^{-8}	99.987	100.009	100.024	$3.49 \cdot 10^{-7}$	$4.92 \cdot 10^{-8}$	$1.04 \cdot 10^{-7}$	$5.02 \cdot 10^{-7}$
10^{-6}	10^{-4}	100.000	100.000	100.002	$6.89 \cdot 10^{-12}$	$6.31 \cdot 10^{-12}$	$1.63 \cdot 10^{-12}$	$1.48 \cdot 10^{-11}$
10^{-6}	10^{-5}	100.004	99.970	99.996	$5.09 \cdot 10^{-8}$	$4.15 \cdot 10^{-8}$	$1.10 \cdot 10^{-8}$	$1.03 \cdot 10^{-7}$
10^{-6}	10^{-6}	100.000	99.997	100.002	$2.54 \cdot 10^{-10}$	$3.74 \cdot 10^{-10}$	$1.03 \cdot 10^{-10}$	$7.31 \cdot 10^{-10}$
10^{-6}	10^{-7}	100.001	99.998	100.000	$2.07 \cdot 10^{-9}$	$4.24 \cdot 10^{-10}$	$4.83 \cdot 10^{-10}$	$2.98 \cdot 10^{-9}$
10^{-6}	10^{-8}	100.001	99.998	100.000	$2.19 \cdot 10^{-9}$	$4.41 \cdot 10^{-10}$	$5.15 \cdot 10^{-10}$	$3.15 \cdot 10^{-9}$
10^{-7}	10^{-4}	100.000	100.000	100.002	$3.33 \cdot 10^{-12}$	$2.15 \cdot 10^{-12}$	$6.36 \cdot 10^{-13}$	$6.12 \cdot 10^{-12}$
10^{-7}	10^{-5}	100.001	99.992	100.000	$3.73 \cdot 10^{-9}$	$2.88 \cdot 10^{-9}$	$7.79 \cdot 10^{-10}$	$7.39 \cdot 10^{-9}$
10^{-7}	10^{-6}	100.000	100.000	100.002	$6.08 \cdot 10^{-12}$	$3.95 \cdot 10^{-12}$	$1.17 \cdot 10^{-12}$	$1.12 \cdot 10^{-11}$
10^{-7}	10^{-7}	100.000	99.998	100.001	$4.83 \cdot 10^{-10}$	$2.22 \cdot 10^{-10}$	$8.80 \cdot 10^{-11}$	$7.93 \cdot 10^{-10}$
10^{-7}	10^{-8}	100.000	99.999	100.002	$2.70 \cdot 10^{-10}$	$1.13 \cdot 10^{-10}$	$4.97 \cdot 10^{-11}$	$4.33 \cdot 10^{-10}$
10^{-8}	10^{-4}	100.000	100.000	100.002	$2.35 \cdot 10^{-14}$	$1.83 \cdot 10^{-14}$	$4.90 \cdot 10^{-15}$	$4.68 \cdot 10^{-14}$
10^{-8}	10^{-5}	100.000	99.999	100.002	$1.14 \cdot 10^{-10}$	$7.39 \cdot 10^{-11}$	$2.17 \cdot 10^{-11}$	$2.09 \cdot 10^{-10}$
10^{-8}	10^{-6}	100.000	100.000	100.002	$9.14 \cdot 10^{-14}$	$5.78 \cdot 10^{-14}$	$1.74 \cdot 10^{-14}$	$1.67 \cdot 10^{-13}$
10^{-8}	10^{-7}	100.000	100.000	100.002	$1.16 \cdot 10^{-12}$	$6.07 \cdot 10^{-13}$	$2.12 \cdot 10^{-13}$	$1.97 \cdot 10^{-12}$
10^{-8}	10^{-8}	100.000	99.999	100.002	$2.91 \cdot 10^{-11}$	$2.27 \cdot 10^{-11}$	$6.12 \cdot 10^{-12}$	$5.79 \cdot 10^{-11}$

Besides the matrices $\mathbf{Q}$ and $\mathbf{R}$, the initial values of the parameters under estimation also interfere with the final values obtained by UKF. We analyze that in this work by considering 30 different initial values for the parameters L_q , D and L_d , randomly chosen between the range of 70% and 130% of the reference values and performing the estimation for these cases. Fig. 20 shows the error J of the 28 converged cases. The variation of the error confirms that the initial values of the estimated parameters really influence the estimation process. To obtain the results presented in Fig. 20, we set ψ and ζ to 10^{-8} and 10^{-4} , respectively, and the values of the parameters of the second subgroup to 110% of their reference values.

It is necessary to highlight that 2 of the 30 cases tested to produce Fig. 20 did not converge. Such result demonstrates that not only the final values but also the UKF convergence itself depend on the initial values of the estimated parameters.

After the estimation of the first subgroup of parameters is complete, we start the estimation of the parameters L_F , r_F , H and r by using the second sampling window. During the estimation of the parameters in the second subgroup, we fix D , L_q and L_d to the values highlighted in Table 6. The initial value of the parameters L_F , r_F , H and r are set to 121.765%, 122.287%, 109.627% and 86.635% of their reference values,

respectively. As in the estimation of the first subgroup, these values are randomly chosen in the range $[70\%, 130\%]$. The obtained results are exhibited in Table 8, where the best set of estimated parameters is highlighted. We can note that for this second sampling window, the minimum error occurs for $\psi = 10^{-8}$ and $\zeta = 10^{-4}$, as in the estimation of the parameters D , L_q and L_d . It is also important to observe that the error in the estimation of the parameter r is higher than in the other parameters. That happens because, as Table 4 shows, r does not influence the responses i_d , i_F and i_q the same way as L_F , r_F and H .

Figure 20: Error for different sets of initial values for the parameters L_q , D and L_d .

Figure 21: Error for different sets of initial values for the parameters L_F , r_F , H and r .

Table 6: Parameters estimated in the first window for Case BC2

ψ	ζ	$L_d(\%)$	$D(\%)$	$L_q(\%)$	J_{i_d}	J_{i_F}	J_{i_q}	J
10^{-4}	10^{-4}	99.248	104.634	101.288	$1.51 \cdot 10^{-3}$	$9.51 \cdot 10^{-4}$	$2.89 \cdot 10^{-4}$	$2.75 \cdot 10^{-3}$
10^{-4}	10^{-5}	99.244	104.614	101.294	$1.52 \cdot 10^{-3}$	$9.45 \cdot 10^{-4}$	$2.89 \cdot 10^{-4}$	$2.75 \cdot 10^{-3}$
10^{-4}	10^{-6}	99.244	104.614	101.294	$1.52 \cdot 10^{-3}$	$9.44 \cdot 10^{-4}$	$2.89 \cdot 10^{-4}$	$2.75 \cdot 10^{-3}$
10^{-4}	10^{-7}	99.244	104.614	101.294	$1.52 \cdot 10^{-3}$	$9.44 \cdot 10^{-4}$	$2.89 \cdot 10^{-4}$	$2.75 \cdot 10^{-3}$
10^{-4}	10^{-8}	99.244	104.614	101.294	$1.52 \cdot 10^{-3}$	$9.44 \cdot 10^{-4}$	$2.89 \cdot 10^{-4}$	$2.75 \cdot 10^{-3}$
10^{-5}	10^{-4}	99.980	100.059	100.047	$3.65 \cdot 10^{-7}$	$2.21 \cdot 10^{-7}$	$7.46 \cdot 10^{-8}$	$6.60 \cdot 10^{-7}$
10^{-5}	10^{-5}	99.986	99.978	100.037	$4.39 \cdot 10^{-8}$	$8.40 \cdot 10^{-9}$	$2.64 \cdot 10^{-8}$	$7.87 \cdot 10^{-8}$
10^{-5}	10^{-6}	99.983	99.958	100.043	$1.18 \cdot 10^{-7}$	$4.43 \cdot 10^{-8}$	$9.24 \cdot 10^{-8}$	$2.55 \cdot 10^{-7}$
10^{-5}	10^{-7}	99.983	99.958	100.043	$1.20 \cdot 10^{-7}$	$4.55 \cdot 10^{-8}$	$9.46 \cdot 10^{-8}$	$2.61 \cdot 10^{-7}$
10^{-5}	10^{-8}	99.983	99.958	100.043	$1.21 \cdot 10^{-7}$	$4.56 \cdot 10^{-8}$	$9.46 \cdot 10^{-8}$	$2.61 \cdot 10^{-7}$
10^{-6}	10^{-4}	99.992	99.988	100.028	$4.10 \cdot 10^{-13}$	$4.34 \cdot 10^{-14}$	$1.68 \cdot 10^{-13}$	$6.21 \cdot 10^{-13}$
10^{-6}	10^{-5}	99.996	99.951	100.020	$6.56 \cdot 10^{-8}$	$5.88 \cdot 10^{-8}$	$1.61 \cdot 10^{-8}$	$1.41 \cdot 10^{-7}$
10^{-6}	10^{-6}	99.992	99.982	100.027	$1.16 \cdot 10^{-9}$	$1.54 \cdot 10^{-9}$	$4.22 \cdot 10^{-10}$	$3.12 \cdot 10^{-9}$
10^{-6}	10^{-7}	99.992	99.988	100.027	$6.68 \cdot 10^{-10}$	$7.79 \cdot 10^{-11}$	$2.30 \cdot 10^{-10}$	$9.76 \cdot 10^{-10}$
10^{-6}	10^{-8}	99.992	99.988	100.027	$7.05 \cdot 10^{-10}$	$7.92 \cdot 10^{-11}$	$2.51 \cdot 10^{-10}$	$1.03 \cdot 10^{-9}$
10^{-7}	10^{-4}	99.992	99.988	100.028	$1.76 \cdot 10^{-12}$	$1.30 \cdot 10^{-12}$	$3.74 \cdot 10^{-13}$	$3.44 \cdot 10^{-12}$
10^{-7}	10^{-5}	99.993	99.979	100.026	$4.43 \cdot 10^{-9}$	$3.82 \cdot 10^{-9}$	$1.06 \cdot 10^{-9}$	$9.31 \cdot 10^{-9}$
10^{-7}	10^{-6}	99.992	99.988	100.028	$1.13 \cdot 10^{-11}$	$8.89 \cdot 10^{-12}$	$2.53 \cdot 10^{-12}$	$2.27 \cdot 10^{-11}$
10^{-7}	10^{-7}	99.992	99.986	100.027	$6.94 \cdot 10^{-10}$	$3.37 \cdot 10^{-10}$	$1.40 \cdot 10^{-10}$	$1.17 \cdot 10^{-9}$
10^{-7}	10^{-8}	99.992	99.987	100.027	$3.96 \cdot 10^{-10}$	$1.65 \cdot 10^{-10}$	$8.07 \cdot 10^{-11}$	$6.42 \cdot 10^{-10}$
10^{-8}	10^{-4}	99.992	99.988	100.028	$1.35 \cdot 10^{-14}$	$1.44 \cdot 10^{-14}$	$2.55 \cdot 10^{-15}$	$3.05 \cdot 10^{-14}$
10^{-8}	10^{-5}	99.992	99.987	100.027	$9.77 \cdot 10^{-11}$	$7.14 \cdot 10^{-11}$	$2.11 \cdot 10^{-11}$	$1.90 \cdot 10^{-10}$
10^{-8}	10^{-6}	99.992	99.988	100.028	$1.82 \cdot 10^{-13}$	$1.37 \cdot 10^{-13}$	$3.73 \cdot 10^{-14}$	$3.57 \cdot 10^{-13}$
10^{-8}	10^{-7}	99.992	99.988	100.028	$2.02 \cdot 10^{-12}$	$1.14 \cdot 10^{-12}$	$4.01 \cdot 10^{-13}$	$3.56 \cdot 10^{-12}$
10^{-8}	10^{-8}	99.992	99.988	100.028	$1.40 \cdot 10^{-11}$	$1.23 \cdot 10^{-11}$	$3.37 \cdot 10^{-12}$	$2.97 \cdot 10^{-11}$

The initial values of the parameters L_F , r_F , H and r influence the estimation performed by UKF, as it can be noticed by analyzing the error for the 30 cases in the graph of Fig. 21. To obtain these results, 30 sets of initial values for the estimated parameters are chosen in the range [70%, 130%], as previously done for the parameters D , L_q and L_d . However, for the second sampling window, all the cases converged and the range of the error J was not as high as the one obtained in the first sampling window.

To assess the SG three-phase model considering the parameters estimated by the proposed approach, the responses i_d , i_F , i_q and ω are exhibited in the graphs of Fig. 22. These curves are obtained taking into account four different sets of parameters: the best sets highlighted in Table 6, 7 and 8, and the set with the reference parameters. The curves obtained by using the reference values of the parameters and the best set of Table 8 are visually overlapped. Comparing the curves obtained by using the best sets of Table 6 and 7 with the reference ones, we can note that the influence of the parameters L_F , r_F , H and r are greater during the transient period. Therefore, a sampling window which includes the response to a disturbance is necessary for the correct estimation of these parameters.

Table 7: Parameters estimated in the first window for Case BC3

ψ	ζ	$L_d(\%)$	$D(\%)$	$L_q(\%)$	J_{i_d}	J_{i_F}	J_{i_q}	J
10^{-4}	10^{-4}	99.312	103.652	101.156	$1.71 \cdot 10^{-3}$	$8.70 \cdot 10^{-4}$	$2.52 \cdot 10^{-4}$	$2.84 \cdot 10^{-3}$
10^{-4}	10^{-5}	99.306	103.662	101.166	$1.74 \cdot 10^{-3}$	$8.77 \cdot 10^{-4}$	$2.55 \cdot 10^{-4}$	$2.87 \cdot 10^{-3}$
10^{-4}	10^{-6}	99.306	103.662	101.166	$1.74 \cdot 10^{-3}$	$8.77 \cdot 10^{-4}$	$2.55 \cdot 10^{-4}$	$2.87 \cdot 10^{-3}$
10^{-4}	10^{-7}	99.306	103.662	101.166	$1.74 \cdot 10^{-3}$	$8.77 \cdot 10^{-4}$	$2.55 \cdot 10^{-4}$	$2.87 \cdot 10^{-3}$
10^{-4}	10^{-8}	99.306	103.662	101.166	$1.74 \cdot 10^{-3}$	$8.77 \cdot 10^{-4}$	$2.55 \cdot 10^{-4}$	$2.87 \cdot 10^{-3}$
10^{-5}	10^{-4}	99.998	100.063	99.994	$3.53 \cdot 10^{-7}$	$1.72 \cdot 10^{-7}$	$5.58 \cdot 10^{-8}$	$5.81 \cdot 10^{-7}$
10^{-5}	10^{-5}	99.999	100.037	99.993	$2.67 \cdot 10^{-7}$	$7.18 \cdot 10^{-8}$	$4.76 \cdot 10^{-8}$	$3.86 \cdot 10^{-7}$
10^{-5}	10^{-6}	99.991	100.058	100.007	$8.99 \cdot 10^{-7}$	$2.43 \cdot 10^{-7}$	$1.60 \cdot 10^{-7}$	$1.30 \cdot 10^{-6}$
10^{-5}	10^{-7}	99.990	100.059	100.007	$9.20 \cdot 10^{-7}$	$2.49 \cdot 10^{-7}$	$1.64 \cdot 10^{-7}$	$1.33 \cdot 10^{-6}$
10^{-5}	10^{-8}	99.990	100.059	100.007	$9.20 \cdot 10^{-7}$	$2.49 \cdot 10^{-7}$	$1.64 \cdot 10^{-7}$	$1.33 \cdot 10^{-6}$
10^{-6}	10^{-4}	100.008	100.011	99.976	$5.10 \cdot 10^{-11}$	$3.42 \cdot 10^{-11}$	$8.96 \cdot 10^{-12}$	$9.42 \cdot 10^{-11}$
10^{-6}	10^{-5}	100.011	99.991	99.972	$3.27 \cdot 10^{-8}$	$2.44 \cdot 10^{-8}$	$6.09 \cdot 10^{-9}$	$6.31 \cdot 10^{-8}$
10^{-6}	10^{-6}	100.008	100.010	99.976	$4.85 \cdot 10^{-11}$	$7.39 \cdot 10^{-11}$	$2.01 \cdot 10^{-11}$	$1.43 \cdot 10^{-10}$
10^{-6}	10^{-7}	100.010	100.008	99.974	$5.00 \cdot 10^{-9}$	$1.49 \cdot 10^{-9}$	$8.56 \cdot 10^{-10}$	$7.35 \cdot 10^{-9}$
10^{-6}	10^{-8}	100.010	100.008	99.974	$5.26 \cdot 10^{-9}$	$1.57 \cdot 10^{-9}$	$9.03 \cdot 10^{-10}$	$7.73 \cdot 10^{-9}$
10^{-7}	10^{-4}	100.008	100.011	99.977	$6.91 \cdot 10^{-12}$	$3.90 \cdot 10^{-12}$	$1.14 \cdot 10^{-12}$	$1.19 \cdot 10^{-11}$
10^{-7}	10^{-5}	100.009	100.006	99.975	$2.80 \cdot 10^{-9}$	$1.92 \cdot 10^{-9}$	$4.96 \cdot 10^{-10}$	$5.22 \cdot 10^{-9}$
10^{-7}	10^{-6}	100.008	100.011	99.977	$6.23 \cdot 10^{-12}$	$3.27 \cdot 10^{-12}$	$1.01 \cdot 10^{-12}$	$1.05 \cdot 10^{-11}$
10^{-7}	10^{-7}	100.008	100.010	99.976	$1.95 \cdot 10^{-10}$	$8.47 \cdot 10^{-11}$	$3.09 \cdot 10^{-11}$	$3.11 \cdot 10^{-10}$
10^{-7}	10^{-8}	100.008	100.011	99.976	$1.03 \cdot 10^{-10}$	$4.59 \cdot 10^{-11}$	$1.62 \cdot 10^{-11}$	$1.65 \cdot 10^{-10}$
10^{-8}	10^{-4}	100.008	100.012	99.977	$5.05 \cdot 10^{-14}$	$2.85 \cdot 10^{-14}$	$9.88 \cdot 10^{-15}$	$8.89 \cdot 10^{-14}$
10^{-8}	10^{-5}	100.008	100.010	99.976	$1.32 \cdot 10^{-10}$	$7.57 \cdot 10^{-11}$	$2.15 \cdot 10^{-11}$	$2.29 \cdot 10^{-10}$
10^{-8}	10^{-6}	100.008	100.012	99.977	$8.52 \cdot 10^{-14}$	$4.19 \cdot 10^{-14}$	$1.51 \cdot 10^{-14}$	$1.42 \cdot 10^{-13}$
10^{-8}	10^{-7}	100.008	100.012	99.977	$3.68 \cdot 10^{-13}$	$1.78 \cdot 10^{-13}$	$6.16 \cdot 10^{-14}$	$6.08 \cdot 10^{-13}$
10^{-8}	10^{-8}	100.008	100.010	99.976	$9.91 \cdot 10^{-11}$	$6.76 \cdot 10^{-11}$	$1.75 \cdot 10^{-11}$	$1.84 \cdot 10^{-10}$

Table 8: Parameters estimated in the second window

ψ	ζ	$L_F(\%)$	$r_F(\%)$	$H(\%)$	$r(\%)$	J_{i_d}	J_{i_F}	J_{i_q}	J
10^{-4}	10^{-4}	120.261	123.277	109.624	100.960	$1.03 \cdot 10^{-6}$	$4.75 \cdot 10^{-7}$	$2.20 \cdot 10^{-7}$	$1.73 \cdot 10^{-6}$
10^{-4}	10^{-5}	120.265	123.277	109.624	100.960	$1.04 \cdot 10^{-6}$	$4.75 \cdot 10^{-7}$	$2.20 \cdot 10^{-7}$	$1.73 \cdot 10^{-6}$
10^{-4}	10^{-6}	120.265	123.277	109.624	100.960	$1.04 \cdot 10^{-6}$	$4.75 \cdot 10^{-7}$	$2.20 \cdot 10^{-7}$	$1.73 \cdot 10^{-6}$
10^{-4}	10^{-7}	120.265	123.277	109.624	100.960	$1.04 \cdot 10^{-6}$	$4.75 \cdot 10^{-7}$	$2.20 \cdot 10^{-7}$	$1.73 \cdot 10^{-6}$
10^{-4}	10^{-8}	120.265	123.277	109.624	100.960	$1.04 \cdot 10^{-6}$	$4.75 \cdot 10^{-7}$	$2.20 \cdot 10^{-7}$	$1.73 \cdot 10^{-6}$
10^{-5}	10^{-4}	110.959	119.431	109.473	109.619	$3.23 \cdot 10^{-7}$	$2.13 \cdot 10^{-7}$	$1.56 \cdot 10^{-9}$	$5.38 \cdot 10^{-7}$
10^{-5}	10^{-5}	110.944	119.401	109.473	109.625	$3.22 \cdot 10^{-7}$	$2.12 \cdot 10^{-7}$	$1.55 \cdot 10^{-9}$	$5.36 \cdot 10^{-7}$
10^{-5}	10^{-6}	110.946	119.403	109.473	109.625	$3.22 \cdot 10^{-7}$	$2.12 \cdot 10^{-7}$	$1.55 \cdot 10^{-9}$	$5.36 \cdot 10^{-7}$
10^{-5}	10^{-7}	110.946	119.403	109.473	109.625	$3.22 \cdot 10^{-7}$	$2.12 \cdot 10^{-7}$	$1.55 \cdot 10^{-9}$	$5.36 \cdot 10^{-7}$
10^{-5}	10^{-8}	110.946	119.403	109.473	109.625	$3.22 \cdot 10^{-7}$	$2.12 \cdot 10^{-7}$	$1.55 \cdot 10^{-9}$	$5.36 \cdot 10^{-7}$
10^{-6}	10^{-4}	100.672	101.173	104.136	109.834	$1.68 \cdot 10^{-9}$	$8.36 \cdot 10^{-10}$	$1.30 \cdot 10^{-10}$	$2.64 \cdot 10^{-9}$
10^{-6}	10^{-5}	100.646	101.049	104.127	109.854	$1.16 \cdot 10^{-9}$	$5.38 \cdot 10^{-10}$	$1.15 \cdot 10^{-10}$	$1.81 \cdot 10^{-9}$
10^{-6}	10^{-6}	100.647	101.050	104.126	109.855	$1.16 \cdot 10^{-9}$	$5.37 \cdot 10^{-10}$	$1.14 \cdot 10^{-10}$	$1.81 \cdot 10^{-9}$
10^{-6}	10^{-7}	100.648	101.052	104.126	109.855	$1.16 \cdot 10^{-9}$	$5.40 \cdot 10^{-10}$	$1.14 \cdot 10^{-10}$	$1.81 \cdot 10^{-9}$
10^{-6}	10^{-8}	100.648	101.052	104.126	109.855	$1.16 \cdot 10^{-9}$	$5.40 \cdot 10^{-10}$	$1.14 \cdot 10^{-10}$	$1.81 \cdot 10^{-9}$
10^{-7}	10^{-4}	100.013	100.046	100.259	109.835	$1.29 \cdot 10^{-10}$	$3.06 \cdot 10^{-11}$	$4.90 \cdot 10^{-11}$	$2.08 \cdot 10^{-10}$
10^{-7}	10^{-5}	100.282	100.418	100.154	109.840	$3.07 \cdot 10^{-10}$	$1.49 \cdot 10^{-10}$	$4.73 \cdot 10^{-11}$	$5.03 \cdot 10^{-10}$
10^{-7}	10^{-6}	100.432	100.653	100.081	109.855	$5.72 \cdot 10^{-10}$	$3.28 \cdot 10^{-10}$	$4.06 \cdot 10^{-11}$	$9.41 \cdot 10^{-10}$
10^{-7}	10^{-7}	100.436	100.659	100.079	109.856	$5.81 \cdot 10^{-10}$	$3.34 \cdot 10^{-10}$	$4.04 \cdot 10^{-11}$	$9.55 \cdot 10^{-10}$
10^{-7}	10^{-8}	100.436	100.659	100.079	109.856	$5.82 \cdot 10^{-10}$	$3.34 \cdot 10^{-10}$	$4.04 \cdot 10^{-11}$	$9.56 \cdot 10^{-10}$
10^{-8}	10^{-4}	100.013	100.051	100.245	109.927	$5.29 \cdot 10^{-11}$	$1.80 \cdot 10^{-11}$	$1.63 \cdot 10^{-11}$	$8.72 \cdot 10^{-11}$
10^{-8}	10^{-5}	100.004	99.985	100.247	109.845	$9.56 \cdot 10^{-11}$	$1.92 \cdot 10^{-11}$	$4.33 \cdot 10^{-11}$	$1.58 \cdot 10^{-10}$
10^{-8}	10^{-6}	100.280	100.417	100.101	109.840	$3.09 \cdot 10^{-10}$	$1.50 \cdot 10^{-10}$	$4.77 \cdot 10^{-11}$	$5.07 \cdot 10^{-10}$
10^{-8}	10^{-7}	100.432	100.644	100.016	109.856	$5.67 \cdot 10^{-10}$	$3.25 \cdot 10^{-10}$	$4.07 \cdot 10^{-11}$	$9.32 \cdot 10^{-10}$
10^{-8}	10^{-8}	100.437	100.651	100.013	109.856	$5.76 \cdot 10^{-10}$	$3.30 \cdot 10^{-10}$	$4.05 \cdot 10^{-11}$	$9.47 \cdot 10^{-10}$

Figure 22: Responses considering four different sets of parameters.

4.3 Unbalanced Cases

This section utilizes the obtained results to better explain how the flowchart in Fig. 8 is employed to estimate the SG parameters under unbalanced conditions. Different from the previous section, only one sampling window is used to estimate the parameters of the SG model. Nonetheless, the number of estimated parameters is smaller when using a sampling window obtained from an unbalanced operation. Since the initial values of the parameters and of the covariance matrices may impact the estimation by using the UKF, as shown for the balanced case in the previous section, we use a GA to determine them (see subsection 3.6.3).

In this section, we consider the impact of the torque angle (δ) estimate on the SG parameter estimation process. That way, the torque angle is treated as an additional parameter, employed to convert the measured voltages and currents v_a, v_b, v_c, i_a, i_b and i_c to the quantities v_0, v_d, v_q, i_0, i_d and i_q by using (4).

To better comprehend the application of the estimation method for the unbalanced cases, we relate the SG inputs and state variables of the model in (60)-(65) to the formulation (75)-(76):

- the input vector $\mathbf{u}$ is given by $[v_a, v_b, v_c, v_F, T_m]^T$;
- the output vector $\mathbf{y}$ is equal to $[i_a, i_b, i_c, i_F]^T$;
- the vector of state variables $\mathbf{x}$ of the system is $[i_d, i_F, i_q, i_0, \delta, \omega]^T$;
- the vector of nonlinear functions $\mathbf{f} = [f_1, \dots, f_6]^T$ is represented by the discretization of the equations (60)-(65);
- the vector of measurements $\mathbf{h}$ is given by $[i_a, i_b, i_c, i_F]^T$.

We employ the steps of the flowchart in Fig. 8 to the three unbalanced cases shown in Table 2. The next subsections show the results of the application of these steps. It is important to stress that with the presentation of results related to the UC1, we practically describe all the details of the estimation approach. Thus, we overpass the repeated details for UC2 and UC3 cases, just highlighting the obtained results.

In the three unbalanced cases, there are parameters which cannot be estimated. That is certainly an issue for the estimation approach since most times the available values for these non-estimated parameters do not correspond to the reference values which should be considered in the SG model, and that may affect the estimation of other parameters. Taking this into account, we apply the estimation approach assuming an error between the values of the non-estimated parameters used in the estimation process and their reference values. That way, for each unbalanced case we analyze the proposed method for three different situations, where the non-estimated parameters are fixed to 90%, 100% and 110% of their respective reference values.

In addition to the error of the non-estimated parameters, the presence of noise in the measurements may also affect the estimation approach. Thus, to verify the performance of the estimation approach under noisy measurements, we consider three different scenarios for each situation described above. The insertion of this noise to the measurements occurs with a random variation of the three-phase loads Z_a , Z_b and Z_c , exhibited in Fig. 16, during the simulation of the SG responses by using the software EMTP-RV. This load variation is applied considering a random value for a portion of the load resistance, which introduces random excitation to the experiment. That can be better understood with Fig. 23, where load resistance of phase a is the sum of a fixed value ($R_{aL_{Fix}}$) and a random value (R_{noise}). The same occurs with the load resistance of phases b and c .

Figure 23: Insertion of noise to the measurements through the load variation

The value of R_{noise} is a percentage of R_{xL} , $x = \{a, b, c\}$, and in this thesis can assume the values 5%, 10% and 15%. To better understand the calculation of R_{noise} , consider the values of R_{aL} , R_{bL} and R_{cL} for the UC1, which are 34.1 Ω , 38.1 Ω and 42.1 Ω , respectively. Assuming a percentage of 10%, the value of R_{noise} for phases a , b and c is equal to 3.41 Ω , 3.81 Ω and 4.21 Ω , respectively. It is also important to point out that although the same percentage is used to calculate R_{noise} in each phase, the random sequence of generated values is different for each phase.

From the information provided in the previous paragraphs, we must point out that the noisy measurements considered in this work are due to the random variation of the load, typical of distributed systems. However, it is possible to add other types of noise to the measurements to make them even more realistic.

4.3.1 Unbalanced Case 1 (UC1)

In this subsection, we apply the estimation approach shown in the flowchart of Fig. 8 to the UC1, which is depicted in Table 2 and in Appendix A. To estimate the parameters of the SG model, we make use of a sampling window containing a small portion of the SG sinusoidal steady-state immediately before a disturbance and the response to this disturbance. The disturbance consists of a step of +5% in the reference of the voltage control (V_{REF}) during 50 ms applied at the instant 10.0 s and the sampling window extends from the instant 9.9 s to 13 s, with a sampling rate equals to 0.02 ms, as shown in Fig. 24.

Figure 24: Sampling window considering a value of 15% for R_{noise} .

In the following, we present the results obtained in the main parts of the flowchart shown in Fig. 8 as well as describe some important details considered to obtain these results.

4.3.1.1 Influence of Parameters in the Model

Before presenting the results related to this step, we must underscore that it is not possible to apply this stage of the approach in practical situations since the reference values of the parameters are not available in these cases. However, this stage is helpful in this thesis to demonstrate that regardless of considering balanced or unbalanced conditions, the rank of the most important parameters in the model does not change significantly. For instance, according to Tables 9, 13, and 17, the parameters L_q , D , L_d and L_F are the ones which most influence the current i_d . We must emphasize that we do not consider any type of noise in the sampling windows to obtain the previously mentioned tables.

Observing Table 9, we can note that the rank of the parameters taking into account $E_{p_i}^{i_d}$ is different from the one obtained considering $E_{p_i}^{i_F}$ or $E_{p_i}^{i_q}$. That way, we must consider one of these three quadratic functions (or a combination of them) to obtain the parameters rank. In this work, we take $E_{p_i}^{i_d}$ into consideration to sort the parameters.

It is important to highlight that the currents i_d and i_q are obtained from the currents i_a , i_b , i_c , and the torque angle δ , which is normally not available in practical situations. Hence, it is not simple to calculate the functions $E_{p_i}^{i_d}$ and $E_{p_i}^{i_q}$ by using field measurements and that can be considered another reason for the elimination of this stage from the proposed approach. Nevertheless, since the software EMTP-RV provides these variables as outputs of the SG, this analysis is important because in practical situations the rank

of parameters is not so different from the ones in this work.

Table 9: Values of the quadratic functions of TSF for UC1

p_i	$E_{p_i}^{i_d}$	$E_{p_i}^{i_F}$	$E_{p_i}^{i_q}$
D	$4.32 \cdot 10^{-2}$	$2.48 \cdot 10^{-1}$	$9.84 \cdot 10^{-1}$
L_d	$3.01 \cdot 10^{-2}$	$9.43 \cdot 10^{-2}$	$1.40 \cdot 10^{-2}$
L_q	$2.21 \cdot 10^{-2}$	$1.59 \cdot 10^{-5}$	$6.24 \cdot 10^{-2}$
L_F	$1.23 \cdot 10^{-4}$	$9.54 \cdot 10^{-5}$	$1.22 \cdot 10^{-5}$
H	$2.40 \cdot 10^{-5}$	$4.27 \cdot 10^{-6}$	$2.22 \cdot 10^{-5}$
r_F	$8.36 \cdot 10^{-6}$	$9.23 \cdot 10^{-6}$	$4.13 \cdot 10^{-6}$
r	$5.59 \cdot 10^{-7}$	$6.88 \cdot 10^{-7}$	$1.77 \cdot 10^{-7}$
L_0	$1.87 \cdot 10^{-16}$	$4.09 \cdot 10^{-17}$	$5.85 \cdot 10^{-17}$

The analysis of the influence of parameters in the model is important to simplify the choice of parameters for estimation, which is the next step of the approach. Nonetheless, the absence of this stage does not prevent that the choice of parameters for estimation be applied, as we shall see below.

4.3.1.2 Choice of Parameters for Estimation

In this thesis, we choose the parameters for estimation by using the values of the quadratic functions of TSF and the flowchart of Fig. 9. By taking into account the quadratic function $E_{p_i}^{i_d}$ in Table 9, we can gather the parameters D , L_d and L_q to the group of parameters which most influence the current i_d . The second group of parameters comprises the parameters L_F , H , r_F and r , which do not influence the current i_d as much as the other parameters of the first group. Finally, the parameter L_0 belongs to the third group of parameters, which practically do not affect the current i_d and certainly cannot have its value estimated.

Considering the quadratic function $E_{p_i}^{i_F}$, we can divide the parameters into three groups, which are different from the ones obtained when taking into account the quadratic function $E_{p_i}^{i_d}$. The first group comprehends the parameters D and L_d , the second comprises the parameters L_F , L_q , r_F , H and r and the third one contains the parameter L_0 .

In this work, the choice of parameters for estimation takes into account the quadratic function $E_{p_i}^{i_d}$. That way, the first estimation includes the parameters of the first group (D , L_d and L_q). The second estimation also considers the most significant parameter of the second group (L_F). As shown in Table 10, the estimation of four parameters results in an error smaller than when estimating only the three parameters of the first group. However, when adding the parameter H of the second group to the estimation list, the error J increases in comparison with the estimation of only four parameters. Therefore, we conclude that only the parameters D , L_d , L_q and L_F must be estimated.

Table 10: Choice of the parameters to be estimated for UC1

Estimated Parameters	Error $J(p)$
D, L_d, L_q	$7.49 \cdot 10^{-2}$
D, L_d, L_q, L_F	$4.98 \cdot 10^{-2}$
D, L_d, L_q, L_F, H	$5.01 \cdot 10^{-2}$

Suppose we are dealing with practical measurements and do not have any knowledge about the reference values of the parameters. Thereby, it is not possible to calculate the quadratic functions $E_{p_i}^{y^j}$ and obtain a table similar to Table 9. Even so, we can obtain a parameter estimation list by combining the parameters and composing several groups of parameters.

Assume that it is possible to estimate only five of the eight parameters at one time because of the lack of information provided by the measurements and a restriction of the UKF. In the worst-case scenario, it is necessary to build 182 groups and check the estimation error J for all these groups. However, if we consider it is extremely difficult to estimate the parameters r_F , r and L_0 , they can be excluded from the list of candidates for estimation. In this case, the maximum number of groups which must be created and have their corresponding estimation error J checked is 16.

4.3.1.3 Creation of Initial Population

To create the initial population, we follow the procedures described in Subsection 3.6.3. From the previous stage, we know that the parameters D , L_d , L_q and L_F must be estimated. That way, the vector of parameters $\mathbf{p}_{UKF}$ shown in (113) is given by

$$\mathbf{p}_{UKF} = [\epsilon, \psi_s, \psi_p, \zeta, \delta_0, D_0, L_{d_0}, L_{q_0}, L_{F_0}]. \quad (124)$$

The minimum and maximum values of the SG model parameters are set to 50% and 150% of their reference values, respectively. We consider this wide range because we may not have a good idea of the value of these parameters when dealing with a practical situation. We can note from (113) that the torque angle is also treated as a parameter since an estimate of its value is important to convert the abc quantities to $0dq$, and vice versa. However, different from the SG parameters in the vector $\mathbf{p}_{UKF}$, the initial value of this parameter is fixed to $\pi/4$.

The adopted range for the parameters ψ_s , ψ_p and ζ is equal to $[10^{-10}, 1]$. For the parameter ϵ , the minimum and maximum values are set to 10^{-5} and 1, respectively. This range is narrower in comparison to the parameters ψ_s , ψ_p and ζ because we know from the literature that the values of the initial error covariance matrix $\mathbf{P}_0$ are generally around 10^{-3} (VALVERDE et al., 2011).

The number of individuals in the population (N_{pop}) is equal to 15. To obtain each hypothesis of the initial population, we make use of a uniform distribution to obtain the parameters between the minimum and maximum possible values.

4.3.1.4 Application of UKF and Fitness Function Calculation

In this subsection, we calculate only one fitness function to analyze the error between the measurements and the outputs of the obtained model. The total error J takes into account the measurement vector $\mathbf{y}_m = [i_a, i_b, i_c, i_F]^T$ and (117).

The values of the parameters α , β , and v , shown in (97) and (100), used for the unbalanced cases are equal to the values adopted for the balanced case. That way, α , β , and v are equal to 0.1, 2, and 0, respectively.

The results obtained for the 12 sub-cases are shown in Tables 11a, 11b, 12a and 12b. Tables 11a and 11b show the best individual obtained during the 20 generations and the values of its parameters for the three sub-cases which do not consider noisy measurements. We can verify that the smallest error J occurs when the non-estimated parameters are fixed to 110% of the reference values. Besides, the error J for the three sub-cases in Table 11b are similar, which indicates that the values of the non-estimated parameters do not affect the estimation of the other parameters when the first ones are inside the range [90%, 110%] for the UC1.

Table 11a: Estimated parameters for the UC1

	ϵ	ψ_s	ψ_p	ζ	Non-Estimated Parameters (%)
1	$1.85 \cdot 10^{-5}$	$1.27 \cdot 10^{-8}$	$8.98 \cdot 10^{-6}$	$4.47 \cdot 10^{-5}$	90
2	$1.05 \cdot 10^{-2}$	$1.35 \cdot 10^{-7}$	$1.26 \cdot 10^{-3}$	$1.37 \cdot 10^{-1}$	100
3	$5.91 \cdot 10^{-3}$	$1.82 \cdot 10^{-5}$	$3.34 \cdot 10^{-4}$	$2.02 \cdot 10^{-1}$	110

Table 11b: Estimated parameters for the UC1

	Initial Values (%)				Final Values (%)				$J(p)$
	D	L_d	L_q	L_F	D	L_d	L_q	L_F	
1	52.344	53.223	150.00	75.250	100.690	100.637	99.230	97.307	$6.17 \cdot 10^{-2}$
2	65.875	116.656	119.830	83.817	100.078	100.987	101.684	100.710	$4.78 \cdot 10^{-2}$
3	106.299	100.812	55.130	76.001	100.010	100.734	99.469	98.549	$3.60 \cdot 10^{-2}$

Analyzing the results of the 9 sub-cases which consider noisy measurements in Tables 12a and 12b, we can see that, regardless of the value of R_{noise} , the smallest errors occur when the non-estimated parameters are fixed to 110% of the reference values. Furthermore, the smallest error in Table 12b occur when the value of R_{noise} is equal to 15%, which indicates that the noise does not considerably affect the estimation approach. The

pretty similar values of the smallest error in Tables 11b and 12b also suggest the noise (for the levels considered in this thesis) does not significantly affect the estimation of the parameters D , L_d , L_q and L_F .

Comparing the errors between the sub-cases of Table 12b which consider the non-estimated parameters fixed to 90% and 110%, we can also verify the error J is smaller when the non-estimated parameters are fixed to 110%, for the three values of R_{noise} . Moreover, these errors are smaller than the ones obtained when the values of the non-estimated parameters are fixed to 100%.

Examining the final values of the estimated parameters in Tables 11b and 12b, we can verify that D is the parameter with the best estimation in most sub-cases. In Table 11b, the error of the estimated values for D are smaller than 1.0%, while this error is lower than 2.0% for the sub-cases in Table 11b, taking into account the reference value of this parameter.

Table 12a: Estimated parameters from noisy measurements for the UC1

	R_{noise} (%)	ϵ	ψ_s	ψ_p	ζ	Non-Estimated Parameters (%)
1	5	$4.43 \cdot 10^{-3}$	$2.67 \cdot 10^{-5}$	$1.28 \cdot 10^{-3}$	$8.37 \cdot 10^{-6}$	90
2	5	$6.60 \cdot 10^{-2}$	$3.34 \cdot 10^{-10}$	$1.34 \cdot 10^{-5}$	$1.60 \cdot 10^{-3}$	100
3	5	$1.19 \cdot 10^{-3}$	$2.98 \cdot 10^{-5}$	$2.91 \cdot 10^{-5}$	$2.78 \cdot 10^{-5}$	110
4	10	$3.38 \cdot 10^{-2}$	$4.00 \cdot 10^{-8}$	$5.86 \cdot 10^{-6}$	$1.86 \cdot 10^{-4}$	90
5	10	$1.33 \cdot 10^{-3}$	$6.92 \cdot 10^{-8}$	$2.15 \cdot 10^{-6}$	$4.35 \cdot 10^{-4}$	100
6	10	$4.05 \cdot 10^{-3}$	$3.28 \cdot 10^{-4}$	$3.43 \cdot 10^{-3}$	$1.55 \cdot 10^{-2}$	110
7	15	$2.81 \cdot 10^{-3}$	$1.03 \cdot 10^{-5}$	$4.86 \cdot 10^{-6}$	$1.09 \cdot 10^{-8}$	90
8	15	$5.86 \cdot 10^{-4}$	$3.86 \cdot 10^{-9}$	$1.90 \cdot 10^{-4}$	$6.06 \cdot 10^{-2}$	100
9	15	$2.12 \cdot 10^{-2}$	$2.20 \cdot 10^{-5}$	$2.45 \cdot 10^{-4}$	$1.66 \cdot 10^{-8}$	110

Table 12b: Estimated parameters from noisy measurements for the UC1

	R_{noise} (%)	Initial Values (%)				Final Values (%)				$J(p)$
		D	L_d	L_q	L_F	D	L_d	L_q	L_F	
1	5	50.000	91.312	80.878	101.587	100.011	101.465	104.727	99.811	$7.13 \cdot 10^{-2}$
2	5	143.561	66.946	150.000	100.879	99.414	101.519	100.422	97.629	$8.37 \cdot 10^{-2}$
3	5	150.000	150.000	70.871	150.000	99.194	101.963	102.508	98.740	$5.18 \cdot 10^{-2}$
4	10	149.857	97.809	82.153	118.787	98.897	101.557	103.684	99.271	$6.46 \cdot 10^{-2}$
5	10	64.844	101.324	75.635	60.995	99.189	101.563	100.618	97.423	$6.26 \cdot 10^{-2}$
6	10	117.224	106.549	112.640	150.000	99.696	102.046	104.738	100.922	$5.65 \cdot 10^{-2}$
7	15	92.224	150.000	56.689	126.624	100.424	102.035	101.959	98.474	$6.89 \cdot 10^{-2}$
8	15	65.894	102.200	75.098	119.977	99.519	101.519	101.086	97.272	$5.54 \cdot 10^{-2}$
9	15	56.308	60.156	83.057	150.000	99.577	101.472	104.686	99.772	$3.95 \cdot 10^{-2}$

4.3.1.5 Population Updating

The process of updating the population is explained in Subsection 3.6.5. However, there are some parameters of this stage that need specifications of their values. For example, we consider four individuals in the population elite ($N_{eli} = 4$). Besides, the number of population individuals is the same for all the generations, $N_{pop} = 15$.

In each generation, we replace the individuals which are not in the elite. For that replacement, we select two individuals in the elite (from the four possibles), which generate a new individual. The process of selection of the parents in the elite and creation of a new individual, which replaces a hypothesis of the previous generation, is repeated until we substitute all the 11 individuals which do not belong to the population elite.

As previously seen in Subsection 3.6.5 and in Fig. 6, the combination of the parent bits can generate two offsprings. However, in this work, we select only one offspring and eliminate the other. The choice of the offspring which is used to compose the population depends on the probability of picking it (both offsprings have the same odds to be chosen). For instance, in Fig. 25 only one parameter is used to replace an individual of the current population. For example, we can select the parameters $\epsilon^{(O2)}$ and $D^{(O1)}$ and ignore the parameters $\epsilon^{(O1)}$ and $D^{(O2)}$.

Figure 25: Examples of crossover employed to obtain the parameters of a new individual.

Fig. 25 shows that we use the one-point crossover operation to obtain an offspring from two parents belonging to the elite. As can be seen in this figure, the number of bits used to represent the parameters is not the same for all of them. For instance, ϵ , ψ_s , ψ_p and ζ hold a mask with four bits before and ten bits after the period while the parameters D , L_d , L_q and L_F have only one bit before and fifteen after it. Since a floating mask is used to perform the crossover, the offspring can be very different or similar to the parents (ϵ and D in Fig. 25, respectively).

Aside from being distinct for different parameters, the crossover mask may change every time we perform the crossover operation. For example, suppose we select the parameter $\epsilon^{(O1)}$ in Fig. 25. Its value is smaller than ϵ_{min} and, therefore, we must perform

the crossover operation once again. This time the crossover mask may be different from the one shown in Fig. 25.

Taking advantage of the previous example, we must highlight that if any of the parameters ϵ , ψ_s , ψ_p or ζ of the selected offspring is smaller than the minimum value or greater than the maximum value, then the crossover operation must be repeated. However, we do not repeat this operation if any of the SG estimated parameters assume values out of the defined range. In this case, for example, if $D \leq 0.5$ or $D \geq 1.5$ p.u., then we must set $D = 0.5$ or $D = 1.5$ p.u.

After the crossover operation, each one of the selected parameters may suffer a mutation. In this thesis, we consider a mutation rate MR equals to 20%, which means that one bit of the sequence (randomly chosen) which represents the parameter is changed with a probability of 20%. If any of the parameters ϵ , ψ_s , ψ_p or ζ gets out of the range $[p_{min}, p_{max}]$ after the application of the mutation operation, then another bit is randomly chosen. In the case of the D , L_q , L_d or L_F , if the parameter after the mutation becomes smaller than p_{min} , we fix its value to p_{min} . Equivalently, if they become greater than p_{max} , we set their value to p_{max} .

4.3.1.6 Model Validation

To validate the SG models with the estimated parameters, we apply a three-phase fault at the terminal of the generator at the instant 10.0 s, with duration of two cycles. The fault resistance is equal to 13.33 Ω for the three phases. We obtain the reference curves by using the values of the parameters shown in Table 21. The outputs obtained with the estimated parameters are simulated and compared to the reference responses of the generator.

In this section, the comparison between the reference and simulated outputs takes into account the estimated parameters of the three sub-cases in Table 11b and the sub-cases 2, 5 and 8 of Table 12b. The currents i_d , i_F , i_q , and the angular speed ω for the aforementioned sub-cases are shown in Figs. 26-31. Appendix B presents the comparison of the responses of the SG models obtained with the estimated parameters in sub-cases 1, 3, 4, 6, 7 and 9 of Table 12b with the reference responses.

Examining the responses of the obtained SG models in Figs. 26-31 and Figs. 44-49, and comparing them with the reference outputs of the generator, we verify that the simulated responses are satisfactorily close to the reference curves. Therefore, the estimated parameters in all the sub-cases of UC1 generate acceptable SG models and they can be considered validated.

It is important to stress that even not utilizing the SG angular speed ω as an output of the UKF to estimate the parameters, this quantity is satisfactorily close to the reference curve for the considered sub-cases. Moreover, in Fig. 47 the simulated angular speed and the reference curve are practically overlapped.

Figure 26: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 90%.

Figure 27: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 100%.

Figure 28: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 110%.

Figure 29: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 100% and $R_{noise} = 5\%$.

Figure 30: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 100% and $R_{noise} = 10\%$.

Figure 31: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 100% and $R_{noise} = 15\%$.

4.3.2 Unbalanced Case 2 (UC2)

In this subsection, we apply the estimation approach shown in the flowchart of Fig. 8 to the UC2, which is depicted in Table 2 and in Appendix A. To estimate the parameters of the SG model, we make use of the same sampling window used for the UC1. All the steps used to estimate the parameters for the UC1 are repeated for the UC2 and, hence, we omit in this subsection the procedures and details previously described for the UC1. However, it is important to state that Table 13 is equivalent to Table 9, obtained in the analysis of the influence of parameters in the model. Besides, Table 14 is analogous to Table 10, which is obtained at the step *Choice of Parameters for Estimation*.

Table 13: Values of the quadratic functions of TSF for UC2

p_i	$E_{p_i}^{i_d}$	$E_{p_i}^{i_F}$	$E_{p_i}^{i_q}$
D	$4.78 \cdot 10^{-2}$	$2.48 \cdot 10^{-1}$	$9.89 \cdot 10^{-1}$
L_d	$3.21 \cdot 10^{-2}$	$9.69 \cdot 10^{-2}$	$1.45 \cdot 10^{-2}$
L_q	$2.19 \cdot 10^{-2}$	$2.54 \cdot 10^{-5}$	$6.14 \cdot 10^{-2}$
L_F	$2.68 \cdot 10^{-4}$	$2.12 \cdot 10^{-4}$	$1.39 \cdot 10^{-5}$
H	$2.39 \cdot 10^{-5}$	$4.25 \cdot 10^{-6}$	$2.23 \cdot 10^{-5}$
r_F	$8.41 \cdot 10^{-6}$	$9.25 \cdot 10^{-6}$	$4.15 \cdot 10^{-6}$
r	$5.62 \cdot 10^{-7}$	$6.92 \cdot 10^{-7}$	$1.85 \cdot 10^{-7}$
L_0	$2.32 \cdot 10^{-16}$	$9.78 \cdot 10^{-17}$	$5.80 \cdot 10^{-17}$

Table 14: Choice of the parameters to be estimated for UC2

Estimated Parameters	Error $J(p)$
D, L_d, L_q	$1.22 \cdot 10^{-1}$
D, L_d, L_q, L_F	$1.04 \cdot 10^{-1}$
D, L_d, L_q, L_F, H	$1.75 \cdot 10^{-1}$

We also apply the step *Application of UKF and Fitness Function Calculation* for the same 12 sub-cases considered for the UC1, including the sub-cases where noisy measurements were used. As a result of this step, we obtain Tables 15a, 15b, 16a and 16b.

Just as for the UC1, we can verify from Tables 15b and 16b that the smallest error J occurs when the non-estimated parameters are fixed to 110% of the reference values. Besides, the error J for the three sub-cases in Table 15b are close, which indicates that the values of the non-estimated parameters do not significantly affect the estimation of the other parameters when the first ones are inside the range [90%, 110%] for the UC2.

Analyzing the results of the 9 sub-cases which consider noisy measurements in Tables 16a and 16b, we can see that the two smallest errors occur when the non-estimated parameters are fixed to 110% of the reference values (sub-cases 3 and 6). Furthermore, the biggest error in Table 16b occur when the value of R_{noise} is equal to 5%, which indicates

that the noise does not considerably affect the estimation approach. The similar values of the smallest error in Tables 15b and 16b also suggest the noise (for the levels considered in this thesis) does not significantly affect the estimation of the parameters D , L_d , L_q and L_F .

Comparing the errors between the sub-cases of Table 16b which consider the non-estimated parameters fixed to 90% and 110%, we can also verify the error J is smaller when the non-estimated parameters are fixed to 110%, for the three levels of noise. Moreover, when the values of R_{noise} are equal to 5% and 10%, the errors for the sub-cases when the non-estimated parameters are fixed to 110% are smaller than the ones obtained when they are fixed to 100%.

Examining the final values of the estimated parameters in Tables 15b and 16b, we can verify that L_q is the parameter with the worst estimation in most sub-cases. Although the error for this parameter is smaller than 2.0% in Table 15b, the largest error for L_q is greater than 6.0% for the sub-cases 5 and 7 in Table 16b, taking into account the reference value of this parameter.

Table 15a: Estimated parameters for the UC2

	ϵ	ψ_s	ψ_p	ζ	Non-Estimated Parameters (%)
1	$6.48 \cdot 10^{-3}$	$4.53 \cdot 10^{-9}$	$2.45 \cdot 10^{-8}$	$1.14 \cdot 10^{-3}$	90
2	$3.62 \cdot 10^{-5}$	$3.23 \cdot 10^{-6}$	$9.67 \cdot 10^{-4}$	$2.22 \cdot 10^{-8}$	100
3	$3.59 \cdot 10^{-4}$	$2.37 \cdot 10^{-9}$	$1.04 \cdot 10^{-6}$	$3.05 \cdot 10^{-6}$	110

Table 15b: Estimated parameters for the UC2

	Initial Values (%)				Final Values (%)				$J(p)$
	D	L_d	L_q	L_F	D	L_d	L_q	L_F	
1	136.133	106.250	85.480	150.000	99.863	102.361	99.533	104.926	$1.12 \cdot 10^{-1}$
2	79.565	132.813	84.702	150.00	100.954	102.330	98.331	98.763	$1.01 \cdot 10^{-1}$
3	56.332	134.406	75.049	132.306	100.780	102.351	98.335	98.741	$8.35 \cdot 10^{-2}$

4.3.2.1 Model Validation

The validation of the SG models obtained for the sub-cases of UC2 follows the same steps used to validate the models for the UC1, including the disturbance applied to the test system.

In this section, the comparison between the reference and simulated outputs takes into account the estimated parameters of the three sub-cases in Table 15b and the sub-cases 2, 5 and 8 of Table 16b. The currents i_d , i_F , and i_q , and the angular speed ω for the aforementioned sub-cases are shown in Figs. 32-37. Appendix B presents the comparison

Table 16a: Estimated parameters from noisy measurements for the UC2

	R_{noise} (%)	ϵ	ψ_s	ψ_p	ζ	Non-Estimated Parameters (%)
1	5	$2.46 \cdot 10^{-5}$	$4.35 \cdot 10^{-3}$	$1.41 \cdot 10^{-4}$	$4.23 \cdot 10^{-6}$	90
2	5	$1.75 \cdot 10^{-4}$	$1.71 \cdot 10^{-6}$	$6.95 \cdot 10^{-3}$	$3.85 \cdot 10^{-3}$	100
3	5	$5.28 \cdot 10^{-2}$	$3.92 \cdot 10^{-7}$	$6.29 \cdot 10^{-4}$	$7.07 \cdot 10^{-2}$	110
4	10	$8.45 \cdot 10^{-4}$	$1.02 \cdot 10^{-8}$	$1.67 \cdot 10^{-4}$	$5.71 \cdot 10^{-2}$	90
5	10	$1.73 \cdot 10^{-4}$	$4.61 \cdot 10^{-10}$	$6.00 \cdot 10^{-5}$	$6.85 \cdot 10^{-6}$	100
6	10	$2.05 \cdot 10^{-2}$	$1.02 \cdot 10^{-6}$	$1.33 \cdot 10^{-5}$	$1.52 \cdot 10^{-3}$	110
7	15	$1.35 \cdot 10^{-3}$	$1.60 \cdot 10^{-5}$	$1.97 \cdot 10^{-4}$	$3.16 \cdot 10^{-9}$	90
8	15	$1.30 \cdot 10^{-1}$	$1.34 \cdot 10^{-10}$	$3.63 \cdot 10^{-8}$	$1.89 \cdot 10^{-5}$	100
9	15	$3.32 \cdot 10^{-2}$	$2.12 \cdot 10^{-9}$	$5.67 \cdot 10^{-7}$	$2.18 \cdot 10^{-5}$	110

Table 16b: Estimated parameters from noisy measurements for the UC2

	R_{noise} (%)	Initial Values (%)				Final Values (%)				$J(p)$
		D	L_d	L_q	L_F	D	L_d	L_q	L_F	
1	5	100.797	50.000	66.309	98.950	100.882	101.840	101.619	102.157	$2.47 \cdot 10^{-1}$
2	5	62.793	100.204	91.714	50.000	102.523	101.661	104.116	100.953	$1.13 \cdot 10^{-1}$
3	5	65.308	106.451	103.717	117.383	99.135	101.282	102.034	98.206	$9.52 \cdot 10^{-2}$
4	10	150.000	54.736	117.212	113.684	99.166	101.324	102.461	97.751	$1.26 \cdot 10^{-1}$
5	10	102.063	150.000	56.616	84.436	100.381	101.209	107.973	100.155	$1.15 \cdot 10^{-1}$
6	10	150.000	75.989	100.378	150.000	98.437	101.386	102.193	98.109	$8.42 \cdot 10^{-2}$
7	15	138.568	102.216	111.328	150.000	99.637	101.209	106.902	100.086	$1.19 \cdot 10^{-1}$
8	15	80.673	120.343	89.114	150.000	99.407	101.267	102.894	97.645	$1.13 \cdot 10^{-1}$
9	15	95.645	50.000	124.918	71.851	98.357	101.270	104.965	99.267	$1.15 \cdot 10^{-1}$

of the responses of the SG models obtained with the estimated parameters in sub-cases 1, 3, 4, 6, 7 and 9 of Table 16b with the reference responses.

Examining the responses of the obtained SG models in Figs. 32-37 and Figs. 50-55, and comparing them with the reference outputs of the generator, we verify that the simulated responses are satisfactorily close to the reference curves. Therefore, the estimated parameters in all the sub-cases of UC2 generate acceptable SG models and they can be considered validated.

However, observing Fig. 35 we can verify that the reference and the simulated curves for the currents i_F and i_q are not as close as for the other sub-cases. That is in line with the error J for this sub-case, which is the largest for this level of noise ($R_{noise} = 5\%$).

With respect to the angular speed ω , the same remark made for the UC1 can be repeated for the UC2. That way, even not utilizing this state as an output of the UKF to estimate the parameters, this quantity is satisfactorily close to the reference curve for the considered sub-cases. Comparing the graphs of Figs. 32-37 and Figs. 50-55, we can see that the SG models with the best angular speed response are the ones obtained for the sub-case 2 of Table 15b and the sub-case 5 of Table 16b.

Figure 32: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 90%.

Figure 33: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 100%.

Figure 34: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 110%.

Figure 35: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 100% and $R_{noise} = 5\%$.

Figure 36: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 100% and $R_{noise} = 10\%$.

Figure 37: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 100% and $R_{noise} = 15\%$.

4.3.3 Unbalanced Case 3 (UC3)

In this subsection, we apply the estimation approach shown in the flowchart of Fig. 8 to the UC3, which is depicted in Table 2 and in Appendix A. To estimate the parameters of the SG model, we make use of the same sampling window used for the UC1 and UC2. All the steps used to estimate the parameters for the UC1 and UC2 are repeated for the UC3 and, hence, we omit in this subsection the procedures and details previously described for these other unbalanced cases. Again, it is important to state that Table 17 is equivalent to Tables 9 and 13, obtained in the analysis of the influence of parameters in the model. Besides, Table 18, analogous to Tables 10 and 14, is obtained at the step *Choice of Parameters for Estimation*.

Table 17: Values of the Quadratic Functions of TSF for UC3

p_i	$E_{p_i}^{i_d}$	$E_{p_i}^{i_F}$	$E_{p_i}^{i_q}$
D	$3.93 \cdot 10^{-2}$	$2.80 \cdot 10^{-1}$	$1.16 \cdot 10^0$
L_q	$2.264 \cdot 10^{-2}$	$1.50 \cdot 10^{-5}$	$5.19 \cdot 10^{-2}$
L_d	$2.258 \cdot 10^{-2}$	$7.23 \cdot 10^{-2}$	$1.15 \cdot 10^{-2}$
L_F	$9.42 \cdot 10^{-5}$	$7.34 \cdot 10^{-5}$	$1.22 \cdot 10^{-5}$
H	$2.18 \cdot 10^{-5}$	$3.98 \cdot 10^{-6}$	$2.24 \cdot 10^{-5}$
r_F	$8.00 \cdot 10^{-6}$	$8.84 \cdot 10^{-6}$	$4.23 \cdot 10^{-6}$
r	$4.30 \cdot 10^{-7}$	$5.49 \cdot 10^{-7}$	$1.51 \cdot 10^{-7}$
L_0	$4.34 \cdot 10^{-17}$	$1.19 \cdot 10^{-17}$	$1.24 \cdot 10^{-17}$

Table 18: Choice of the Parameters to be Estimated for UC3

Estimated Parameters	Error $J(p)$
D, L_q, L_d	$1.86 \cdot 10^{-1}$
D, L_q, L_d, L_F	$2.89 \cdot 10^{-2}$
D, L_q, L_d, L_F, H	$6.86 \cdot 10^{-2}$

We also apply the step *Application of UKF and Fitness Function Calculation* for the same 12 sub-cases considered for the UC1 and UC2, including the sub-cases where noisy measurements were used. As a result of this step, we obtain Tables 19a, 19b, 20a and 20b.

Just as for the UC1 and UC2, we can verify that the smallest error J of Tables 19b and 20b occurs when the non-estimated parameters are fixed to 110% of the reference values. However, the error J for the three sub-cases in Table 19b are not as close as in Tables 11b and 15b.

Analyzing the results of the 9 sub-cases which consider noisy measurements in Tables 20a and 20b, we cannot verify that the influence of the noise on the estimation process is not evident since the errors for the sub-cases 3, 6 and 9 are quite close and, moreover, the

error for the sub-case 6 is smaller than for the sub-case 3. Besides, the obtained error for the sub-case 6 is smaller than all the errors in Table 19b. Therefore, we can conclude that the noise (for the levels considered in this thesis) almost does not affect the estimation of the parameters D , L_d , L_q and L_F for the UC3.

Comparing the errors between the sub-cases of Table 20b which consider the non-estimated parameters fixed to 90% and 110%, we can also verify the error J is smaller when the non-estimated parameters are fixed to 110%, for the three levels of noise. Moreover, when the values of R_{noise} are equal to 10% and 15%, the errors for the sub-cases when the non-estimated parameters are fixed to 110% are smaller than the ones obtained when they are fixed to 100%.

Examining the final values of the estimated parameters in Tables 19b, we can verify that L_d is the parameter with the best estimation. However, in Table 20b, L_F presents the smallest error in 6 of the 9 sub-cases, even being the parameter which less influence the outputs i_d , i_F and i_q in comparison to D , L_q and L_d , as can be seen in Table 17.

Table 19a: Estimated Parameters for the UC3

	ϵ	ψ_s	ψ_p	ζ	Non-Estimated Parameters (%)
1	$6.78 \cdot 10^{-3}$	$1.08 \cdot 10^{-9}$	$1.08 \cdot 10^{-4}$	$3.20 \cdot 10^{-2}$	90
2	$1.12 \cdot 10^{-1}$	$5.33 \cdot 10^{-8}$	$4.83 \cdot 10^{-6}$	$4.22 \cdot 10^{-6}$	100
3	$1.22 \cdot 10^{-2}$	$1.68 \cdot 10^{-8}$	$2.77 \cdot 10^{-8}$	$5.32 \cdot 10^{-6}$	110

Table 19b: Estimated Parameters for the UC3

	Initial Values (%)				Final Values (%)				$J(p)$
	D	L_d	L_q	L_F	D	L_d	L_q	L_F	
1	150.000	131.277	64.752	137.500	100.118	100.564	98.379	99.279	$1.14 \cdot 10^{-1}$
2	150.000	69.604	78.308	87.531	100.548	100.505	97.496	99.268	$5.78 \cdot 10^{-2}$
3	62.936	50.000	93.103	115.625	101.577	100.040	97.958	99.407	$4.80 \cdot 10^{-2}$

4.3.3.1 Model Validation

The validation of the SG models obtained for the sub-cases of UC3 follows the same steps used to validate the models for the UC1 and UC2, including the disturbance applied to the test system.

In this section, the comparison between the reference and simulated outputs takes into account the estimated parameters of the three sub-cases in Table 19b and the sub-cases 2, 5 and 8 of Table 20b. The currents i_d , i_F , and i_q , and the angular speed ω for the aforementioned sub-cases are shown in Figs. 38-43. Appendix B presents the comparison

Table 20a: Estimated Parameters from noisy measurements for the UC3

	R_{noise} (%)	ϵ	ψ_s	ψ_p	ζ	Non-Estimated Parameters (%)
1	5	$2.78 \cdot 10^{-5}$	$3.18 \cdot 10^{-5}$	$2.62 \cdot 10^{-3}$	$1.55 \cdot 10^{-6}$	90
2	5	$4.67 \cdot 10^{-4}$	$5.14 \cdot 10^{-7}$	$1.72 \cdot 10^{-3}$	$1.59 \cdot 10^{-5}$	100
3	5	$4.13 \cdot 10^{-4}$	$1.44 \cdot 10^{-6}$	$5.00 \cdot 10^{-6}$	$1.41 \cdot 10^{-4}$	110
4	10	$1.32 \cdot 10^{-1}$	$2.34 \cdot 10^{-9}$	$3.55 \cdot 10^{-7}$	$6.92 \cdot 10^{-6}$	90
5	10	$1.19 \cdot 10^{-4}$	$1.44 \cdot 10^{-5}$	$7.97 \cdot 10^{-5}$	$1.11 \cdot 10^{-2}$	100
6	10	$2.19 \cdot 10^{-4}$	$1.36 \cdot 10^{-10}$	$1.50 \cdot 10^{-6}$	$3.26 \cdot 10^{-4}$	110
7	15	$2.24 \cdot 10^{-5}$	$1.11 \cdot 10^{-8}$	$3.78 \cdot 10^{-3}$	$1.77 \cdot 10^{-7}$	90
8	15	$5.13 \cdot 10^{-5}$	$1.30 \cdot 10^{-9}$	$5.27 \cdot 10^{-4}$	$4.41 \cdot 10^{-2}$	100
9	15	$5.55 \cdot 10^{-4}$	$9.39 \cdot 10^{-10}$	$7.76 \cdot 10^{-4}$	$1.77 \cdot 10^{-2}$	110

Table 20b: Estimated Parameters from noisy measurements for the UC3

	R_{noise} (%)	D	Initial Values (%)			Final Values (%)				$J(p)$
			L_d	L_q	L_F	D	L_d	L_q	L_F	
1	5	78.519	62.650	83.429	128.128	101.718	101.317	103.406	99.854	$5.39 \cdot 10^{-2}$
2	5	87.891	150.000	100.208	130.286	101.368	101.310	103.423	99.814	$4.21 \cdot 10^{-2}$
3	5	50.000	68.750	78.543	95.837	98.282	101.949	102.712	99.951	$4.40 \cdot 10^{-2}$
4	10	75.867	117.200	145.782	112.500	98.794	101.671	103.877	99.462	$1.27 \cdot 10^{-1}$
5	10	53.955	53.516	88.495	150.000	99.244	101.678	100.365	97.332	$5.23 \cdot 10^{-2}$
6	10	100.787	54.236	80.273	150.000	99.318	101.622	100.497	97.079	$3.16 \cdot 10^{-2}$
7	15	88.672	90.527	71.124	77.673	102.467	101.314	103.642	99.955	$5.89 \cdot 10^{-2}$
8	15	95.615	125.394	63.248	149.664	99.450	101.629	100.891	98.102	$5.28 \cdot 10^{-2}$
9	15	51.953	109.351	73.068	67.288	99.290	101.589	103.410	99.499	$5.18 \cdot 10^{-2}$

of the responses of the SG models obtained with the estimated parameters in sub-cases 1, 3, 4, 6, 7 and 9 of Table 20b with the reference responses.

Examining the responses of the obtained SG models in Figs. 38-43 and Figs. 56-61, and comparing them with the reference outputs of the generator, we verify that the simulated responses are satisfactorily close to the reference curves. Therefore, the estimated parameters in all the sub-cases of UC3 generate acceptable SG models and they can be considered validated. However, Figs. 56 and 60 show that the simulated responses may not be so precise when the non-estimated parameters are fixed to 90% of their reference values.

With respect to the angular speed ω , the same remark made for the UC1 and UC2 can be repeated for the UC3: even not utilizing this state as an output of the UKF to estimate the parameters, this quantity is satisfactorily close to the reference curve for the considered sub-cases. Comparing the graphs of Figs. 38-43 and Figs. 56-61, we can see that the SG model with the best angular speed response is the one obtained for the sub-case 2 of Table 19b. Nevertheless, we must highlight the precision of the simulated angular speed for the sub-cases 2, 5, and 8 of Table 20b, shown in Figs. 41-43, respectively.

Figure 38: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 90%.

Figure 39: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 100%.

Figure 40: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 110%.

Figure 41: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 100% and $R_{noise} = 5\%$.

Figure 42: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 100% and $R_{noise} = 10\%$.

Figure 43: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 100% and $R_{noise} = 15\%$.

4.4 Final Remarks

In this chapter, we assess the performance of the proposed approach under several situations. We can see from the results that it is possible to estimate more parameters by using measurements coming from balanced operations in comparison with the estimation which utilizes signals from unbalanced operating conditions. Although it is not possible to estimate all the parameters of the SG model under this second set of conditions, the proposed approach is capable of efficiently estimating the four more important parameters of the model. Furthermore, the results show the method can estimate these parameters even when only noisy measurements are available. In fact, the noise excites the experiments, which facilitates the parameter estimation.

Regarding the unbalanced conditions, we also analyze the performance of the approach when the non-estimated parameters are different from the reference values. It would be expected that the error in the estimation process increased in these situations. However, this error does not significantly increase, and in some situations even decreases. For instance, in almost all the situations of the three unbalanced conditions tested in this thesis the functional error J presents the smallest value when the non-estimated parameters are equal 110% of their reference values.

Conclusion

This work has investigated the influence of the parameters of a three-phase SG model suitable for the description of unbalanced operating conditions, proposing an approach to estimate the main parameters of this model without the need to have further knowledge of the SG controls or the grid parameters. It has also analyzed the difference in the responses of the generator between balanced and unbalanced conditions and its consequences for the proposed estimation process.

The estimation process is based on the UKF, which is basically the optimization method used to estimate the SG parameters. However, the application of the UKF only does not guarantee satisfactory estimations since the initial values of the estimated parameters interfere with the estimation process. Besides, UKF has some covariance matrices that are important for the optimization process and also influence the estimation. Due to the dependency of UKF on the initial values of the estimated parameters and on the covariance matrices, we used a GA to search for a set of UKF parameters which makes this optimization method work efficiently. That way, UKF estimates the SG parameters with acceptable precision.

It is necessary to emphasize that it is not possible to estimate a parameter by using a measurement which is not affected by it. Besides, the parameters that most influence the response of a measured output can be estimated with higher precision. For that reason, we applied the TSF to identify the parameters that affect more significantly the responses of the SG model. The application of these functions was very useful in this work to select the most important parameters of the SG model. Furthermore, the four parameters that most influence the direct-axis current are the same for the three unbalanced conditions tested in this work. This situation also occurs in the field and quadrature-axis currents. Hence, there is solid evidence the most important parameters are the same in practical cases.

In the cases of this thesis, we could verify that the proposed method can estimate more parameters from measurements that come from balanced conditions. Besides, the accuracy of the estimation of the four more relevant parameters of the model is higher

for balanced operations in comparison to unbalanced conditions since the non-estimated parameters interfere less with the response of the measured outputs in the first case. Nonetheless, when the SG is connected to a distribution system, which typically presents a high level of imbalance, the proposed approach works satisfactorily to estimate the four more relevant parameters of the three-phase SG model. Moreover, even not using the angular speed of the generator as an output, the UKF can adequately estimate a mechanical parameter of the model.

The proposed approach has also shown to be efficient to estimate the parameters. Besides, the noise caused by load variation excites the experiments and facilitates the estimation. The results obtained for the three unbalanced conditions are not significantly affected by the three levels of noise considered in this work. Another important aspect of the estimation approach that we must highlight is the precision of the estimated parameters, even with the non-estimated ones not set to the reference values. The validation process demonstrates the efficiency of the proposed approach to obtain adequate models for the description of SG operation under unbalanced operating conditions.

5.1 Future Work

Based on the work presented in this thesis, future research may explore the following subjects:

- To estimate the mechanical torque of the SG model in the same way we estimate the torque angle since we usually cannot measure that variable with satisfactory accuracy. Thereby, this quantity would not be an input of the estimation method;
- To take into account the saturation of the SG in the three-phase model by inserting additional terms into the SG equations. That way, there may be more parameters in the model to be estimated;
- To add a preprocessing stage to the approach to filter the negative sequence component of the measurements. This filtering process may permit the estimation of more parameters.

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APPENDIX **A**

System data employed in this research

This appendix presents the necessary data to carry out the tests shown in Chapter 4. It is important to highlight that although we considered several operating conditions to verify the efficiency of the estimation method, the value of the SG parameters employed to produce the measurements, called reference values, are the same for all the tested cases.

A.1 Synchronous Generator Reference Parameters

The SG reference parameters used to carry out the simulations in EMTP-RV and obtain the measurements for all the tested cases are shown in Table 21. The nominal power, voltage, and frequency of the SG are 10 MVA, 20 kV (line-to-line) and 60 Hz, respectively. In these simulations, we considered a 2-pole and a value of field current for 1.0 p.u. armature voltage equals to 500 A. In addition, the SG has a Y-connection with a grounding resistance (r_n) equals to 1000 Ω . The grounding inductance (L_n) is zero.

A.2 Distribution Line Parameters

The parameter values of the distribution line in Fig. 16 are shown in Table 22. The mutual inductances of the line are zero. It is important to highlight that the parameters of distribution line are in fact the sum of a Thevenin impedance and the impedance of a distribution line (SALIM, 2011; ABREU, 2005).

A.3 Load Flow Data

The voltages of the buses IB_a , IB_b and IB_c (reference buses) employed to carry out the system load flow are the same for all the tested cases. Table 23 exhibits theses values. The considered base power and voltage are 10 MVA and 20 kV (line-to-line), respectively.

Table 21: Values of the SG reference parameters.

Parameter	Value
L_q	1.3530 p.u.
D	1.8476 p.u.
M_F	0.8040 p.u.
L_d	1.3940 p.u.
L_F	1.4426 p.u.
r_F	0.0067 p.u.
H	0.7106 s
r	0.0020 p.u.
L_0	0.1880 p.u.

Table 22: Values of the distribution line parameters.

Parameter	R_{L_a}	R_{L_b}	R_{L_c}	$L_{L_{aa}}$	$L_{L_{bb}}$	$L_{L_{cc}}$
Value (Ω)	14.7050	14.7050	14.7050	7.3313	7.3313	7.3313

Table 23: Voltage values of the buses IB_a , IB_b and IB_c

	Magnitude (p.u.)	Angle ($^\circ$)
V_{IB_a}	1.00	0
V_{IB_b}	1.00	-120
V_{IB_c}	1.00	120

The SG terminal bus is taken as a PV bus for the load flow. The value of the three-phase active power as well as the magnitude of the phase- a voltage of this bus for each of the tested conditions are shown in Table 24.

Table 24: Data of the PV bus

Condition	V_a (p.u.)	P (p.u.)	Condition	V_a (p.u.)	P (p.u.)
Balanced	1.02	1.00	UC2	1.02	1.00
UC1	1.02	1.00	UC3	1.02	0.9

A.4 Parameters of the three-phase load

The resistance and inductance of each one of the loads Z_a , Z_b and Z_c connected to the generator terminal buses GB_a , GB_b and GB_c vary according to the operating condition of the system. Table 25 exhibits the values of these parameters for each one of the conditions tested in this work.

Table 25: Values of load parameters

Condition	Parameter	Value (Ω)	Condition	Parameter	Value (Ω)
Balanced Case (BC)	R_{aL}	38.1	UC2	R_{aL}	31.6
	R_{bL}	38.1		R_{bL}	38.1
	R_{cL}	38.1		R_{cL}	44.6
	L_{aL}	9.538		L_{aL}	7.653
	L_{bL}	9.538		L_{bL}	9.538
	L_{cL}	9.538		L_{cL}	11.423
UC1	R_{aL}	34.1	UC3	R_{aL}	38.1
	R_{bL}	38.1		R_{bL}	42.1
	R_{cL}	42.1		R_{cL}	46.1
	L_{aL}	8.030		L_{aL}	8.030
	L_{bL}	9.538		L_{bL}	9.538
	L_{cL}	11.046		L_{cL}	11.046

A.5 Parameters of the SG controls

Almost all the parameters of the SG speed and voltage controls are the same for all the tested cases. However, the setpoint values of these two controls may be different for each one of the conditions. That way, these parameters are shown in two different tables. Table 26 showcases the parameters of the voltage regulator and speed governor that remain constant for the whole set of tested cases, while Table 27 exhibits the control setpoints utilized in each operating condition.

Table 26: Values of the SG control parameters.

Voltage Regulator		Speed Governor	
K_a	20.0	R_{SC}	0.05
T_a	0.001 s	T_1	0.5 s
T_b	1.0 s	T_2	1.0 s
T_c	0.6 s	T_3	1.0 s
		D_t	0.0

Table 27: Setpoint values

Condition	V_{REF} (V)	REF (p.u.)	Condition	V_{REF} (V)	REF (p.u.)
Balanced	13592	0.14249	UC2	13592	0.14249
UC1	13592	0.14249	UC3	13400	0.1375

APPENDIX **B**

Simulated SG responses for the validation process

This appendix presents the graphs obtained in the validation stage for some sub-cases of UC1, UC2, and UC3. We did not show them in Chapter 4 so as not to make it too long.

B.1 Unbalanced Condition 1

This section shows the comparison of the simulated and reference curves for the sub-cases 1, 3, 4, 6, 7, and 9 of Tables 12a and 12b. The graphs for the aforementioned sub-cases are shown in Figs. 44-49.

Figure 44: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 90% and $R_{noise} = 5\%$.

Figure 45: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 110% and $R_{noise} = 5\%$.

Figure 46: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 90% and $R_{noise} = 10\%$.

Figure 47: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 110% and $R_{noise} = 10\%$.

Figure 48: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 90% and $R_{noise} = 15\%$.

Figure 49: Comparison between the reference curves and the responses of the SG model obtained for the UC1, with the non-estimated parameters fixed to 110% and $R_{noise} = 15\%$.

B.2 Unbalanced Condition 2

This section shows the comparison of the simulated and reference curves for the sub-cases 1, 3, 4, 6, 7, and 9 of Tables 16a and 16b. The graphs for the aforementioned sub-cases are shown in Figs. 50-55.

Figure 50: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 90% and $R_{noise} = 5\%$.

Figure 51: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 110% and $R_{noise} = 5\%$.

Figure 52: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 90% and $R_{noise} = 10\%$.

Figure 53: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 110% and $R_{noise} = 10\%$.

Figure 54: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 90% and $R_{noise} = 15\%$.

Figure 55: Comparison between the reference curves and the responses of the SG model obtained for the UC2, with the non-estimated parameters fixed to 110% and $R_{noise} = 15\%$.

B.3 Unbalanced Condition 3

This section shows the comparison of the simulated and reference curves for the sub-cases 1, 3, 4, 6, 7, and 9 of Tables 20a and 20b. The graphs for the aforementioned sub-cases are shown in Figs. 56-61.

Figure 56: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 90% and $R_{noise} = 5\%$.

Figure 57: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 110% and $R_{noise} = 5\%$.

Figure 58: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 90% and $R_{noise} = 10\%$.

Figure 59: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 110% and $R_{noise} = 10\%$.

Figure 60: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 90% and $R_{noise} = 15\%$.

Figure 61: Comparison between the reference curves and the responses of the SG model obtained for the UC3, with the non-estimated parameters fixed to 110% and $R_{noise} = 15\%$.