FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Stochastic Location of FACTS Devices in Electric Power Transmission Networks

Rui Pinto Quádrio Alves

Mestrado Integrado em Engenharia Electrotécnica e de Computadores

Supervisor: Vladimiro Miranda (Full Professor)

31 July 2013

Resumo

Esta tese visa o estudo da localização de FACTS (Flexible Alternating Current Transmission Systems) em redes de transmissão de energia, dando-se uma atenção especial à localização de transformadores esfasadores. São propostos dois modelos distintos para localizar este tipo de equipamento tendo por base sistemas de geração puramente convencionais ou sistemas constituídos por geração convencional e eólica. Neste último caso é adoptada uma formulação baseada em programação estocástica de forma a garantir a localização óptima de FACTS perante cenários incertos de vento.

Com vista à resolução do problema referido são utilizadas duas meta-heurísticas: EPSO (Evolutionary Particle Swarm Optimization) e um novo método identificado como DEEPSO (Differential Evolutionary Particle Swarm Optimization). O DEEPSO é apresentado como um modelo híbrido baseado no EPSO e no DE (Differential Evolution). É efectuada uma comparação entre o comportamento dos dois métodos no problema da localização óptima de transformadores esfasadores, tendo-se observado uma clara superioridade do DEEPSO sobre o modelo clássico do EPSO.

Apresentam-se também os resultados obtidos para a localização óptima de FACTS numa rede de teste, IEEE 24-bus Reliability Test System, considerando diferentes cenários de carga e de vento, com vista à validação dos modelos propostos. Os resultados obtidos são coerentes, confirmando a consistência dos modelos desenvolvidos. A localização dos transformadores esfasadores foi efectuada com sucesso nas diversas simulações, tendo estes um papel importante na diminuição dos cortes de carga e de geração eólica, garantindo a minimização dos custos de investimento.

Abstract

This thesis discusses the optimal location of Flexible Alternating Current Transmission Systems devices in electric power transmission networks with a particular focus on the location of Phase Angle Regulating transformers. Throughout this document two different models to optimally locate the devices are proposed in order to be able to perform the optimizations in both systems with purely conventional generation and with mixed conventional and wind generation. A formulation based on stochastic programming is adopted in order to ensure the optimal location of FACTS when dealing with uncertain wind scenarios.

Two distinct heuristic methods are evaluated for this specific problem, the Evolutionary Particle Swarm Optimization, EPSO, and a new method called Differential Evolutionary Particle Swarm Optimization, DEEPSO. The DEEPSO algorithm is presented as a new hybrid between EPSO and Differential Evolution. A comparison between the performance of EPSO and DEEPSO is made, where DEEPSO shows consistent superiority over the classical EPSO in the optimal Phase Angle Regulating location problem.

Results are presented for a realistic power network, IEEE 24-bus Reliability Test System, where a multiple load and wind scenarios approach is considered in order to validate the proposed models. These results show that the models have been correctly developed. The Phase Angle Regulating transformers have been properly placed in the simulations carried out, presenting as an important contribution in reducing both load and wind generation curtailments, while minimizing investment costs.

Keywords: Differential Evolutionary Particle Swarm Optimization; Evolutionary Particle Swarm Optimization; FACTS location; PAR location; Stochastic optimization; Wind power.

"Excellence is doing a common thing in an uncommon way."

Albert Einstein

Contents

1 Introduction **1**

2 State of the Art **3**
2.1 Electric Power Transmission Networks 3
2.2 Flexible Alternating Current Transmission Systems 5
2.2.1 FACTS Concept 5
2.2.2 Phase Shifting Transformers 6
2.2.3 Phase Angle Regulating Transformer Application 8
2.3 Location of FACTS Devices 10

3 EPSO and DEEPSO Methods **15**
3.1 Evolutionary Particle Swarm Optimization 15
3.1.1 Evolutionary Algorithms - EA 16
3.1.2 Particle Swarm Optimization - PSO 16
3.1.3 Evolutionary Particle Swarm Optimization - EPSO 17
3.2 Differential Evolutionary Particle Swarm Optimization 19
3.2.1 Differential Evolution - DE 19
3.2.2 Differential Evolutionary Particle Swarm Optimization - DEEPSO 19
3.3 Location of FACTS Based on a Meta Heuristic 21
3.4 EPSO vs. DEEPSO: Performance Comparison 26

4 Wind Power on Location of FACTS Devices **31**
4.1 Wind Speed Model 31
4.2 Wind to Power Model 34
4.3 Wind Power Integration Through Stochastic Programming 36

5 Case Study **43**
5.1 IEEE 24-bus Reliability Test System 43
5.2 Phase Angle Regulating Data 45
5.3 Single Load Scenarios 46
5.4 Multiple Load Scenarios 49
5.5 Multiple Load and Wind Scenarios 51

6 Conclusions **55**
6.1 Future Work 55

A Publications **57**
A.1 "Differential Evolutionary Particle Swarm Optimization (DEEPSO): a successful hybrid" 57
A.2 "Stochastic Location of PAR in Power Networks with Wind Power" 64

References **69**

List of Figures

2.1 Transmission networks: present and future challenges. 4
2.2 Equivalent circuit for Phase Shifting Transformer. 7
2.3 Power network configuration - PAR application. 8
2.4 Power flow - Line 1 overloaded. 9
2.5 Power flow - Generation re-despatching - Line 1 at maximum capacity. 9
2.6 Power flow - Impact of the implementation of a PAR transformer in line 2. 10

3.1 Particle structure. 21
3.2 Capital cost of each PAR. 22
3.3 Proposed algorithm to optimally locate FACTS devices - EPSO/DEEPSO-based model. 25
3.4 Average error and RMSE achieved for different communication probabilities. . . 27
3.5 Average error and RMSE achieved for different communication probabilities - Comparison of different methods. 27
3.6 Evolution of the average best fitness for 100 runs of EPSO and all DEEPSO variants. 28
3.7 Evolution of the number of hits on the optimum for 100 runs of EPSO and all DEEPSO variants. 29

4.1 Wind speed model - Weibull probability density function. 32
4.2 Wind speed model - Weibull cumulative function. 33
4.3 Stratification of the Weibull probability density function. 33
4.4 Typical power curve of a wind turbine generator. 34
4.5 Stratification of the Weibull probability density function - Wind to power model. 35
4.6 Wind generation curtailed calculation. 37
4.7 Outline of the fitness function to evaluate each possible solution to locate FACTS devices in a system with wind power. 39

5.1 IEEE 24-bus Reliability Test System. 44
5.2 Number of devices for different load factors - 8 possible locations. 48
5.3 Capital cost of devices for different load factors - 8 possible locations. 48
5.4 Power not supplied for different load factors - 8 possible locations. 49
5.5 Power not supplied for different load scenarios. 51
5.6 Wind generation and load curtailed for different levels of wind power installed capacity. 53

List of Tables

2.1 Power network data - PAR application. 8
2.2 Literature review. 13

3.1 Comparison between the different methods in finding the optimal solution. 29
3.2 Mean value and variance achieved by the different methods for 100 runs. 29

4.1 Wind to power model - Predicted output power. 35

5.1 Capital costs of PAR transformers. 45
5.2 Possible locations to install PAR transformers. 45
5.3 Solutions to install PAR transformers in power network. 45
5.4 Load scenarios considered for the optimal PAR location. 46
5.5 Optimal PAR location - 2 possible locations. 46
5.6 Optimal PAR location - 5 possible locations. 46
5.7 Optimal PAR location - 8 possible locations. 47
5.8 Optimal PAR location - 2 possible locations. 50
5.9 Optimal PAR location - 5 possible locations. 50
5.10 Optimal PAR location - 8 possible locations. 50
5.11 Wind power installed capacity for different simulated cases. 52
5.12 Optimal PAR location - 8 possible locations. 52

Abbreviations and Symbols

DE	Differential Evolution
DEEPSO	Differential Evolutionary Particle Swarm Optimization
EA	Evolutionary Algorithms
EC	Evolutionary Computation
EP	Evolutionary Programming
EPSO	Evolutionary Particle Swarm Optimization
ES	Evolution Strategies
FACTS	Flexible Alternating Current Transmission Systems
GA	Genetic Algorithms
IEEE	Institute of Electrical and Electronics Engineers
OPF	Optimal Power Flow
PAR	Phase Angle Regulating
PSO	Particle Swarm Optimization
PST	Phase Shifting Transformer
RTS	Reliability Test System
SA	Simulated Annealing
TCSC	Thyristor-Controlled Series Capacitor
TCPST	Thyristor-Controlled Phase Shifting Transformer
TS	Tabu Search

Chapter 1

Introduction

Transmission networks are being pushed to their thermal limits as a consequence of the significant changes that have been observed in electrical power systems over the last few years. The expansion of transmission infrastructures has become a delicate matter, due to several reasons, namely political and environmental affairs. More than ever, transmission networks need to be explored as efficiently as possible to guarantee a reliable operation of power systems.

As a solution to overcome some of these problems, the application of Flexible Alternating Current Transmission Systems (FACTS) can assume an important role. These are power electronics devices able to act on different parameters of the network, enhancing transmission networks controllability with considerable operational advantages such as increased security and reduced operation costs, among others.

Specifically, the utilization of Phase Shifting Transformers (PST) or Thyristor-Controlled Phase Shifting Transformers (TCPST) in overloaded mashed three phase transmission networks to control active power flow, allows the power to be shifted from overloaded lines to lines with available capacity, reducing the eventual need to curtail load. Furthermore, in power systems with high levels of wind power, the installation of such devices may significantly contribute to an increased wind power penetration, ensuring the maximization of wind generation.

The considerable capital cost of FACTS devices makes their cost-effective utilization imperative and the careful analysis of their location a topic of great importance. The appropriate location of FACTS is a complex combinatorial problem, differently defined according to the goals to be achieved, as well as the types of devices considered.

The objective of this thesis is to propose a methodology to optimize the location of FACTS devices in transmission networks, with a special attention for the optimal location of PST and TCPST. In order to achieve this goal, a meta-heuristic based model is used to find the suitable location of FACTS in power networks. Additionally, an extension to the proposed model, based on stochastic programming, is developed in order to optimize the location of FACTS devices in systems with wind power integration. Included in this research work is the development of a tool to implement and validate the proposed models, so that the optimal location of PST on realistic power networks can be performed.

Chapter 2

State of the Art

2.1 Electric Power Transmission Networks

Historically, the electricity sector has been a regulated monopoly operated by a single large utility owning generation, transmission and, most of the times, distribution. Although electric utility industry has been operating in a vertically integrated environment, with bundled electricity services, this was not the most efficient way to operate power systems. Vertically integrated utilities had no incentives to operate efficiently since they could recover their costs anyway [1].

Since the nineties, electric power industry has been undergoing significant changes, with countries such as Chile, Norway, England, Wales and Argentina being pioneers in industry restructuring [1]. This reorganization resulted in the unbundling of the electricity sector throughout a deregulation process, with generation, transmission and distribution becoming independent activities. Competition among generators became a reality, while transmission networks remained a monopoly subject to regulation by public authorities. Different stages of deregulation process are ongoing in different countries all over the world, each of them having its own particularities, but all aiming to move towards a more competitive, efficient and reliable electricity market.

Consequently, transmission systems require non-discriminatory open access to transmission infrastructure, increasing technical requirements of transmission networks [2]. Transmission grids have been planned to withstand specific levels of power flow that may be significantly modified under open access to electricity markets, leading to increase of unexpected power exchanges and a more intensive usage of existing transmission lines [3, 4]. Additionally, electrical load is expected to grow worldwide. Even if in some developed countries electrical consumption has stabilized or even decreased, as it is happening in some European countries, there are several developing countries with a significant economic growth that is reflected in increased levels of electrical load [3].

Moreover, the widespread concern about greenhouse gas emissions, a likely cause for global warming, is creating the need of generating electric power from clean energies. Following this paradigm, renewable energy systems are being increasingly installed, with the connection of large wind power plants to the grid. Connecting considerable quantities of renewable power to the network can result in major problems regarding transmission systems operation. Power from renewable sources is not guaranteed since it depends on primary resources availability, with the aggravating factor of being normally located in remote places, where transmission infrastructures are weak.

Under this scenario, some transmission lines are being operated closer to their stability and thermal limits, increasing the risk of congestion, resulting in overload of transmission lines. As a consequence, the need to install new transmission lines emerges, in order to increase transmission capacity and ensure proper transmission services. However, due to political and environmental issues, construction of new transmission lines is an extremely difficult and expensive task, following highly bureaucratic processes that can take several years to be resolved. Therefore, efficiency improvement of existing transmission lines can be the most pragmatic way to minimize congestion problems, postponing the construction of new transmission infrastructures.

Facing times of great changes, electric power transmission networks are now dealing with new challenges, which need to be carefully managed, in order to keep high standards of electric power delivery, while considering other important external factors such as environmental issues.

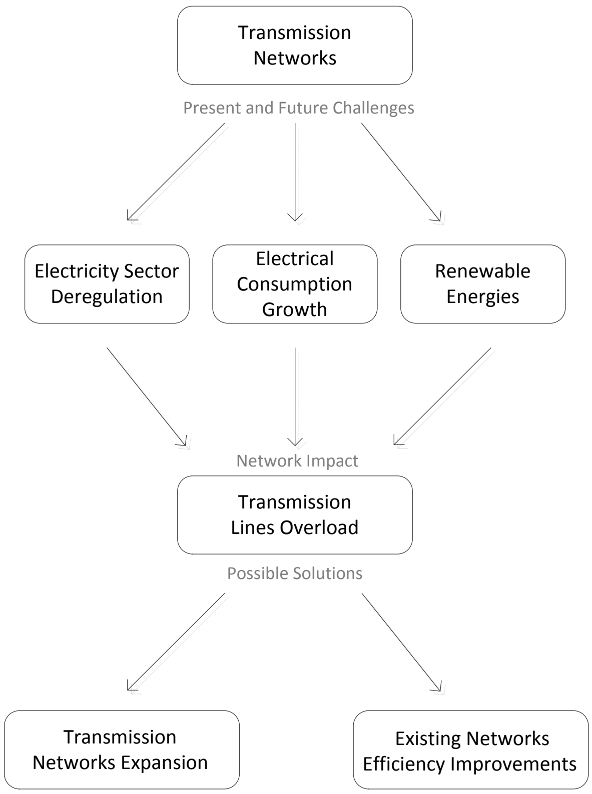

Figure 2.1: Transmission networks: present and future challenges.

2.2 Flexible Alternating Current Transmission Systems

Formerly, insufficient transmission capability was an issue generally handled by building new transmission lines, which has proven to be a very costly, time-consuming and questionable strategy [5]. It is now clear that an improved control of transmission networks to alleviate overloaded lines and, consequently, postponing the expansion of transmission grids, is a more feasible strategy.

Following that principle, some new concepts have emerged in order to allow an improved power flow control. Electromechanical devices such as tap-changing and phase-shifting transformers as well as switched inductors or capacitor banks have been extensively used [6]. Application of these equipment can result in many benefits such as active and reactive power flow control and voltage regulation. Additionally, re-dispatching generator units has also been a very common action to avoid congestion problems.

However, significant changes have been observed in operation of transmission networks. The implementation of electromechanical devices and rescheduling of generators may not be the most efficient actions. On one hand, in an unbundling electricity market, production reallocating is not a feasible action since it does not secure the maximum level of competition among producers. On the other hand, even though electromechanical devices served well the needs of electricity supply industry for long time, they are sometimes inefficient [3, 7]. They are slow equipment, with a very restrict switching frequency, once they tend to wear out rapidly, and need a high level of maintenance resulting in high associated costs [3].

In parallel with the restructuring of electrical power industry, significant technological improvements have been made in the field of power electronics which led to the development of a new and revolutionary technology to enhance transmission networks controllability. Known as Flexible Alternating Current Transmission Systems (FACTS), this equipment is gradually replacing electromechanical devices, filling the main gaps present in those devices, such as slowness and wear. FACTS have high control capabilities, allowing a fast and efficient way to act on network parameters.

2.2.1 FACTS Concept

Flexible Alternating Current Transmission Systems were firstly introduced by Hingorani in 1988, USA [8]. Thereafter, significant improvements have been made in this field, turning FACTS into solid state technology devices, which have already been installed in several circumstances with great results, making their potential widely recognized by power systems community.

Depending on the type of technology, FACTS devices can act on one or more of the main transmission networks parameters. They allow control of terminal bus voltage, line impedance and phase angle difference between the transmission line ends. The choice of the parameters to be controlled depends on the purpose of the control action. Control of active power can be done by managing the line impedance or the voltage phase angle, whereas reactive power control depends on the voltage magnitude parameter.

Flexible Alternating Current Transmission Systems can be divided in three main categories, according to the type of compensation: series controllers, shunt controllers and combined series-shunt controllers. Within each category there are specific FACTS devices with its own particularities that can be selected depending on the goals to be achieved [3].

Proper utilization of FACTS devices results in improved system operation, delaying the construction of new transmission infrastructures, reducing environmental footprint and investment costs [5]. Improved power flow control allows power to be shifted from overloaded lines to other lines with available capacity, permitting a closer exploration of transmission lines to its thermal limits. A proper power flow control can increase system loadability while enhancing system security and reliability. FACTS devices can also play an important role in system stability improvement and in voltage regulation. Furthermore, they may have a significant impact on system operational costs, allowing an economical dispatch and loss minimization [9].

One of the main drawbacks of FACTS technology was the associated investment cost, but with the increased utilization of solid state technology they are now (in most of the cases) a very cost-effective solution.

2.2.2 Phase Shifting Transformers

Phase Shifting Transformers (PST) have been extensively used in transmission systems to provide active power flow control. Furthermore, taking advantages of recent developments in power systems flexibility, PST are recently being coupled to power electronic devices, turning the use of Thyristor-Controlled Phase Shifting Transformers (TCPST) an even more efficient device to control transmission systems.

PST and TCPST can be crucial in resolving congestion problems in meshed transmission networks by appropriately controlling active power flow. As mentioned, the deregulation of electricity markets, the need to increase the fraction of electrical power produced from renewable sources and the increased demand of electricity are important factors responsible for the need to enhance transmission networks capacity. Also, the unequal utilization of parallel transmission lines, dictated by their different impedances, possibly resulting in the overload of one line and operation of the other line bellow its nominal capacity, is an important limiter factor to an efficient exploration of transmission lines. By controlling the amount and direction of active power exchanged over transmission lines it is possible to avoid the mentioned problems, exploring lines closer to their rated capacity.

Active and reactive power (P,Q) over a transmission line are functions of three main network parameters: voltage magnitude at both sending (V_s) and receiving (V_r) ends, line reactance (X_L) and voltage angle difference (θ). Specifically, it can be determined by the following expressions:

$$P = \frac{|V_s||V_r|}{X_L}\sin(\theta) \tag{2.1}$$

$$Q = \frac{|V_s||V_r|}{X_L}\cos(\theta - \frac{|V_s|}{|V_r|}) \tag{2.2}$$

By manipulating the stated parameters it is possible to control active power. However, acting on voltage magnitude is an unattractive solution since it considerably influences reactive power. Phase shifting transformers control active power by predominantly modifying the voltage angle difference, θ.

A phase shifting transformer can be modeled as a reactance and a phase shift in series with the transmission line where it is installed. The active power flowing through the line is altered by adding a phase shift angle α. Changing the angle amplitude, within PST limits, enables the control of the amount of active power transported over the line.

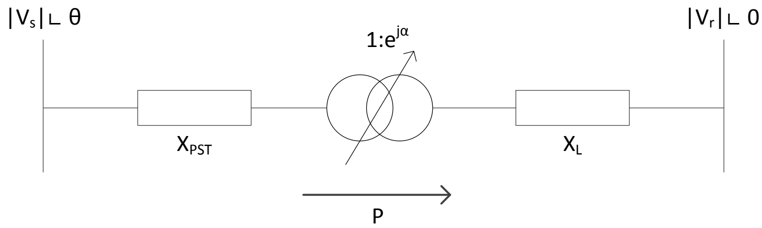

Figure 2.2: Equivalent circuit for Phase Shifting Transformer.

Depending on the type of technology PST can be classified in four different categories: direct asymmetrical PST, direct symmetrical PST, indirect asymmetrical PST and indirect symmetrical PST [10]. Direct PST consist on one three-phase core transformer, whereas indirect PST are formed by two distinct transformers. Asymmetrical PST acts on both phase angle and amplitude of the input voltage, while symmetrical PST only consents the control of the phase angle of the input voltage, with the output and input voltages having the same amplitude [10]. Phase Angle Regulating (PAR) transformers are a special arrangement of PST, belonging to symmetrical category, which will receive distinct attention throughout the present work.

All the introduced concepts concerning PST also apply to FACTS technology, specifically with respect to Thyristor-Controlled Phase Shifting Transformers. TCPST are based on the technologies stated above with the addition of power electronics components. While in PST the phase shift is mechanically controlled by acting on a variable tap that is tele-operated from a control station, with TCPST it can be automatically adjusted by means of power electronics devices, resulting in a faster and more efficient control of tap changes [10].

2.2.3 Phase Angle Regulating Transformer Application

In order to obtain a better understanding of the influence of a PST of the type PAR in a meshed power network, a simple example , designed to emphasize some of the benefits resulting from the utilization of a PAR, is presented. A simple meshed transmission system is used, with three 230 kV buses, one thermal generator and a wind farm, with different operational costs, and a single load:

Table 2.1: Power network data - PAR application.

Generator	Capacity (MW)	Cost ($/MW)
G1	500	100
G2	500	200

Load	(MW)
L1	500

Line	X (Ω)	Capacity (MW)
1	15	200
2	7.5	400
3	7.5	400

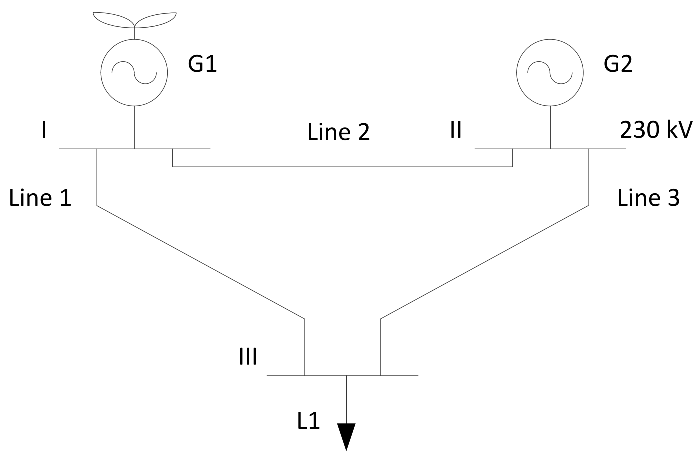

Figure 2.3: Power network configuration - PAR application.

Considering that 500 MW of wind power are available, it can be easily concluded that the most economical way to operate the system above is by supplying the entire load by means of generator *G1* since it is cheaper than *G2*. However, this situation results in overload of line 1:

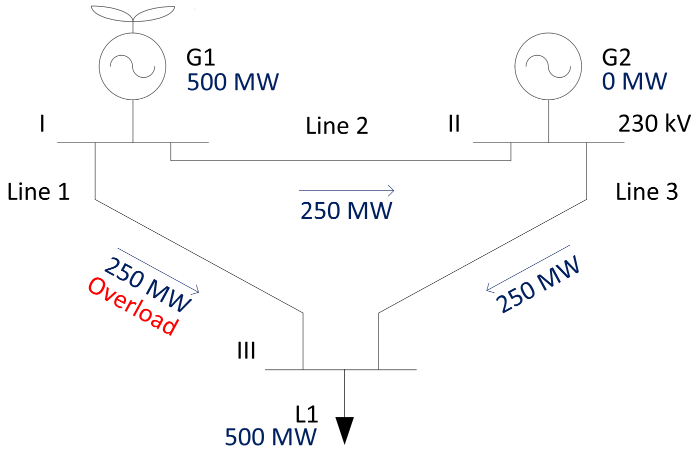

Figure 2.4: Power flow - Line 1 overloaded.

By producing 500 MW in generator *G1* the active power flow through line 1 is greater than its rated capacity, which results in a technical problem due to overload. Obviously, the power generated in *G1* splits between lines 1 and 2 according to the respective impedance, with the active power flowing in the meshed network accordingly to Kirchhoff's law.

Without the installation of any PAR to control the active power flow transported over the lines, the only way to supply the entire load without violating the capacity of line 1 is by re-dispatching generators. In this case, the power generated in *G1* should be as much as possible, adjusting its production in order to explore line 1 to its rated capacity, thus ensuring the most economical production. As previously mentioned, this is not a feasible solution in an unbundled power system. It will result in higher operational costs, restricting generator *G1* to produce at its maximum capacity, leading to wind generation curtailment.

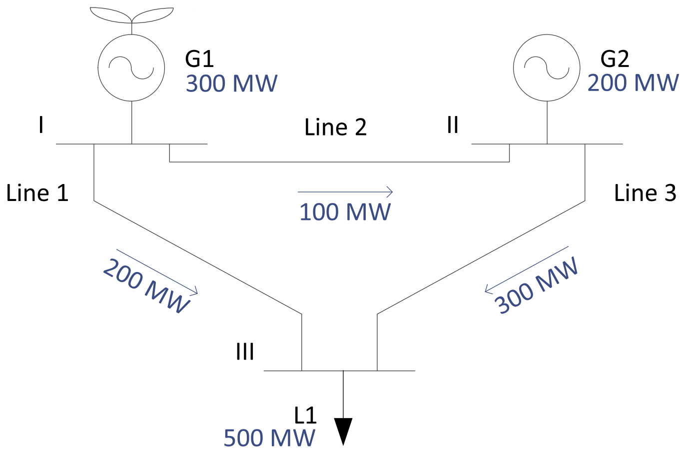

Figure 2.5: Power flow - Generation re-despatching - Line 1 at maximum capacity.

The situation above is the most economical system operation that ensures the maximum wind generation, without overload problems. However, it results in wind generation curtailment, with generator *G1* not being able to produce at its maximum capacity.

The use of a PAR is an alternative to the stated problem. The installation of such device in line 2 will allow the operation of line 1 at its rated capacity by shifting the power flow transported over line 1 to lines 2 and 3. This will enable the maximum production of generator *G1* without violating any of the constraints regarding transmission lines capacity and consequently minimizing operational costs. The installation of a Phase Angle Regulating transformer, only acting on phase angle difference and with no impact on voltage magnitude, is analyzed. Additionally, in order to have a better visibility of its impact, the PAR impedance is neglected.

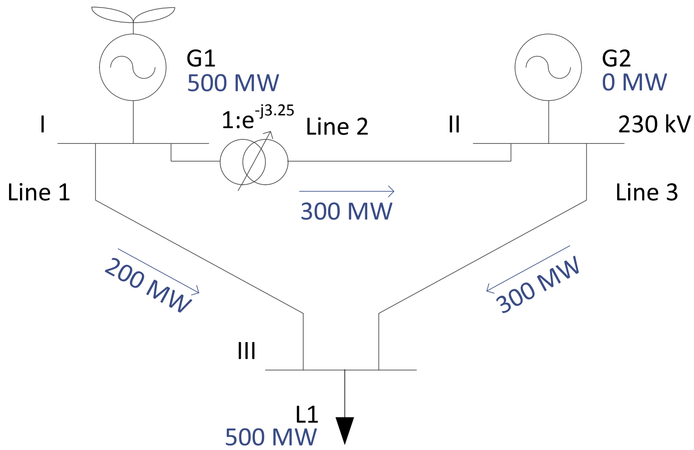

Figure 2.6: Power flow - Impact of the implementation of a PAR transformer in line 2.

The implementation of a PAR transformer injecting an angle of approximately -3.25 degrees allows the maximum wind power penetration. Moreover, this solution results in a reduction of the operational cost by 30000 $, when comparing with the solution of re-dispatching generators.

2.3 Location of FACTS Devices

An appropriate location of FACTS devices, when considering the installation of such equipment in transmission grids, is of extreme importance. Those imply considerable investment costs and should be used as cost-effectively as possible. Unquestionably, FACTS devices can reduce investment costs when comparing with the expansion of transmission networks [11]. Furthermore, they allow a more flexible operation with higher security and reduced operational costs.

However, finding the suitable placement and sizing of FACTS is a complex and challenging task. The allocation of several FACTS in a transmission network can result in adverse interactions between them, a question of great importance that makes the optimal location of FACTS a critical topic.

Different factors can be taken into account in the optimal installation and sizing of FACTS devices. Implementation of this equipment in transmission networks can have different purposes, and, depending on that, different strategies may be adopted. The following factors can be considered in the allocation of FACTS controllers: increase system loadability, increase system security, reduce transmission system losses, reduce investment costs and reduce operational costs.

There are several publications concerning the location of FACTS in which different optimization methods are applied. Also, the authors of the different works aim to achieve the optimal location of FACTS devices based on different criteria. In the following paragraphs the most relevant contributions in this field are briefly described, highlighting the main extracted conclusions, making a summarized literature survey.

In [12], Paterni et al. have used a Genetic Algorithm (GA) to optimally locate a given number of phase shifters. The behavior of the phase shifters is studied, namely the influence they have on one another. This model was successfully applied to a study network and to the French network. The optimization was made in order to find the most economical production pattern by taking advantage of phase shifters placement.

An optimal location of multi-type FACTS devices is presented in [3]. The authors rely their study on a Genetic Algorithm to perform the optimization based on three parameters: location of devices, their type and capacity. Simulations have been made on a 118 bus system, where the system loadability was applied as a measure of system performance. Results have revealed that a multi-type devices approach was a better solution than the single-type method.

The behavior of three distinct heuristic methods is evaluated by Gerbex et al. in [13] to optimally locate multi-type devices in order to enhance power system security. Simulated Annealing (SA), Tabu Search (TS) and Genetic Algorithms were the methods applied and led to similar results with TS and GA converging faster than SA to an optimal solution. The security margin of the system was improved as the number of devices increases.

Dealing with a methodology based on a Genetic Algorithm, the work developed in [11], conducted by Ippolito et al., identifies the optimal number and location of thyristor-controlled phase shifters in order to maximize system capabilities, social surplus and comply with contractual requirements in an open market. The model is validated by several simulations using the IEEE 30-bus system. Once more, the authors of this publication claim that the simultaneous use of several kinds of FACTS represent the most efficient solution to increase system loadability.

Singh and David [9] present a simple and efficient model for the optimal location of FACTS devices for congestion management. A sensitivity-based approach has been developed where the choice to allocate the devices was based on the reduction of the congestion cost. The success of the proposed method is demonstrated by using a 5-bus system.

An evolutionary algorithm, specifically Evolution Strategies (ES), is used by the authors of [7]. The optimal placement of FACTS controllers is the one that maximizes the system loadability while maintaining the security margin within its limits. Results obtained through the IEEE 30-bus system proved that ES algorithm is an adequate technique for solving complex numerical optimization problems such as the one of the allocation of FACTS devices.

In [14] the optimal location of the devices aims to achieve an improved economic dispatch. The algorithm to find the appropriate location of FACTS is based on the decomposition-coordination method and the network compensation technique. The proposed approach has shown to be very effective.

Lima et al. [4] used a Mixed Integer Linear Programming technique to find the number, network location and settings of phase shifters that maximize loadability in large-scale systems. The model developed turned out to be very efficient computationally and suitable for preliminary loadability studies on large-scale systems. Presented results are for the IEEE 24, 118, 300 and 904-bus networks.

Particle Swarm Optimization (PSO) is also a very popular algorithm used to allocate controller devices [2, 15]. It is used in [2] to optimally allocate FACTS devices with the objective of achieving maximum system loadability and minimum cost of installation. Simulations performed on IEEE 6 and 30-bus systems were successfully done for single and multi-type FACTS using PSO.

In the paper published by Rashed et al. [15] authors compare the performance of PSO and GA on the optimal location of Thyristor Controlled Series Capacitors (TCSC) to minimize the active power losses in the power network. Both GA and PSO techniques showed to have good capabilities in finding the optimal location and the best parameters of TCSC, although PSO converged faster than GA.

A hybrid meta-heuristic is proposed in [16] to allocate FACTS devices. The method combines Tabu Search with Evolutionary Particle Swarm Optimization (EPSO). It determines the optimal allocation of devices with TS and evaluates the output variables of the devices with EPSO. This technique was successfully applied to the IEEE 30-bus system. The method was also compared with a TS-PSO strategy giving consistently better results.

Table 2.2: Literature review.

Authors	Type of Problem	Objective	Method
P.Paterni et al. [12]	Optimal location of phase shifters.	Find the most economical production pattern.	Genetic Algorithm.
S. Gerbex et al. [3]	Optimal location of multi-type FACTS devices.	Maximize system loadability.	Genetic Algorithm.
L. Ippolito and P. Siano [11]	Optimal location of thyristor-controlled phase shifters.	Maximize system capabilities, social surplus and satisfy contractual requirements.	Genetic Algorithm.
S.N. Singh and A.K. David [9]	Optimal location of multi-type FACTS devices.	Congestion management.	Sensitive-based approach.
M.Santiago-Luna et al. [7]	Optimal location of multi-type FACTS devices.	Maximize system loadability.	Evolution Strategies.
T. T. Lie and W. Deng [14]	Optimal location of multi-type FACTS devices.	Improve economic dispatch.	Decomposition-coordination.
F. G. M. Lima et al. [4]	Optimal location of thyristor-controlled phase shifters.	Maximize system loadability.	Mixed Integer Linear Programming.
M. Saravan et al. [2]	Optimal location of multi-type FACTS devices.	Maximize system loadability and minimize cost of installation.	Particle Swarm Optimization.
G. I. Rashed et al. [15]	Optimal location of thyristor controlled series capacitors.	Minimize active power losses.	Genetic Algorithm and Particle Swarm Optimization.
H. Mori and Y. Maeda [16]	Optimal location of unified power flow controllers.	Maximize transmission capability.	Tabu Search and Evolutionary Particle Swarm Optimization.

The search for new methods to allocate FACTS devices has been intense during the past years. There is a clear trend towards the utilization of heuristic methods to solve such a problem. Due to its characteristics, meta-heuristics seem to be an appropriate tool to optimize the location of FACTS in power networks, with several methods being successfully applied, as mentioned before. In this work other methods will be tested and their behavior will be analyzed in detail. A new algorithm is presented and its performance is compared with other methods.

During this literature review, a lack of documentation regarding the optimal location of FACTS devices in systems with wind power penetration was detected. The integration of high levels of renewable power is increasingly becoming a reality in power systems and it may considerably influence the optimal location of FACTS devices. Having that in mind, in addition to testing new methods, this work also has the objective of proposing a new model that allows a realistic optimization of the location of FACTS devices in systems with wind power generation.

Chapter 3

EPSO and DEEPSO Methods

Heuristic methods are optimization algorithms based on natural processes, commonly used to optimize problems with high level of complexity, namely the ones with a combinatorial nature. Meta-heuristics can be applied to resolve problems from different fields independently of the nature of the variables involved [17]. In the specific case of power systems, meta-heuristics are an important tool with extensive potential to solve several problems from daily operation to planning studies. The dimension associated to such problems, as well as the need to obtain appropriate solutions within a limited period of time, favors the application of meta-heuristics, which are being more and more popular among the power systems research community.

The optimal location of FACTS is a complex combinatorial problem that qualifies for the utilization of meta-heuristics. In the sections below a general description of the Evolutionary Particle Swarm Optimization (EPSO) and the Differential Evolutionary Particle Swarm Optimization (DEEPSO) will be made. The application of these two methods to optimally locate FACTS devices is explained, describing in detail the model developed to solve this optimization problem. Results comparing the performance of the tested algorithms will be presented.

3.1 Evolutionary Particle Swarm Optimization

Evolutionary Particle Swarm Optimization is a method based on Evolutionary Algorithms (EA) and Particle Swarms Algorithms (PSA), gathering the advantages of each one, so that an effective meta-heuristic can be achieved [17, 18]. Evolutionary Algorithms simulate the evolution of individual structures based on processes like selection, mutation and recombination, which allows the survival of the individuals with better characteristics, from generation to generation, in order to achieve the optimum value [19]. On the other hand, Particle Swarm Optimization (PSO) is based on social behavior of animal swarms, flocks or schools, in which each particle moves in the search space according to three different parameters: inertia, memory and cooperation [18].

EPSO then results in a PSO approach with self-adaptive evolutionary process acting on the strategic parameters of the algorithm [18]. This hybrid method allows the attenuation of some of the problems verified in PSO, considerably enhancing convergence possibilities.

3.1.1 Evolutionary Algorithms - EA

Evolutionary Algorithms are inspired by Darwinist theories in an attempt to imitate biological evolution mechanisms [17]. There are a variety of EA, with Evolution Strategies (ES), Evolutionary Programming (EP) and Genetic Algorithms (GA) as three of the most popular ones. Besides their differences, namely in the way they represent possible solutions of the problem (individuals), they all share the general ideas present in Evolutionary Computation (EC).

Evolutionary Algorithms optimization methodology is based on the definition of an initial population, composed by a set of elements randomly generated, usually called individuals, which are possible solutions for the problem in question. Then, a reproduction procedure of the initial population is executed, which alters it by means of a mutation or recombination process. Different individuals of the population are evaluated by a fitness function, being subject to a selection process where the general principle is the selection of the individuals with better fitness. This technique is repeated generation after generation until a certain stop criterion is reached. Lastly, the individual with best fitness is defined as the final solution of the problem.

Two basic variants of Evolutionary Algorithms can be identified based on the way they represent problem solutions: phenotypic representation and genetic representation. ES and EP are based on phenotypic EC where the solutions of the problem are directly represented by its variables, while GA are based on genetic representation of the solutions by means of binary chromosomes.

EA have a big potential for applications in the field of power systems and have been successfully used in many other areas [19]. With this type of methods, very complex problems can be solved, resulting in good final solutions. However, using EA for large scale problems can have the drawback of taking too long time. To avoid this, self-adaption models can be used, where both individuals and some of the characteristics of the algorithms evolve, so that the whole process becomes self learning about the most appropriate path to achieve the optimum value [18]. This approach is normally very efficient, offering better chances to find the global optimum.

3.1.2 Particle Swarm Optimization - PSO

Particle Swarm Optimization (PSO) was firstly introduced by Kennedy and Eberhart [20] in 1995. This optimization algorithm relies on social behavior of animals, based on a set of solutions, identified as particles, to explore the search space. From one iteration to the following, each particle X_i obeys to a movement rule which depends on a velocity term, which in turn depends on three main factors known as inertia, memory and cooperation:

$$X_i^{New} = X_i + V_i^{New} \tag{3.1}$$

$$V_i^{New} = Dec(t) w_{i0} V_i + Rnd_1 w_{i1} (b_i - X_i) + Rnd_2 w_{i2} (b_g - X_i) \tag{3.2}$$

The first term of V_i^{New} represents the inertia of the particle, making it to move in the direction it had previously moved, which is affected by a function *Dec(t)* responsible to decrease the importance of the inertia term during the course of the algorithm. The second term represents the memory of the particle, making its movement being attracted to the best point found by the particle in its past life, b_i. The last term denotes cooperation, with the particles exchanging information to define the current best point found by the swarm, b_g, and moving in that direction. The parameters w_{ik} are the weights of each term and Rnd_x are random numbers generated from an uniform distribution in [0,1].

PSO proved to be an adequate method to make the swarm converge to an accurate optimum, nonetheless it is extremely sensitive on an adequate tuning of the parameters, with the appropriate definition of the weights w$_{ik}$ being particularly important [18]. This is a delicate point of PSO, since there is no specific rule to determine the weights value, being necessary to define those external parameters recurring to a trial and error methodology in order to achieve the best possible tuning of the algorithm.

3.1.3 Evolutionary Particle Swarm Optimization - EPSO

Evolutionary Particle Swarm Optimization puts together concepts from both EA and PSO. It was firstly introduced by Miranda et al. [18], using the search capabilities of EA and the aptitudes of PSO in exploring the search space around the optimum value [21]. Gathering the advantages of both algorithms, EPSO has proven to be a very successful optimization algorithm, having very interesting convergence properties. It has been successfully used to solve different problems in the field of power systems [22, 21].

EPSO, as a hybrid algorithm, uses the same movement rule as PSO, where the swarm evolves in the search space, with the particularity of the strategic parameters being defined according to a self-adaptive evolution strategy procedure [18]. This method counters one of the main problems of PSO, making EPSO in a successful self-tuning algorithm in which the definition of initial weights is not as crucial as in the case of PSO [22].

In an EPSO algorithm, having a particle X_i, a new particle X_i^{New} is obtained by the following rule:

$$X_i^{New} = X_i + V_i^{New} \tag{3.3}$$

$$V_i^{New} = w_{i0}^* V_i + w_{i1}^* (b_i - X_i) + w_{i2}^* (b_g^* - X_i) \tag{3.4}$$

According to the expressions, and in opposition to what happens with PSO, the weights, w_{ik}^*, undergo mutation, which is defined by a random variable based on a Lognormal distribution with mean equals to 0 and variance equals to 1:

$$w_{ik}^* = w_{ik}[LogN(0,1)]^\tau \tag{3.5}$$

Where τ is the learning rate of the algorithm, externally defined to control mutation amplitudes. There is also an important difference between EPSO and PSO in the way they treat the value b_g, present in the cooperation term. In EPSO, the global best is randomly distributed based on a Gaussian distribution in [0,1], N(0,1), and on a new weight, w_{i3}^*, that should also be subject to a mutation process:

$$b_g^* = b_g + w_{i3}^* N(0,1) \tag{3.6}$$

The approach of EPSO consists of a replication process where each particle is replicated r times, originating identical particles, followed by the mutation of the weights of each particle. Then, a reproduction process of the particles is performed, based on the movement rule previously described, generating a set of offspring. Each offspring is consequently evaluated by a fitness function and selected based on its fitness, forming a new generation of particles. This process is repeated for several generations until a certain stop criterion is reached [18].

In an attempt to increase convergence capabilities of EPSO, the adoption of a stochastic star communication topology has been presented in [23] with proven improvements in the algorithm behavior. The stochastic star communication topology consists on the introduction of a communication factor P on the movement rule of EPSO, randomly controlled by a communication probability p [23].

$$V_i^{New} = w_{i0}^* V_i + w_{i1}^* (b_i - X_i) + w_{i2}^* P(b_g^* - X_i) \tag{3.7}$$

The communication factor P is represented by a diagonal matrix, composed by binary variables, which the correspondent value depends on the communication probability p. For all the dimensions of a particle, the binary variables will have a value of 1 with a probability p and 0 with a probability *(1-p)* [23]. Since the communication factor acts on the cooperation term of EPSO equation, there is a probability *(1-p)* in which a certain dimension of a particle will not be aware of the best particle found by the swarm [23].

The stochastic approach varies from a star arrangement, where p is equal to 1 and, consequently, all the dimensions of a particle receive the information regarding the best global particle, to a selfish version, where the communication probability is zero. An appropriate control of the exchange of information concerning the global best particle may avoid premature convergence [23]. In [23] it was shown that a proper definition of the communication probability value may result in better convergence of EPSO when compared with the full star communication topology. Furthermore, the stochastic star communication topology is extremely easy to implement, increasing, even more, the potential of this approach.

3.2 Differential Evolutionary Particle Swarm Optimization

The Differential Evolutionary Particle Swarm Optimization presents itself as new way to create a hybrid method between Evolutionary Programming, Particle Swarm Optimization and Differential Evolution. The new hybrid, denoted DEEPSO (DE-EA-PSO), is a variant of the EPSO algorithm that keeps its self-adaptive characteristics but uses the concept of rough gradient from Differential Evolution algorithms [24].

The concept of DEEPSO emerged from the advanced version of EPSO in which a communication probability among the particles is successfully included. Consequently, if some noise could be positively added to EPSO search by embedding a DE operator in the procedure of generating new particles, the search for the optimum could be possibly improved [24].

3.2.1 Differential Evolution - DE

The idea of Differential Evolution was proposed in [25], as a fast and general optimization method, and it has motivated many other proposals for enhancements and variants. Considering a population (swarm) of individuals (particles), the basic idea of DE is to produce a new solution from an existing individual by adding some fraction of the difference between two other points, X_{r1} and X_{r2}, randomly selected from the current population [24]. After generating a new population, a recombination process ensures more diversity and a new population is defined as a consequence of a selection procedure. This selection is elitist and one-on-one based, where parents compete for survival directly with their single offspring [24].

Among all the different variants of DE, there is one of great interest, denominated DE2 in [25], where a new individual is generated based on the following expressions:

$$X_i^{New} = X_i + V_i^{New} \tag{3.8}$$

$$V_i^{New} = w_{i1}(X_{r1} - X_{r2}) + w_{i2}(b_g - X_i) \tag{3.9}$$

There are some similarities in the process by which DE and PSO generate new individuals. The general idea of DE relies on the optimization of an objective function, sampling a local macro-gradient by picking up two random individuals from the population, which is, in a way, what PSO does, but picking up the current position and the particle past best [24].

3.2.2 Differential Evolutionary Particle Swarm Optimization - DEEPSO

The DEEPSO algorithm intends to join characteristics from EPSO and DE. DEEPSO is based on EPSO sequence, but, in order to include some principles of DE, the memory parameter of the movement rule is modified according to:

$$X_i^{New} = X_i + V_i^{New} \tag{3.10}$$

$$V_i^{New} = w_{i0}^* V_i + w_{i1}^*(X_{r1} - X_{r2}) + w_{i2}^* P(b_g^* - X_i) \tag{3.11}$$

As stated, when considering DE, X_{r1} and X_{r2} correspond to two distinct individuals sampled from the current population. However, further improvements have been made, leading to a new proposal, preserving some basis of DE but closer to PSO. Firstly, the two particles, X_{r1} and X_{r2}, should be ordered depending on the function value associated to the two particles, such that, for minimization:

$$\begin{cases} V_i^{New} = w_{i0}^* V_i + w_{i1}^* (X_{r1} - X_{r2}) + w_{i2}^* P(b_g^* - X_i) & if,\ f(X_{r1}) < f(X_{r2}) \\ V_i^{New} = w_{i0}^* V_i + w_{i1}^* (X_{r2} - X_{r1}) + w_{i2}^* P(b_g^* - X_i) & if,\ f(X_{r1}) > f(X_{r2}) \end{cases} \tag{3.12}$$

Then, the set of particles from which X_{r1} should be sampled is enlarged. Instead of sampling X_{r1} only from the particles of the current generation, the set may be extended in order to include all the historical past best particles. Lastly, in the DEEPSO method, X_{r2} is defined as being equal to X_i and only X_{r1} is randomly selected [24].

Four distinct versions of DEEPSO can then result, based on the methodology stated above, depending on how X_{r1} is sampled:

- **DEEPSO S$_g$** (same generation): the particle X_{r1} is sampled **once** from the current generation, with $\{X_{r1},X_i\}$ being ordered as in 3.12 [24].

$$V_i^{New} = w_{i0}^* V_i + w_{i1}^* (X_{r1} - X_i) + w_{i2}^* P(b_g^* - X_i) \tag{3.13}$$

- **DEEPSO S$_g$-rnd**: the same as previously, but with X_{r1} being re-sampled in the current generation for **each component** of V. In this case, X_{r1} is calculated from a uniform recombination of all the particles from the current generation [24].

- **DEEPSO P$_b$** (past bests): the particle b_{r1} is sampled **once** from the set of historical past best particles, b_i [24].

$$V_i^{New} = w_{i0}^* V_i + w_{i1}^* (b_{r1} - X_i) + w_{i2}^* P(b_g^* - X_i) \tag{3.14}$$

- **DEEPSO P$_b$-rnd**: the same as previously, but with b_{r1} being re-sampled in the set of historical past best particles for **each component** of V. In this case, b_{r1} is calculated from a uniform recombination of all the historical past best particles [24].

3.3 Location of FACTS Based on a Meta Heuristic

During the course of this work a software tool to optimally locate FACTS devices was developed. It has been implemented in the MATLAB environment using a meta heuristic for such optimization problem. In the following paragraphs the developed model will be detailed and the main assumptions will be referred as well as properly justified.

It should be mentioned that this model is based on the EPSO and DEEPSO algorithms, meaning that it is specifically adapted to those methods. However, it can be easily modified in order to use other meta-heuristics. Even more, this model seeks the optimal location of Phase Shifting Transformers and Thyristor-Controlled Phase Shifting Transformers, specifically of the type Phase Angle Regulating Transformers. Obviously, it can be modified to locate other types of FACTS devices by slightly changing some of its characteristics.

In the proposed model each particle of the swarm represents a possible solution to the location problem. The length of a particle is defined by the number of candidate locations in the power network where a PAR can be installed. Each component of the particle denotes the placement of a PAR in a certain location, corresponding, in the case of a PAR transformer, to a certain line, as well as the maximum angle the PAR may inject in that line. Thus, it is possible not only to represent a suitable location of PAR transformers but also their dimensioning in terms of their maximum angle.

α_1^{Max}	α_2^{Max}	...	...	...	α_{N-1}^{Max}	α_N^{Max}

Figure 3.1: Particle structure.

Given a set of N candidate locations to install a PAR, a particle will have a length of N and each component i is a proposal for the maximum angle introduced by the device at location i, α_i^{Max}. Each possible solution is then evaluated by a fitness function which values two factors, the capital cost of each PAR and the eventual need to curtail load.

The capital cost of a PAR is considered as being composed of a fixed cost plus a non-linear variable cost which is a function of the maximum angle introduced by the PAR. This is a discontinuous function where there is a gap at the point corresponding to the non-installation of the device, where the capital cost is, of course, null.

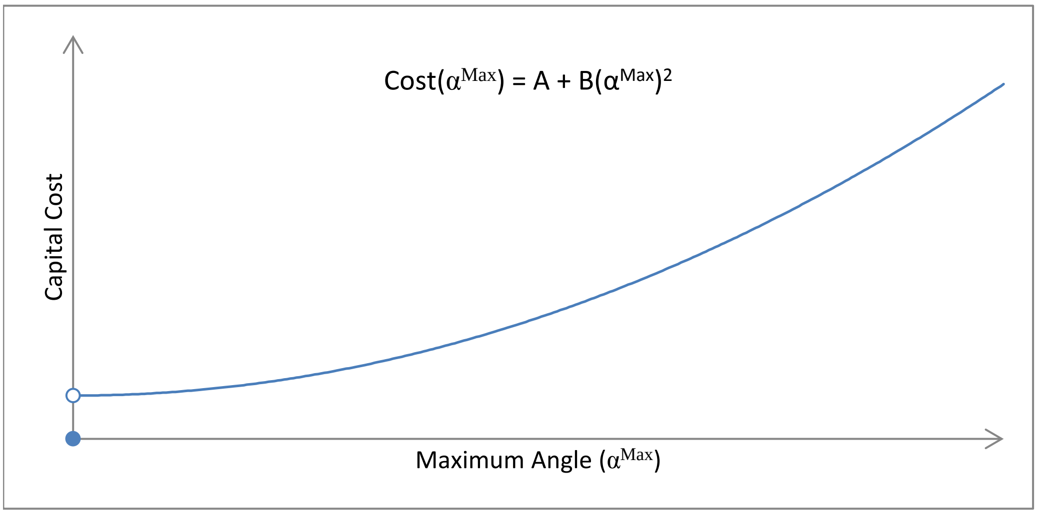

Figure 3.2: Capital cost of each PAR.

Regarding the need to curtail load, it must be evaluated, for each possible solution, by solving the power flow equations in all load scenarios considered. This leads to an optimal power flow problem since it is also necessary to find the most appropriate generation pattern as well as the set of angles values, corresponding to each PAR, in order to evaluate the possibility of avoiding load curtailment.

The allocation and sizing of PAR transformers is, therefore, defined by the following minimization:

$$min\ J \quad = \quad \sum_{i=1}^{N} u_i(A + B(\alpha_i^{Max})^2) + Penalties \tag{3.15}$$

Where u_i is a binary variable representing the installation of a PAR at location i, A and B are the cost constants and α_i^{Max} is the maximum angle introduced by the device at location i. The penalty term will be included if the optimal power flow problem results in the need to curtail load. It is also possible to evaluation several load scenarios by increasing the penalty term as the number of scenarios with load curtailment rises.

In order to solve the optimal power flow problem for each possible solution it is necessary to include the effect of the PAR in the power network, modelling its influence in the power flow equations. The proposed model implements a DC Optimal Power Flow (OPF) to evaluate the system performance. Although the DC OPF is a linearization of the AC OPF and consequently a less accurate model, due to its simplicity it can be properly used for multiple power systems calculations, needing low computational requirements.

The equivalent circuit adopted for a PAR is the one described in 2.2.2 , where the active power transported over a line with an installed PAR is given by:

$$P_{sr} = \frac{\theta_{sr} - \alpha}{X_{sr}} = \frac{\theta_{sr}}{X_{sr}} - \frac{\alpha}{X_{sr}} \tag{3.16}$$

This is equivalent to have a power injection resulting from the utilization of the PAR, which corresponds to connect an additional load on the sending bus, s, and an additional generation on the receiving bus, r. In consequence, the influence of a PAR device can be directly represented in the vector of bus active power injections, P, of the classic DC Power Flow formulation. Accordingly, the matrix representation of the linear power flow can be easily adapted to include the impact of PAR transformers:

$$P_s^{PST} = -P_r^{PST} = -\frac{\alpha}{X_{sr}} \tag{3.17}$$

$$\left[P + P^{PST}\right] = \left[B'\right][\theta] \tag{3.18}$$

$$[\theta] = \left[B'\right]^{-1}\left[P + P^{PST}\right] \tag{3.19}$$

Where P+P^{PST} stands for the vector of bus active power injections including the effect of PAR transformers, *B'* is the bus susceptance matrix and θ is the vector of bus voltage angles. This formulation represents a very effective and simple method to model the effect of PAR devices in the DC Power Flow equations, allowing the power flow model to be written as a function of α. To solve the DC Optimal Power Flow problem, the constraints regarding the limits on generation and on line flows as well as the limits on the PAR angles have to be considered. Using an optimization tool it is possible to solve the DC OPF constrained as follows:

$$\sum Pg_j = P_{Load} \tag{3.20}$$

$$Pg_j^{Min} \leq Pg_j \leq Pg_j^{Max} \tag{3.21}$$

$$F_k^{Min} \leq F_k \leq F_k^{Max} \tag{3.22}$$

$$\alpha_i^{Min} \leq \alpha_i \leq \alpha_i^{Max} \tag{3.23}$$

With Pg_j being the power generated by the unit j, F_k the power flow through line k affected by the eventual impact of PAR transformers and α_i the angle introduced by the PAR at location i. For such formulation the aim is only to evaluate if, for a certain placement of PAR devices, the system is able to supply the entire load or if there is a need to curtail load. As stated before, if the evaluated possible solution leads to load curtailment, then a penalty is applied in equation 3.15 since only solutions leading to no load curtailment are desirable.

However, in a more complex DC OPF model it is also possible to evaluate the quantity of load curtailed by means of fictitious generators. In this case, the penalty applied to the fitness function 3.15 varies with the amount of load curtailed being representative of the cost for load curtailment. The DC OPF model needs to be slightly modified:

$$min\ J = \sum PNS_m \tag{3.24}$$

$$\sum Pg_j + \sum PNS_m = P_{Load} \tag{3.25}$$

$$Pg_j^{Min} \leq Pg_j \leq Pg_j^{Max} \tag{3.26}$$

$$0 \leq Pg_j \leq P_{Load\,m} \tag{3.27}$$

$$F_k^{Min} \leq F_k \leq F_k^{Max} \tag{3.28}$$

$$\alpha_i^{Min} \leq \alpha_i \leq \alpha_i^{Max} \tag{3.29}$$

In this situation it is essential to define the objective function of the problem in order to minimize the sum of the power not supplied on each load m, PNS_m. Though this formulation allows the quantification of the power not supplied for each possible solution, giving more information when compared with the previous model, it requires considerable additional computational resources. However, since this is a more accurate model, it was the one implemented in the developed tool.

The proposed EPSO/DEEPSO-based model described above to locate FACTS devices can be outlined as follows:

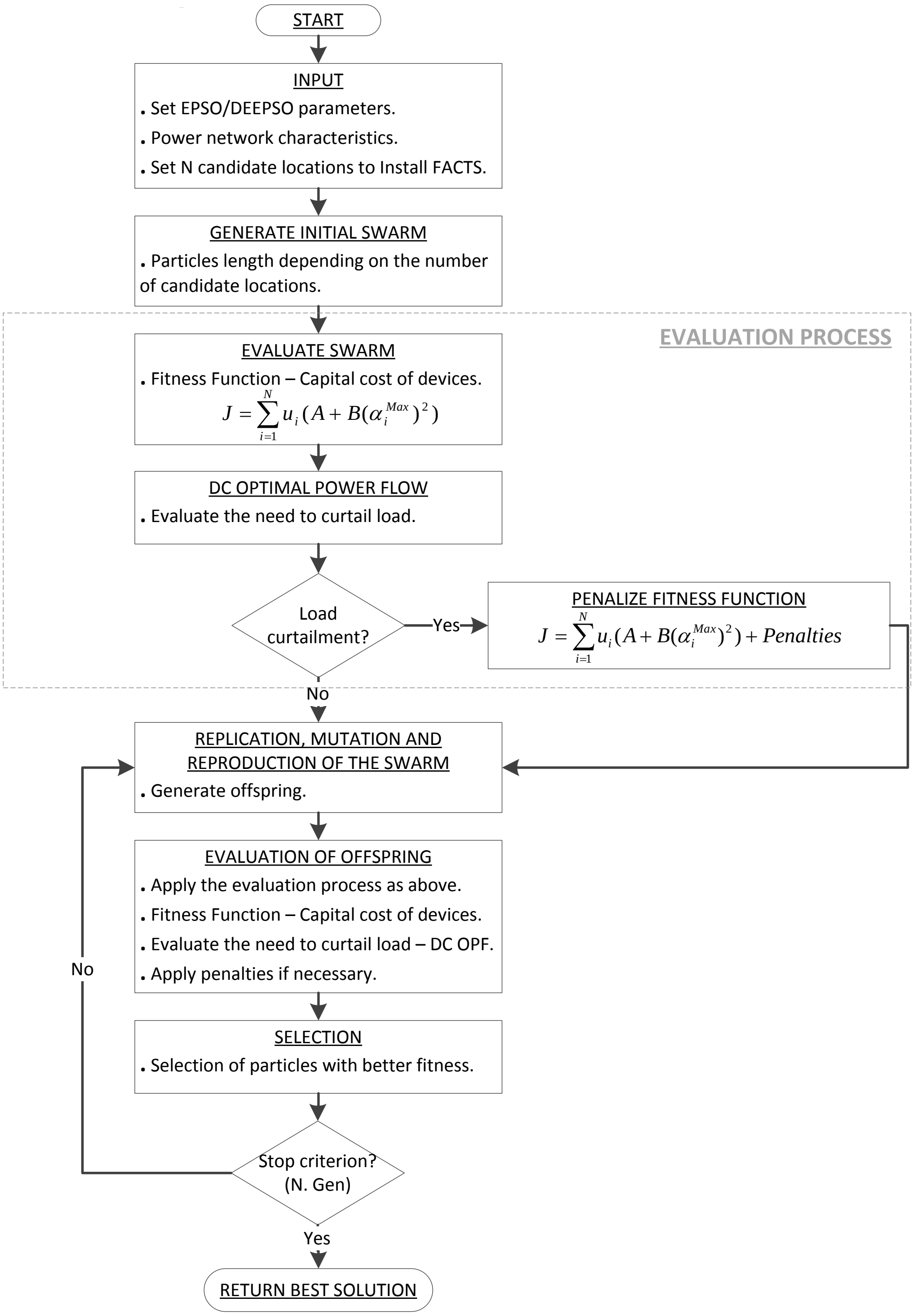

Figure 3.3: Proposed algorithm to optimally locate FACTS devices - EPSO/DEEPSO-based model.

3.4 EPSO vs. DEEPSO: Performance Comparison

Having implemented two different meta heuristics to optimally locate PAR transformers, this section presents a detailed analysis of the behavior of the Evolutionary Particle Swarm Optimization and all the different versions of the Differential Evolutionary Particle Swarm Optimization, doing a thorough comparison between them. The results presented come from the application of the developed tool to the IEEE 24-bus Reliability Test System. The characterization of this test system will not be detailed in this section and no comments will be made to the solutions obtained to optimally locate the devices, once the intentions are only to evaluate the performance of the algorithms. Comments regarding these issues will be carried out in the succeeding chapters.

The strategic parameters of the algorithms (weights) were initially defined with the value of 0.5 for the inertia, memory and cooperation terms and 0.1 for the weight concerning the global optimum. The learning rate (τ) was set as being equal to 0.25 and it was considered a swarm of 30 particles each of them representing a possible placement of PAR for 8 candidate locations in the power network (particles length equal to 8). Those values have been defined based on a trial error methodology in order to achieve a satisfactory performance for both EPSO and DEEPSO methods.

Another important parameter of those methods is the communication probability which should be appropriately defined. It has been proven that a stochastic star communication topology is of extreme importance for the performance of the EPSO algorithm, leading to better convergence capabilities. Since there is no rule of thumb to define the communication probability, once it depends on the topology of the search space, different tests were performed in order to determine its most appropriate value. For each different value of the communication probability and for each of the different algorithms, 20 runs have been executed with a stop criterion of 100 generations, where the algorithms are evaluated by its average error (AE) and root mean square error (RMSE):

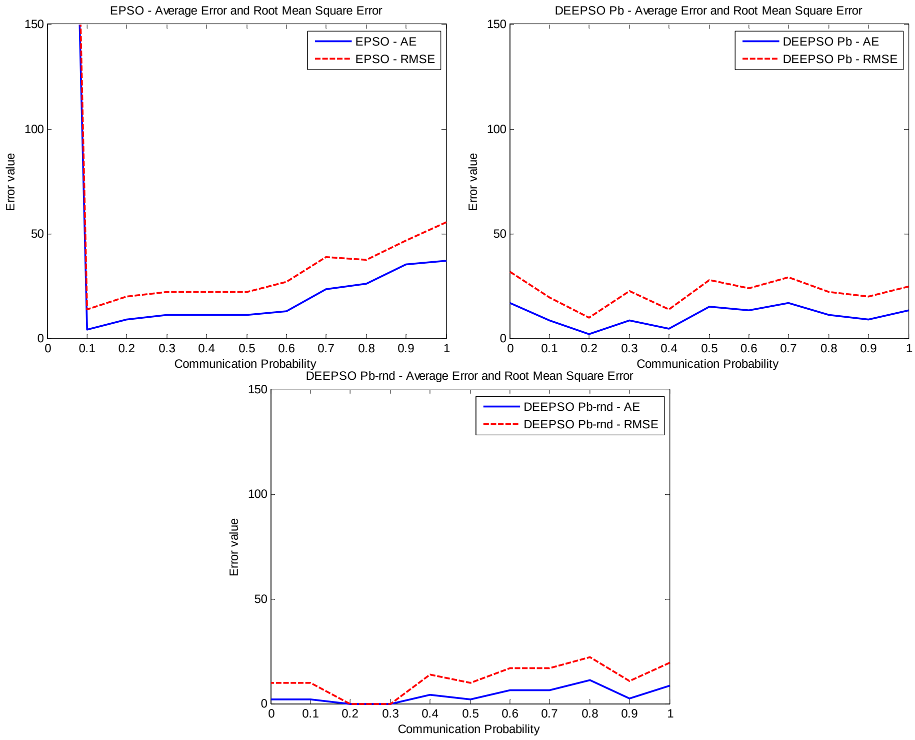

Figure 3.4: Average error and RMSE achieved for different communication probabilities.

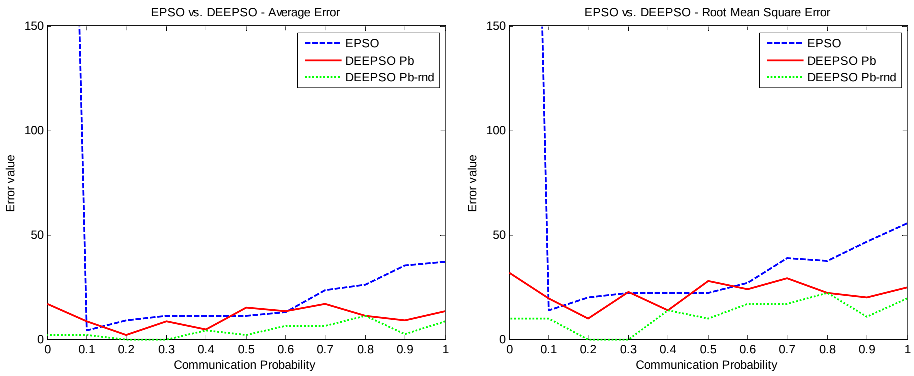

Figure 3.5: Average error and RMSE achieved for different communication probabilities - Comparison of different methods.

As expected, there is an important advantage in implementing the stochastic star communication topology. The most interesting values of the communication probability seem to be around 0.1 and 0.3 where the average error and the root mean square error are lower. This means that a high restriction on the communication among the different particles in the swarm appears to be favorable. From the graphics above it is also possible to notice some superiority in the performance of two of the DEEPSO variants leading to lower error values (both AE and RMSE) than the EPSO. For the best communication probability values, the minimum value of the average error achieved by the EPSO is 1.1% while the DEEPSO P_b guarantees approximately half of that value, 0.56%, and the DEEPSO P_b-rnd hits the optimum value in all the 20 runs. This already represents a major breakthrough regarding the comparison of those methods, although some more detailed and complete tests need to be done in order to guarantee the accuracy of these statements.

An extensive comparison between the classical EPSO and all the different variants of the DEEPSO method has been performed. The presented results are for the simulation of 100 runs of each algorithm with a stop criterion of 300 generations.

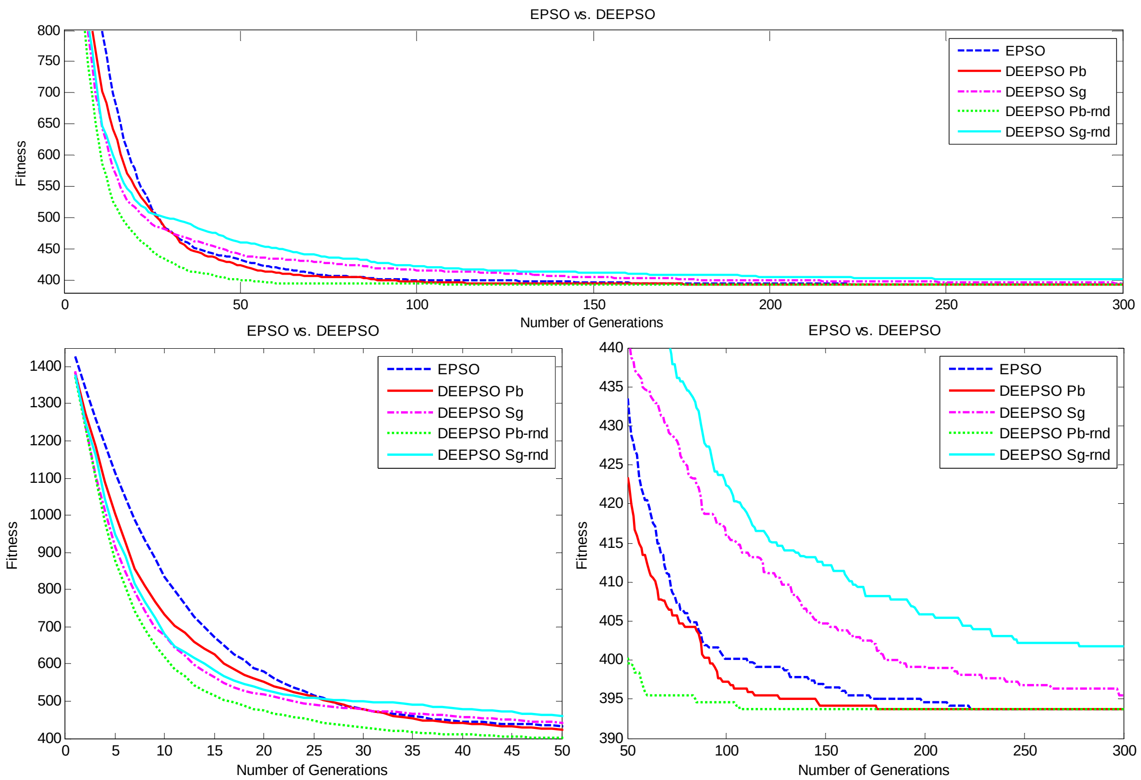

Figure 3.6: Evolution of the average best fitness for 100 runs of EPSO and all DEEPSO variants.

From the graphics above, it is possible to observe the superiority of the DEEPSO P_b-rnd algorithm over the others. The average value of the fitness function in this algorithm begins to stand out from the others at the fifth generation, clearly having a more desirable value. For the DEEPSO P_b-rnd the optimum value of the problem is reached for all the 100 runs, where the latest (in terms of generations) optimum value is achieved at the generation number 108, meaning that the algorithm has needed 108 generations to find the optimum value in all the 100 runs. The DEEPSO P_b and the EPSO have demonstrated to have the second and third best capabilities in finding the optimum value. In those two cases, the optimum value of all the 100 runs was reached at generation number 176 and 222, respectively, which represents an increase of 63% and 106% when comparing with the DEEPSO P_b-rnd. The DEEPSO S_g and S_g-rnd variants have the poorest convergence capabilities, proving to have some difficulties in finding the optimum value. In such cases, contrary to what was achieved by EPSO, DEEPSO P_b and DEEPSO P_b-rnd, the methods were not able to find the global optimum in all the runs performed. The number of times the optimal solution was discovered for each method is indicated in the following table:

Table 3.1: Comparison between the different methods in finding the optimal solution.

EPSO	DEEPSO S_g	DEEPSO P_b	DEEPSO S_g-rnd	DEEPSO P_b-rnd
100%	96%	100%	83%	100%

The figure below displays the number of hits on the optimum value with varying number of generations. The DEEPSO P_b-rnd has an extraordinary behavior, showing considerable supremacy over all the other methods, reaching 96% of efficiency in finding the optimum only at 60 generations. The algorithms using the DE trick with particles in the same generation confirm their poorest performance.

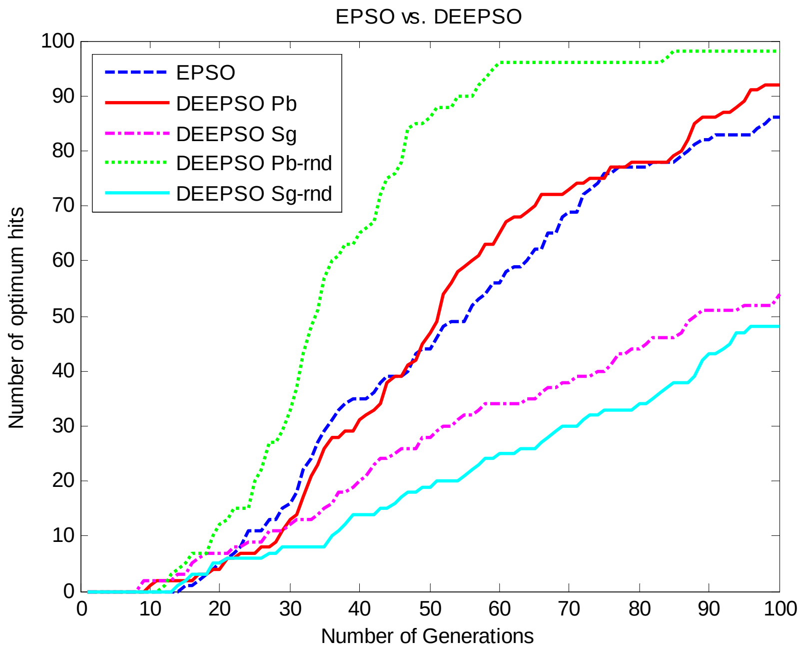

Figure 3.7: Evolution of the number of hits on the optimum for 100 runs of EPSO and all DEEPSO variants.

In terms of the average number of generations each algorithm needed to achieve the optimum, as well as the associated variance, the algorithms behaved as follows:

Table 3.2: Mean value and variance achieved by the different methods for 100 runs.

Method	Mean Value (μ)	Variance (σ^2)
EPSO	65.4	1895.1
DEEPSO S_g	109	5853.6
DEEPSO P_b	58.2	910.6
DEEPSO S_g-rnd	137.93	8896.9
DEEPSO P_b-rnd	37.3	273.8

The obtained values reinforce the consistency of the DEEPSO P_b-rnd method, which has not only the best mean value regarding the number of generations needed to achieve the optimum but also the smallest variance. Once again, in second and third place it is possible to find the DEEPSO P_b and EPSO algorithm, however they present considerably worse results than the DEEPSO P_b-rnd variant.

Undoubtedly, the DEEPSO algorithm, specifically the variant DEEPSO P_b-rnd, has a far superior performance than the others methods to solve this specific problem regarding the location of FACTS devices. Above all, the DEEPSO P_b-rnd has proven to have better convergence capabilities than the classic EPSO, showing that for some specific problems it can be advantageously used.

Chapter 4

Wind Power on Location of FACTS Devices

Production of energy from renewable resources is an alternative to the traditional thermal generation, having considerable associated advantages, namely environmental. Particularly, the integration of wind turbine generators in electric power systems became a reality, with a significant increase of wind power penetration happening during the course of years. Traditional power systems, where generation systems were composed mainly by conventional units, are now being replaced by modern systems with large amount of produced power coming from wind resources.

Under this context, the evaluation of power systems with high degree of wind power integration has to consider the intermittence associated to the wind resource which is responsible for wind power variations, having an important impact on power systems operation. The output power of wind turbines is extremely dependent on wind speed characteristic which has a probabilistic behavior that should be properly modeled in order to consider the influence of wind in power systems.

Due to the probability associated to the occurrence of a certain wind scenario, the location of FACTS devices with wind power integration becomes a stochastic optimization problem. Having that in mind, a simplified, realistic and computationally efficient model based on stochastic programming is presented in order to include the impact of wind power integration on the optimal location of FACTS devices. The proposed model should be seen as an extension of the one stated in 3.3, where most of the considerations previously made are still applicable.

4.1 Wind Speed Model

Wind resource availability depends on geographical characteristics, varying from site to site, where the wind speed fluctuates randomly with time. An appropriate probabilistic representation of the wind speed is extremely important to accurately model the predictable output power from wind turbine generators. Commonly, wind speed probability distributions are represented by a Weibull distribution, which is widely accepted and recognized in the wind energy industry as an appropriate technique to represent wind speed variations. The Weibull probability density function is given by the expression:

$$f(v) \quad = \quad \frac{k}{\lambda}(\frac{v}{\lambda})^{k-1}e^{(-\frac{v}{\lambda})^k} \tag{4.1}$$

Where *f(v)* is the probability density of the wind speed v, k the shape parameter and λ the scale parameter. To the vast majority of wind conditions the shape parameter varies from 1 to 3. With an appropriate combination of the shape and scale parameters it is possible to accurately describe the probabilistic characteristic of wind speed, allowing for the representation of different wind scenarios. The following figure represents three different wind scenarios for a scale parameter of 7.5 m/s and different values of the shape parameter:

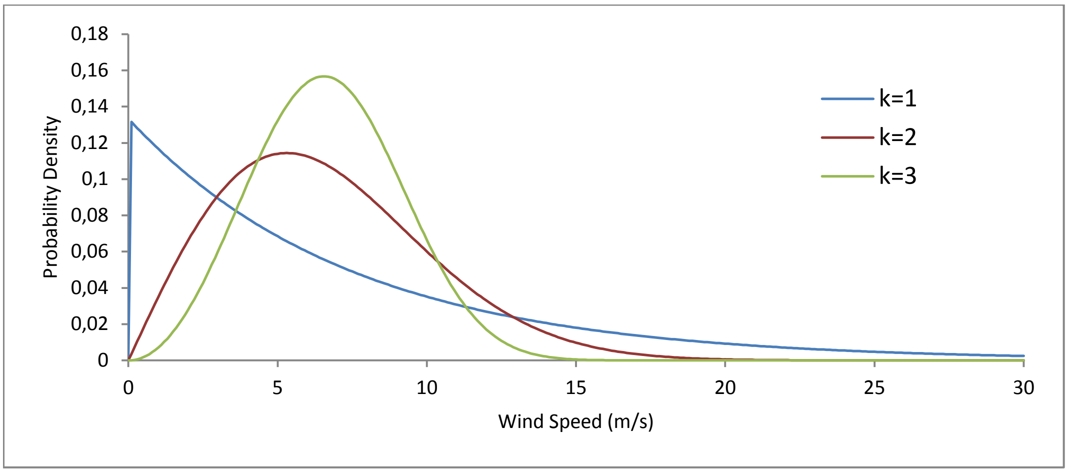

Figure 4.1: Wind speed model - Weibull probability density function.

The Weibull cumulative distribution function is given by the integral of the Weibull probability density function and allows the determination of the probability of occurrence of certain wind speeds ranges. The Weibull cumulative distribution function is given by:

$$F(v) \quad = \quad 1 - e^{(-\frac{v}{\lambda})^k} \tag{4.2}$$

For the different wind scenarios presented above, the respective cumulative distribution functions are the following:

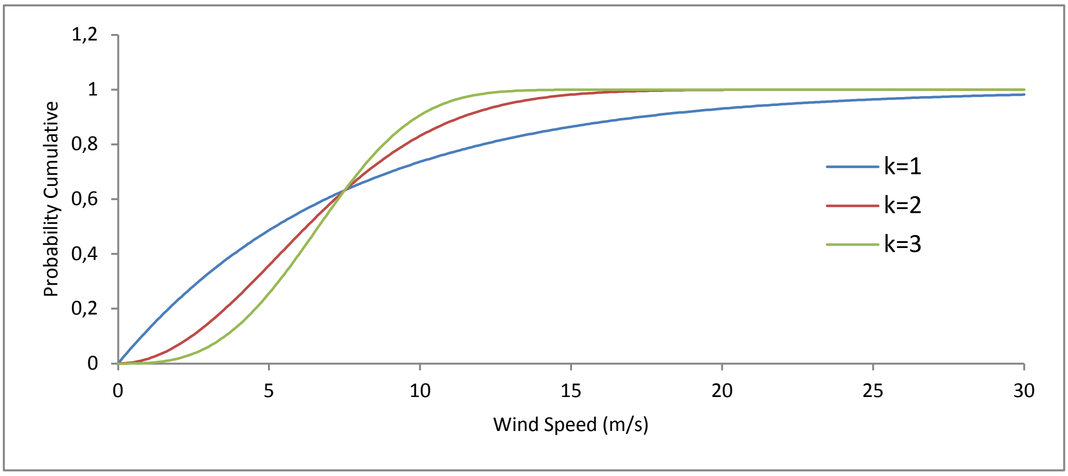

Figure 4.2: Wind speed model - Weibull cumulative function.

According to the values obtained in the cumulative distribution function it is possible to stratify the Weibull probability density function in order to associate the respective probability of occurrence to different wind speed ranges. In practice, the Weibull distribution is discretized and distributed in a set of intervals, each of them representing a wind scenario, having an associated probability of occurrence.

With a purely explanatory intention, a possible stratification of a wind scenario in five different intervals (wind scenarios) is presented in the figure below, where each interval of wind speeds has an associated probability of 0.2:

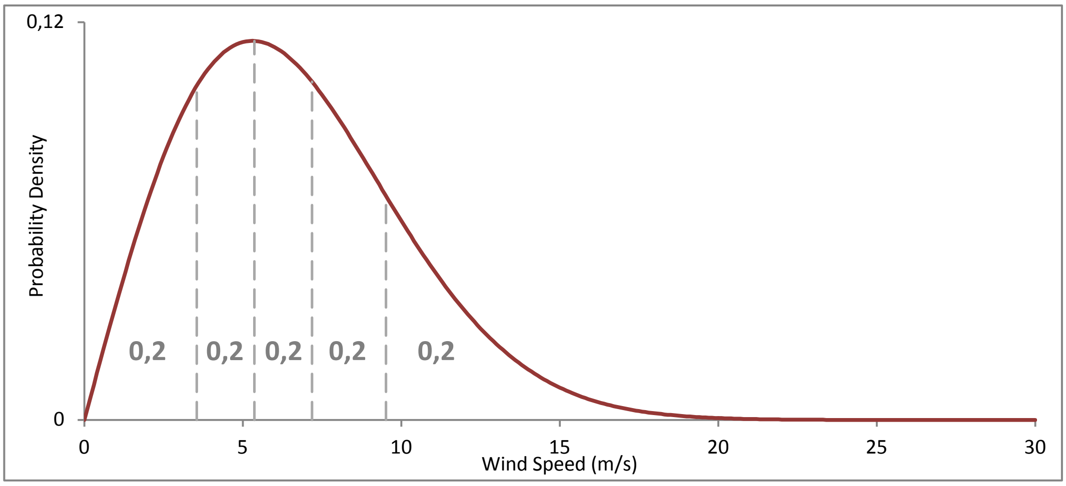

Figure 4.3: Stratification of the Weibull probability density function.

As it will be explained further ahead, this approach is of extreme importance to evaluate the power system behavior when having different wind conditions, allowing the development of a stochastic optimization model for the location of FACTS devices.

4.2 Wind to Power Model

An efficient model to estimate the electric power generated by a wind turbine at a specific site can be determined by combining an accurate characterization of the wind speed, as presented before, and the information regarding its power curve. A typical power curve of a wind turbine generator as a function of the wind speed is presented below:

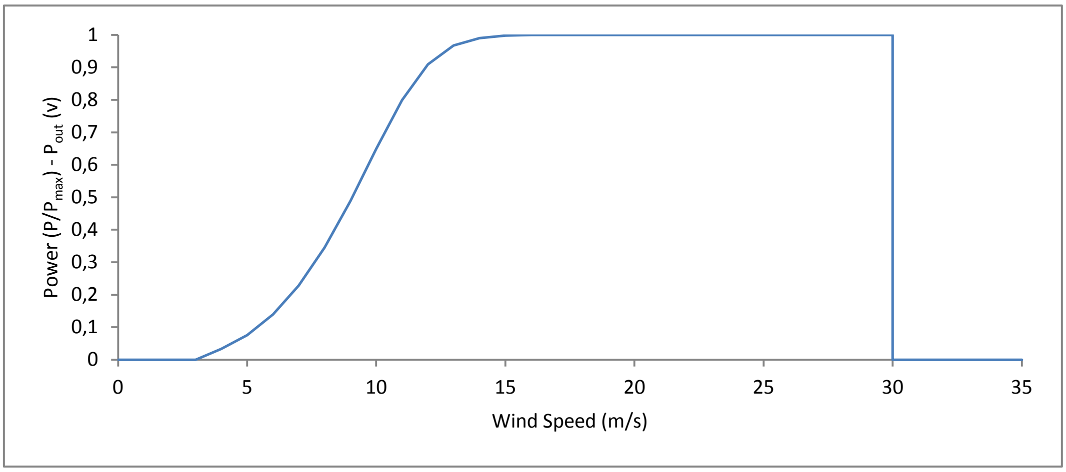

Figure 4.4: Typical power curve of a wind turbine generator.

As it can be observed, the wind turbine generator has three different operation modes. The wind turbine is designed to be shut down when the wind speed is less than the cut-in speed and greater than the cut-out speed, in order to guarantee a proper preservation of the machine. In this specific case, the cut-in and cut-out speeds are respectively 3 m/s and 30 m/s. Within the range of 3 m/s and 17 m/s, the cut-in and rated speeds, the power from the wind turbine varies proportionally to the cube of the wind speed. The last mode of operation concerns the wind speed ranges between the rated and cut-out speeds, where the turbine generates at its rated capacity.

Having defined the wind speed model as well as the power curve of a wind turbine, its output power model can be obtained. The probability associated to a certain output power range will correspond to the probability of occurrence of the wind speed range that originates that produced power, accordingly to the power curve of the generator. This can be easily made if the wind speed Weibull distribution is stratified as demonstrated in figure 4.3. However, in some cases, depending on the numbers of intervals in which the density function of the wind speed is stratified, diverse wind speeds intervals may originate the same electric power from the wind turbine. This may happen for the wind speed ranges in which the wind turbine is supposed to be shut down or producing at rated capacity. In those two cases, if there is more than one interval of wind speeds resulting in the same output power, the probability of the respective output power is obtained by adding all the probabilities of occurrence of all the wind speed intervals.

The power generation model of a wind turbine with a power curve as presented in figure 4.4, considering a wind scenario corresponding to the figure 4.1 for k=2, is presented below. In this specific case, the wind speed Weibull distribution is divided in eight intervals, with different associated probabilities. The definition of the width of each interval was made considering the power characteristic of the wind turbine, in order to have diverse output power intervals. This is a very important detail, to guarantee the evaluation of a power system performance when dealing with different values of wind power penetration, as it will be clearly explained in the following section.

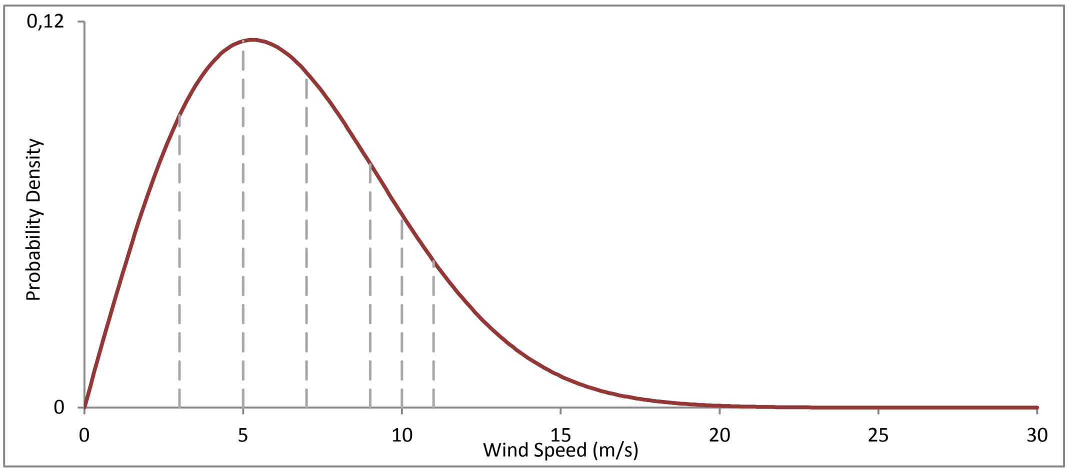

Figure 4.5: Stratification of the Weibull probability density function - Wind to power model.

Table 4.1: Wind to power model - Predicted output power.

Wind Scenario	**Wind Speed - v(m/s)**	**Power (P/P_{Max}) - $P_{out}(v)$**	**Probability**
1;8	[0;3] U [30;>30[	0	0.148
2	]3;5[	]0;0.076[	0.211
3	[5;7[	[0.076;0.2285[	0.223
4	[7;9[	[0.2285;0.489[	0.182
5	[9;10[	[0.489;0.648[	0.068
6	[10;11[	[0.648;0.799[	0.053
7	[11;30[	[0.799;1[	0.116

Therefore, the combination of the wind speed model with the output power curve of a wind turbine allowed the determination of a simplified wind power model of a wind turbine generator. Even though the stratification in figure 4.5 may appears to be strange, since the intervals have different associated probabilities, this makes all the sense since the aim is to be able to achieve a generation model that allows the stratification of different levels of wind power. As seen from table 4.1 it was possible to determine the predictable output power from a wind turbine, having different intervals covering diverse levels of power.

4.3 Wind Power Integration Through Stochastic Programming

In the presence of wind power, the proper allocation of FACTS devices may have an important impact in allowing an increase of wind power penetration in power systems. In the daily operation of power systems, the need to curtail wind generation may arise in order to satisfy the network constraints. This may result in the replacement of curtailed wind generation by conventional generation, which has considerable associated costs. The increased cost of conventional generation as well as the need to compensate wind producers for the wind generation curtailed lead to an increased operational cost. Consequently, in a system with wind power, the location of FACTS must seek not only the reduction of the need to curtail load, but also wind generation.

Considering the wind power modeled as explained above, 4.2, where the wind resource is represented by a set of S wind scenarios stratified according to a Weibull distribution, associating each scenario h with a probability value p_h, a stochastic programming based model can be implemented to properly evaluate each possible solution to locate FACTS devices in all the S scenarios. By slightly adapting the fitness function presented in equation 3.15 is then possible to find an appropriate location and sizing of PAR transformers in a system with wind power, where each solution is evaluated according to:

$$min\, J = \sum_{i=1}^{N} u_i(A+B(\alpha_i^{Max})^2) + k_1(\sum_{h=1}^{S} u_h p_h) + k_2(\sum_{h=1}^{S} p_h Pwc_h) \tag{4.3}$$

The first term remains the same as in equation 3.15, referring to the cost of PAR installation. The second term represents the need to curtail load for each wind scenario h; u_h is a binary variable expressing the need to curtail load for the wind scenario h and p_h stands for the probability associated to the wind scenario h. The last term expresses the need to curtail wind generation, where Pwc_h is the quantity of wind power curtailed on wind scenario h. Constant values, k_1 and k_2, introduce the penalties given to load and wind generation curtailment. Once the need to curtail load has a worse impact on power systems than the need to curtail wind generation, in terms of costs, the constant value k_1 must have a considerably higher value than k_2 in order to penalize much more the solutions leading to load curtailment.

The DC OPF formulation also has to be adapted in relation to the one presented in 3.3, in order to evaluate, for each possible solution, if and how much power must be curtailed and of what nature: wind generation or load. The DC OPF has to be performed for all the S wind scenarios considered. The constraints regarding the limits on generation and on line flow as well as the limits on PAR angles still have to be considered as before, however the formulation of the problem should ensure the maximum production of wind power. This means that the DC OPF objective function aims the maximization of wind power, guaranteeing that the limits on wind generation are defined accordingly to the predicted wind resource. Consequently, the DC OPF formulation can be expressed as follow:

$$max\ J = \sum Pgw_f \tag{4.4}$$
$$\sum Pg_j + \sum Pgw_f = P_{Load} \tag{4.5}$$
$$Pg_j^{Min} \leq Pg_j \leq Pg_j^{Max} \tag{4.6}$$
$$Pgw_f^{Min} \leq Pgw_f \leq Pgw_f^{Max} \tag{4.7}$$
$$F_k^{Min} \leq F_k \leq F_k^{Max} \tag{4.8}$$
$$\alpha_i^{Min} \leq \alpha_i \leq \alpha_i^{Max} \tag{4.9}$$

Where Pgw_f represents the power generated in wind generator f and all the other variables have the meaning described in 3.3. The wind generation curtailed, Pwc_h, according to expression 4.3, can be easily obtained by comparing the wind power generated on each wind generator, Pgw_f, with the minimum predictable wind power on each wind scenario. Obviously, if the output power of a wind farm, Pgw_f, is inferior to the minimum predictable output power, there is a need to spill wind, and the wind generation curtailed can be approximately calculated by the difference between those two values. The wind generation curtailed can then be estimated by adding all the wind generation curtailed on each wind generator f, Pgw_f.

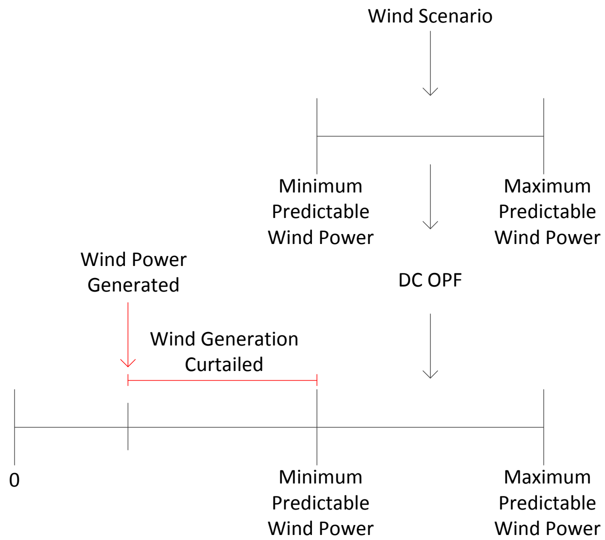

Figure 4.6: Wind generation curtailed calculation.

The DC OPF model presented above allows the determination of the need to curtail load, however the quantification of the load curtailed implies the inclusion of fictitious generators, exactly as it was made in the proposed model in 3.3. The DC OPF formulation including the fictitious generators has to consider the addition of a high constant value, B, in the objective function, in order to avoid as much as possible, the load curtailment. This formulation should be given by:

$$max\ J = \sum Pgw_f - B * \sum PNS_m \tag{4.10}$$

$$\begin{aligned}
\sum Pg_j + \sum Pgw_f + \sum PNS_m &= P_{Load} && (4.11)\\
Pg_j^{Min} \quad \leq Pg_j \leq &\quad Pg_j^{Max} && (4.12)\\
Pgw_f^{Min} \quad \leq Pgw_f \leq &\quad Pgw_f^{Max} && (4.13)\\
0 \quad \leq PNS_m &\quad \leq P_{Loadm} && (4.14)\\
F_k^{Min} \quad \leq F_k \leq &\quad F_k^{Max} && (4.15)\\
\alpha_i^{Min} \quad \leq \alpha_i \leq &\quad \alpha_i^{Max} && (4.16)
\end{aligned}$$

In this case, the fitness function to evaluate each possible solution should include the total power not supplied, PNS, obtained by solving the DC OPF:

$$min\ J = \sum_{i=1}^{N} u_i(A + B(\alpha_i^{Max})^2) + k_1(\sum_{h=1}^{S} p_h PNS_h) + k_2(\sum_{h=1}^{S} p_h Pwc_h) \tag{4.17}$$

The proposed EPSO/DEEPSO-based model to locate FACTS devices can be outlined as presented in figure 3.3, with the respective modifications on the evaluation process of each solutions as explained above:

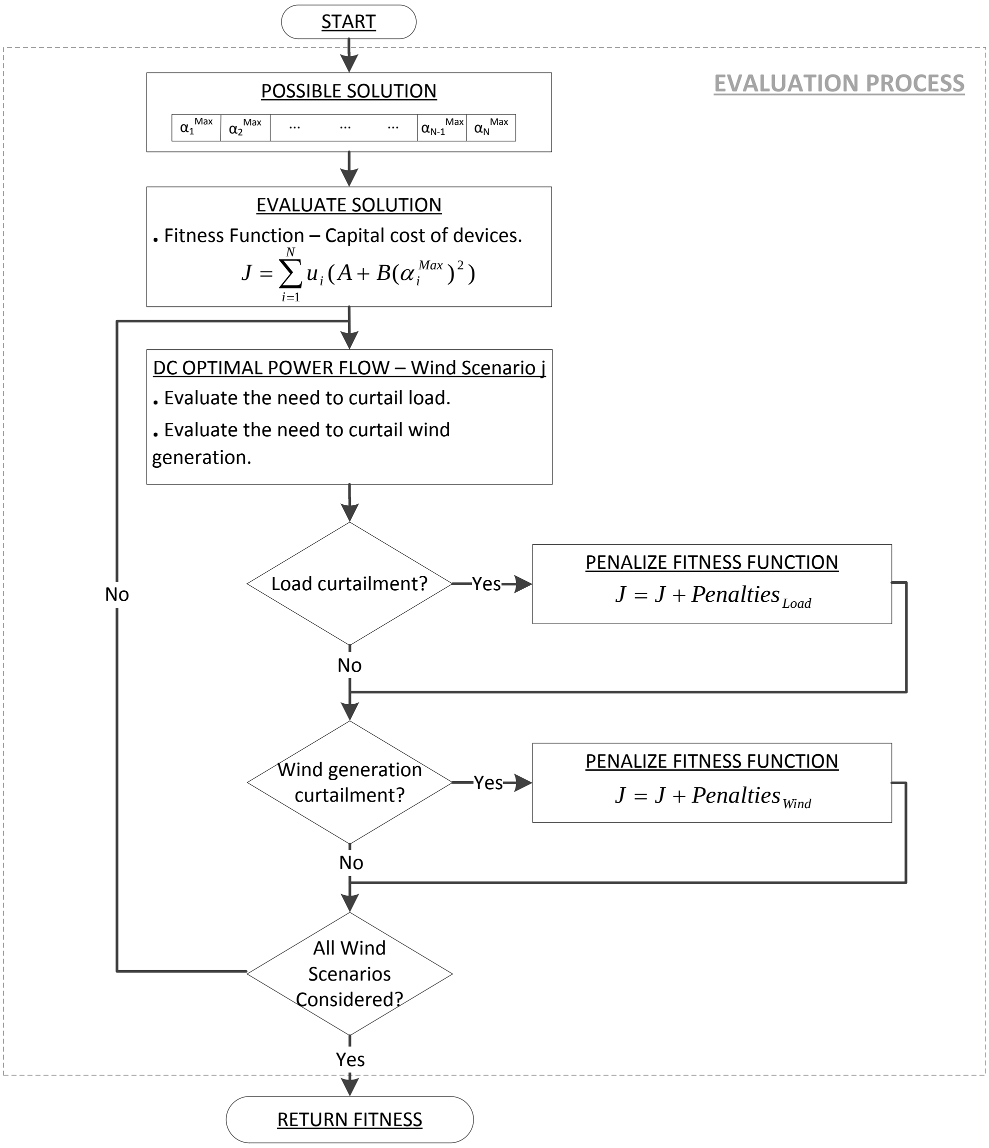

Figure 4.7: Outline of the fitness function to evaluate each possible solution to locate FACTS devices in a system with wind power.

The implementation of the proposed model to locate PAR transformers in a power system with wind power is, undoubtedly, more complex than the one previously presented to locate the devices in a system without wind power. For each single possible solution to locate PAR transformers it is necessary to solve a more complex DC OPF problem and for numerous times, in order to evaluate the system performance under different wind and load conditions. This may have an important impact in terms of computational requirements and the performance of the algorithm to allocate PAR transformers may be compromised, being potentially time-consuming. To overcome those difficulties, some assumptions have been made in the proposed model aiming to increase the computational efficiency of the developed tool, as described in the next paragraphs.

Hereupon, if the number of solved DC OPF could be substantially reduced, the application would become much more efficient. This implies, indispensably, the reduction of the number of wind scenarios for which a solution is evaluated. If the evaluation sequence of each possible solution is carefully defined in terms of the order by which each wind scenario is considered, it may be possible, in some occasions, to understand the behavior of the system in all the wind scenarios, only by evaluating some of them. The basic idea consists on the evaluation of a solution under extreme wind scenarios, with highest and lowest predictable wind power penetration, to assume the power system behavior under all the other intermediaries wind conditions. Based on this assumption, the proposed model can be adjusted simply by adopting the following steps, in order to achieve a faster and simpler method:

1. Firstly, the DC OPF problem should be solved considering the wind scenario with the highest predicted wind power. Two different solutions may result in terms of load curtailed:

   1.1. There is a need to curtail load and no more DC OPF problems have to be performed to consider the others wind scenarios. In this case, if the system is not able to supply all the load when having the maximum generation available it is considered that it will lead to load curtailment in any of the others wind scenarios. This is an extreme situation, where the consideration of a single wind scenario is enough to understand system behavior in all the others wind scenarios. This specific situation may result in significant savings on the number of DC OPF problems solved.

      1.1.1 Accordingly, the fitness of the solution under evaluation can be calculated and the process goes back again to step 1 in order to evaluate the following possible solution.

   1.2. There is no load curtailment and forcibly more wind scenarios have to be considered. However, it is important to evaluate the need to curtail wind generation. In this case, it is essential to retain the wind power production on each wind generator since the obtained values correspond to the maximum wind power that the system can withstand and will be needed to estimate the wind power curtailed on others wind scenarios. The process continues to 2.

2. The next step is to solve the DC OPF considering the wind scenario leading to the lowest predictable wind power, in opposition to the one in 1. This allows the evaluation of the system performance when the wind power penetration is minimal.

   2.1. If the DC OPF does not result in load curtailment, no more wind scenarios have to be considered. It is assumed that if the system is able to supply all the load when having the highest and the lowest levels of wind power penetration, then it also leads to no load curtailment under all the others intermediaries wind scenarios. In this case, only by evaluating two wind scenarios (1 and 2) it is possible to estimate the system behavior in all the others wind scenarios.

      2.1.1. Still, it is necessary to calculate the wind generation curtailment in all the intermediaries wind scenarios not considered. Having the maximum level of wind power penetration that the system can withstand, obtained in 1.2, the wind curtailed on each intermediary wind scenario can be estimated by comparing the minimum predictable wind power penetration with that value.

2.1.1.1. The fitness of the solution under evaluation can be calculated and the process goes back again to step 1 in order to evaluate the following possible solution.

2.2. However, if the DC OPF performed for the wind scenario with the lowest level of wind power penetration results in load curtailment, it is necessary to sequentially evaluate other wind scenarios, increasingly in terms of predicted wind power penetration, until a wind scenario leading to no load curtailment is reached.

2.2.1. After achieving a wind scenario leading to no load curtailment, the same principles of 2.1., 2.1.1. and 2.1.1.1. should be applied.

Chapter 5

Case Study

In this section the proposed models described throughout this document are applied to determine the location of PAR transformers on a realistic power network. The models described have been implemented in a tool developed in MATLAB environment, with the assistance of Gurobi, an optimization tool, in order to accelerate some of the calculations performed. Different simulations are carried out on a modified IEEE 24-bus Reliability Test System (RTS) in order to validate the proposed models.

5.1 IEEE 24-bus Reliability Test System

The IEEE 24-bus Reliability Test System is a commonly adopted power network to perform different power system analysis. Some of its characteristics are now presented, as well as some of the modifications and assumptions made in order to fit the problem of optimal PAR location.

The transmission system of the IEEE 24-bus RTS has two voltage levels, 138 kV and 230 kV, containing a total of 38 lines and 24 buses. The total generation installed capacity is 3405 MW, divided by 10 different buses. The annual load peak for the test system is 2850 MW allocated by 17 buses. Regarding the rated capacity of the transmission network, it was reduced by 45%, in comparison with the standard network, in order to adequate the system to the optimal PAR location problem. This adjustment aims the overload of the transmission system when having high load levels, leading to the need of install PAR transformers.

Those are some of the characteristics of the modified IEEE 24-bus RTS used to test the models developed, however specific changes may be held for some of the simulations performed. Further information regarding this test system can be found in [26].

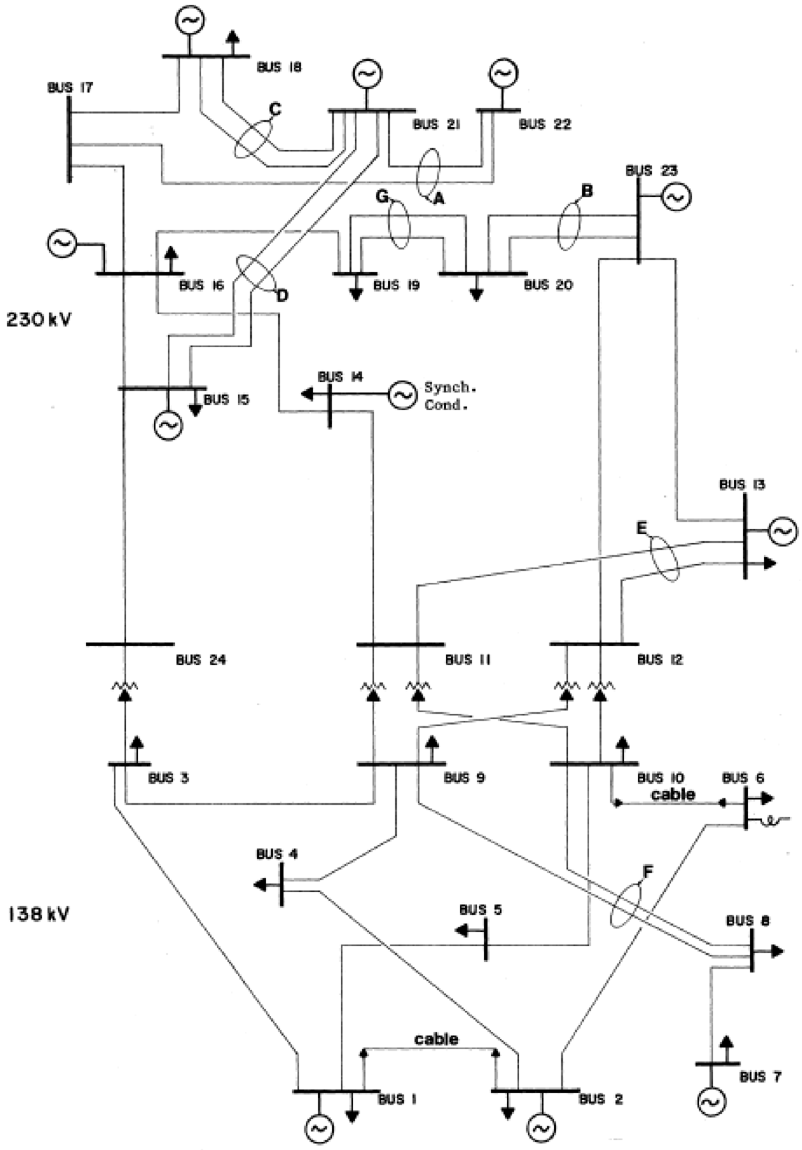

Figure 5.1: IEEE 24-bus Reliability Test System.

5.2 Phase Angle Regulating Data

Different possible locations to install PAR transformers were defined, as well as their associated capital costs. The following data is considered in all the simulations performed:

Table 5.1: Capital costs of PAR transformers.

Location Number	**Line Location**	**Capital Cost - A+Bα^2_{Max}**	
		A	**B**
1	1-2	25	0.75
2	14-16	75	0.6
3	6-10	50	0.6
4	8-10	75	0.8
5	3-24	60	0.6
6	17-22	100	0.75
7	12-13	50	0.75
8	8-9	80	0.75

In some simulations only a limited number of possible locations to install PAR transformers will be considered in order to enlarge the analysis carried out. In general, three different possible situations are explored:

Table 5.2: Possible locations to install PAR transformers.

Possible Locations	**Line Location**
2	1-2; 14-16
5	1-2; 14-16; 6-10; 8-10; 3-24
8	1-2; 14-16; 6-10; 8-10; 3-24; 17-22; 12-13; 8-9

Concerning the maximum angle injected by each PAR transformer on each location, it was defined the installation of PAR transformers with the maximum angle injected being a multiple of 5 degrees with a maximum possible value of 30 degrees. Moreover, the installation of a PAR transformer with a maximum angle of α_{Max} allows a variable phase shift within the range $[-\alpha_{Max};$ $\alpha_{Max}]$. Different solutions to install a PAR transformer were taken into account:

Table 5.3: Solutions to install PAR transformers in power network.

Maximum Angle - α^2_{Max}	**Variable Phase Shift Range**
0	0
5	[-5; 5]
10	[-10;10]
15	[-15; 15]
20	[-20;20]
25	[-25; 25]
30	[-30;30]

5.3 Single Load Scenarios

Several simulations have been done considering different single load scenarios in order to optimally locate and size the PAR transformers in the IEEE 24-bus RTS, which is composed only by conventional generation. The load scenarios evaluated are a result from a proportional growth of all the individual loads relatively to the load base case. The following load scenarios were studied:

Table 5.4: Load scenarios considered for the optimal PAR location.

Load Factor	Total Load (MW)
1	2850
1.1	3135
1.15	3277.5
1.17	3334.5
1.19	3391.5

The optimal location of PAR transformers was performed for three different situations to allocate the devices, where two, five and eight possible locations have been taken into account, accordingly to table 5.2. The following results were obtained:

Table 5.5: Optimal PAR location - 2 possible locations.

Load Factor	Total Load (MW)	Number of Devices	Location Number	Max. Angle (Deg)	Capital Cost ($)	PNS (MW)
1	2850	0	-	-	0	0
1.1	3135	1	1	5	43.75	0
1.15	3277.5	2	1; 2	5; 5	133.75	0
1.17	3334.5	2	1; 2	5; 5	133.75	19.66
1.19	3391.5	1	2	5	93.64	51.08

Table 5.6: Optimal PAR location - 5 possible locations.

Load Factor	Total Load (MW)	Number of Devices	Location Number	Max. Angle (Deg)	Capital Cost ($)	PNS (MW)
1	2850	0	-	-	0	0
1.1	3135	1	1	5	43.75	0
1.15	3277.5	2	1; 2	5; 5	133.75	0
1.17	3334.5	3	2; 3; 5	5; 5; 5	233.77	5.31
1.19	3391.5	1	2	5	93.64	51.08

Table 5.7: Optimal PAR location - 8 possible locations.

Load Factor	**Total Load (MW)**	**Number of Devices**	**Location Number**	**Max. Angle (Deg)**	**Capital Cost ($)**	**PNS (MW)**
1	2850	0	-	-	0	0
1.1	3135	1	1	5	43.75	0
1.15	3277.5	2	1; 2	5; 5	133.75	0
1.17	3334.5	4	2; 3; 5; 6	10; 5; 5; 5	393.7	0
1.19	3391.5	3	2; 5; 6	5; 5; 5	283.75	41.5

The outcomes are quite illustrative and the allocation of PAR transformers appears to be correctly carried out, showing coherent placements. In all the three different situations considered to possibly locate PAR transformers, the number of devices to be installed increases with the load factor, for load scenarios without load curtailment. As the load increases, the transmission network becomes stressed and transmission lines get overloaded. This leads to the need to install PAR transformers in order to avoid overload of the transmission network by re-routing active power flow through other lines, allowing a closer exploration of transmission system to its rated capacity. However, when having load curtailment, the number of devices to be installed may not increase with the load factor, comparatively to load scenarios without load curtailment. This happens because of the fictitious generators model adopted, which will find the most appropriate place to curtail load in order to minimize the capital cost of devices.

With respect to the load base case (load factor unitary) there is no need to install any PAR transformer. For this load pattern the system is able to supply the entire load by properly dispatching generators units avoiding transmission system overload and, therefore, the installation of PAR transformers is not considered. In load scenarios with a load factor of 1.1 and 1.15 the placement of PAR transformers becomes essential to avoid load curtailment. The solutions obtained are the same in all the three different situations, as expected, since the places where the devices are supposed to be installed are available in the three cases. Lastly, the scenarios having a load factor of 1.17 and 1.19 lead to load curtailment in all the three situations, except for the load scenario 1.17 when considering 8 possible locations to install PAR transformers. In those two load scenarios it is possible to observe better results when having 8 possible locations to install the PAR transformers. As the number of possible locations to install PAR transformers increases, the number of devices to be installed may also increase and the congestion of the transmission network may be reduced, allowing the achievement of lower levels of power not supplied. Undoubtedly, the number of possible locations to install PAR transformers in a power network is of extreme importance, with a higher possibility of reducing load curtailment when the number of possible locations to install devices increases.

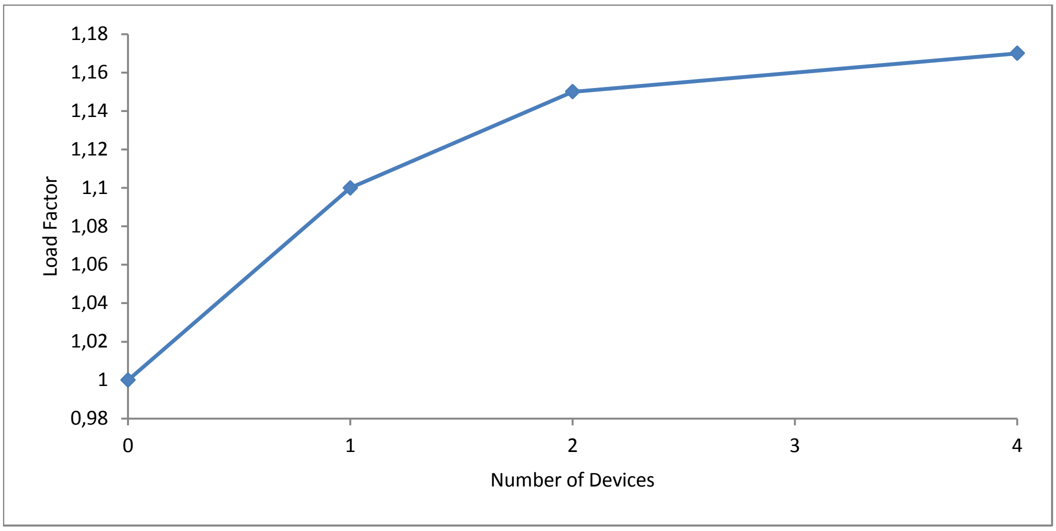

Figure 5.2: Number of devices for different load factors - 8 possible locations.

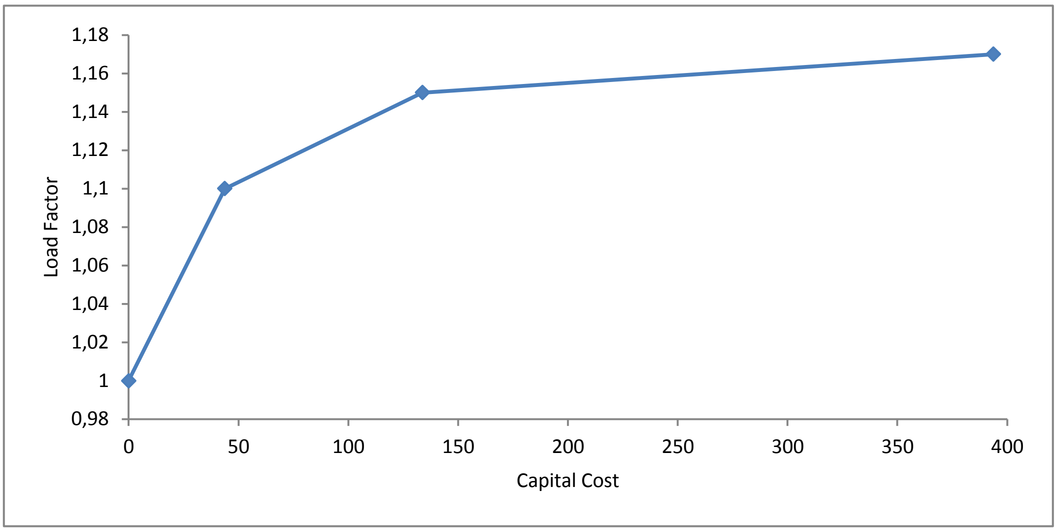

Figure 5.3: Capital cost of devices for different load factors - 8 possible locations.

Relatively to the capital cost of the devices, it increases with the number of devices installed, which seems logical. As explained before, since the number of devices increase with the load factor, the capital cost also increases.

Concerning the quantity of power not supplied, it is observed that it increases with the load factor and decreases with the number of possible locations to install the devices. This is evident for load factor 1.17, where for 8 possible locations there is no load curtailment, and for 5 and 2 possible locations the load curtailment is respectively 5.31 and 19.36 MW. For load factor 1.19 the quantity of power not supplied increases in all the three situations when comparing with the scenario with a load factor of 1.17.

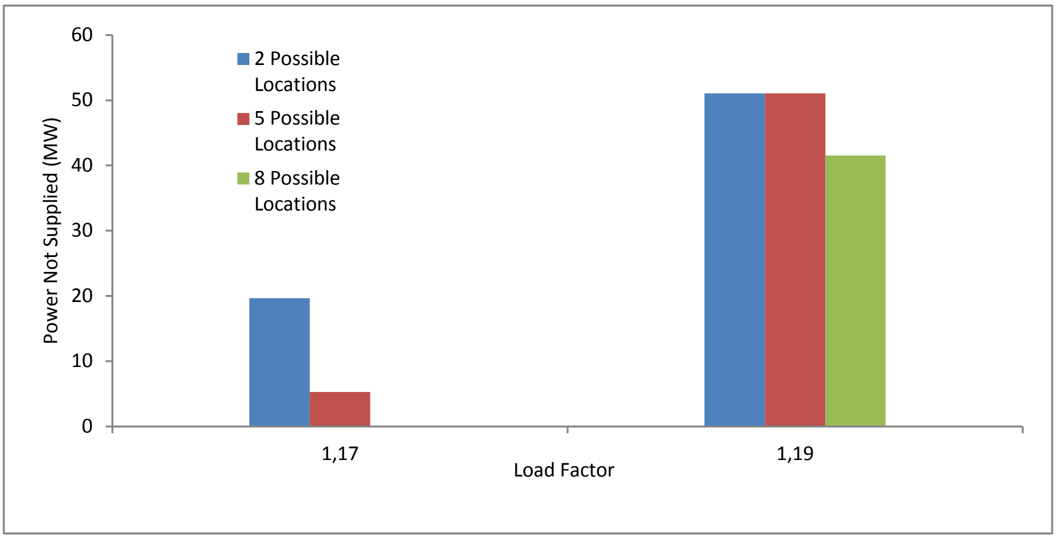

Figure 5.4: Power not supplied for different load factors - 8 possible locations.

Even though some of the obtained results appear to be rather obvious they are essential to validate the proposed model. The developed tool showed consistent results and the method applied proved to be very effective in the optimal location of PAR transformers.

5.4 Multiple Load Scenarios

In the analysis performed above, the allocation and size of PAR transformers was done considering a single load scenario. However, when optimizing the installation of PAR transformers the uncertainties regarding the load forecast may compromise the solution obtained. In a more realistic approach a multiple load scenario should be considered, composed by several single load scenarios, each of them having an associated probability of occurrence. In this section different multiple load scenarios have been considered to optimal locate PAR transformers.

Three different multiple load scenarios have been analyzed, each of them having a total load of 3277.5, 3334.5 and 3391.5 MW, the same amount of load corresponding to the load factors of 1.15, 1.17 and 1.19. For each multiple load scenario, three different single load scenarios have been considered, all of them having the same amount of load, however, differently distributed among the different individual loads. One of the single load scenarios corresponds to a proportional growth of the individual loads, the same as considered in table 5.4, while in the two others load scenarios the load is more concentrated in buses 1 to 10 or in 13 to 24 buses. The following results were achieved:

Table 5.8: Optimal PAR location - 2 possible locations.

Total Load (MW)	**Number of Devices**	**Location Number**	**Max. Angle (Deg)**	**Capital Cost ($)**	**PNS (MW)**
3277.5	2	1; 2	5; 5	133.75	3.59
3334.5	2	1; 2	5; 5	133.75	21.25
3391.5	2	1; 2	5; 5	133.75	52.34

Table 5.9: Optimal PAR location - 5 possible locations.

Total Load (MW)	**Number of Devices**	**Location Number**	**Max. Angle (Deg)**	**Capital Cost ($)**	**PNS (MW)**
3277.5	3	2; 3; 5	5; 5; 5	230	0
3334.5	4	1; 2; 3; 5	5; 10; 10; 5	363.75	6.6
3391.5	2	2; 5	5; 5	165	51.08

Table 5.10: Optimal PAR location - 8 possible locations.

Total Load (MW)	**Number of Devices**	**Location Number**	**Max. Angle (Deg)**	**Capital Cost ($)**	**PNS (MW)**
3277.5	3	2; 3; 5	5; 5; 5	230	0
3334.5	5	2; 3; 4; 5; 6	10; 10; 5; 10; 5	578.755	0
3391.5	4	2; 3; 5; 6	10; 5; 5; 5;	393.75	41.5

In general, the number of devices to be installed and the respective maximum angle have increased when comparing with the equivalent (in terms of total load) single load scenario. The multiple load scenario approach aims to reduce load curtailment in all the different single load scenarios and, for that reason, the set of PAR transformers to be installed is enlarged. Different load scenarios may lead to congestion in different points of the transmission network, which implies the installation of PAR transformers in different places of the network. The levels of power not supplied have also increased when comparing with the single load scenario analysis.

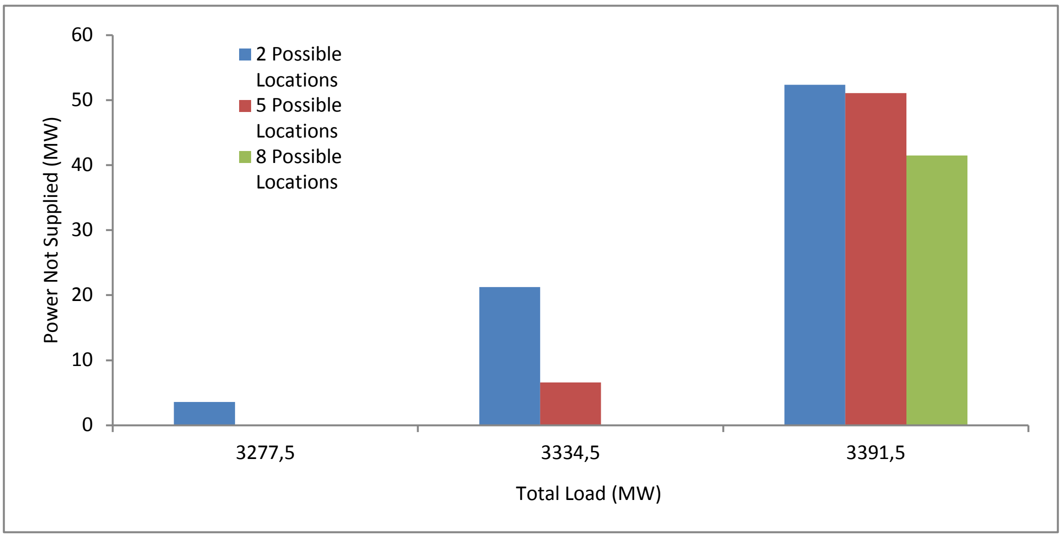

Figure 5.5: Power not supplied for different load scenarios.

5.5 Multiple Load and Wind Scenarios

In a more complex analysis, the integration of wind power in the generation system is considered. In this section, a multiple load and wind scenarios approach is adopted to optimally locate PAR transformers. With the intention of making this analysis as much realistic and elucidative as possible, some more considerations have been made concerning the characteristics of the modified IEEE 24-bus RTS. The capacity of the generation system was tripled, while the capacity of lines 14-16 and 17-22 was reduced by 72.5%. The changes applied to those two lines intend to create congestion problems when integrating wind power in the system, as it will be seen further ahead.

The multiple load scenarios analyzed are exactly the same as previously, 5.4 , for a total load of 3277.5 MW. A different wind scenario represented by a Weibull distribution, as presented in figure 4.1, is considered for each of the three single load scenarios studied. The same wind scenario has been assumed for all the wind generators.

A progressive increase of the wind power installed capacity was taken into account in order to evaluate the optimal location of PAR transformers for different levels of wind power integration. The conventional generation of the IEEE 24-bus RTS was replaced by wind generation as follows:

Table 5.11: Wind power installed capacity for different simulated cases.

Total Installed Capacity (MW)	**Wind Generators Location**	**Wind Power Installed Capacity (MW)**	**Wind Power Installed Capacity (%)**
10215	18	720	7.05
10215	18; 22	1260	12.33
10215	16; 18; 22	1539	15.07
10215	15; 16; 18; 22	1926	18.85

By applying the stochastic model previously proposed, 4.3, the optimal location of PAR transformers for a multiple load and wind scenarios approach has resulted in the following placements and sizing:

Table 5.12: Optimal PAR location - 8 possible locations.

Load (MW)	**Wind Power Capacity (MW)**	**No. Devices**	**Location Number**	**Max. Angle (Deg)**	**Capital Cost ($)**	**Pwc (MW)**	**PNS (MW)**
3277.5	0	2	1; 2	5;10	178.75	-	0
	720	2	1; 2	5;15	253.75	10.28	0
	1260	3	1; 2; 6	5; 15; 5	372.5	121	0
	1539	4	1; 2; 6; 7	5; 15; 5; 5	441.25	123.96	0
	1926	7	1; 2; 3; 5; 6; 7; 8	5; 15; 5; 10; 5; 5; 10	781.25	132.74	8.42

From the obtained results, it is clear that the increase of wind power installed capacity, and the subsequent need to guarantee the maximum wind generation, has led to an increased number of PAR transformers to be placed, as well as their maximum angle. Obviously, the need to reduce load curtailment, especially when having low wind speeds, is also responsible for such increase. Since the conventional generators have been replaced by wind generators, the number of conventional units has been reduced. This results in more power being generated in each conventional unit, when having a lack of wind resource, which may also result in overload of transmission lines, leading to the need to install more PAR transformers.

Regarding the simulation without wind power, the optimal PAR location suggests the installation of two PAR transformers. In this case, the installation of PAR transformers aims to avoid load curtailment, while minimizing investment costs. When a wind generator is introduced in bus 18, replacing a conventional generator, the PAR in location 2 increases its maximum angle, which possibly results from the need to maximize wind generation. The case where the total installed capacity of wind power is 1260 MW is rather illustrative. The inclusion of a wind generator on bus 22 leads to the congestion of line 17-22 for high wind levels. As explained above, the capacity of line 17-22 has been considerably reduced. This has led to its congestion when the wind generator on bus 22 is generating a considerable amount of power. In this case, as the wind generation must be maximized, a PAR transformer must be introduced on line 17-22, which is precisely the location number 6. This alleviates line 17-22, changing the active power flow to line 21-22, ensuring the maximization of wind power generation. In all the other cases, the number of devices continues to increase as the wind power installed capacity increases. For the case with more wind power installed capacity, the optimal PAR location requires the installation of 7 devices.

Unfortunately, the predictable wind generation curtailed, *Pwc*, has increased with the quantity of wind power installed, suggesting that the possible locations to install PAR transformers are not enough to avoid wind generation curtailment. However, nothing ensures that if more possible locations to install PAR transformers were considered, the wind generation curtailed could be reduced. Furthermore, for the case with more wind power installed capacity there is also the need to curtail load. This is an expected outcome, since for low levels of wind resource there is a considerable amount of wind power not available and the conventional generators are not enough to ensure the supply of the entire load, without violating transmission capacity limits.

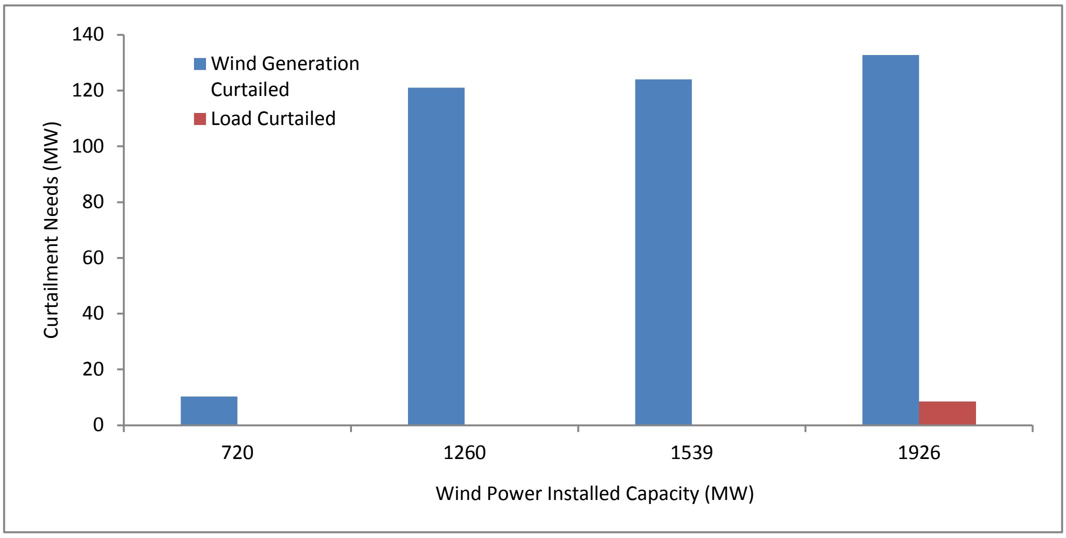

Figure 5.6: Wind generation and load curtailed for different levels of wind power installed capacity.

The stochastic method implemented to locate PAR transformers in a system with wind power has been successfully applied, showing consistency in the results presented. The integration of wind power has considerably influenced the optimal PAR location.

Chapter 6

Conclusions

Two major achievements have been accomplished through the course of this thesis:

1. The development of a stochastic model suitable to allocate FACTS devices in systems with wind power integration.
2. The confirmation of DEEPSO as a successful new hybrid method to optimize the location of FACTS devices in power networks.

From the perspective of the models proposed, a significant contribution is given on the development of stochastic models to locate FACTS devices. This research work led to the suggestion of a stochastic programming based model to optimally locate FACTS devices in systems with wind power penetration. The stochastic model allowed the optimal PAR location on a realistic power network given a set of load and wind scenarios with associated probabilities of occurrence. The exposed model has been effectively validated, giving consistent results for the optimal PAR location.

New variants of DEEPSO were proposed and used in the optimal location of FACTS devices, resulting in important progresses on the algorithmic field of this thesis. In the simulations performed to optimally locate PAR transformers both EPSO and Pb variants of DEEPSO showed good capabilities in discovering the optimal solution. However, the DEEPSO Pb-rnd variant has led to a far better performance than the classical EPSO. This is an extremely important outcome, showing that for some specific problems the DEEPSO algorithm may be favorably applied as an alternative to EPSO.

Further research is needed to evaluate in depth the performance of DEEPSO, which appears to have a better performance than EPSO in solving fixed-cost mixed integer problems, where a deceptive landscape makes the achievement of the optimal solution very problematic.

6.1 Future Work

The work developed throughout this thesis is a contribution to future work aiming to study the location of FACTS devices in transmission networks and also some of the methodologies proposed.

Suggestions are now presented to develop new work taking as starting point the results presented in this thesis:

- An important improvement on the work developed could be the adoption of an AC Optimal Power Flow, replacing the DC Optimal Power Flow approach used in this work. This would lead to a more complex methodology but could guarantee a more accurate model to locate FACTS devices in power networks.

- The integration of hydro power plants with pumped storage in the proposed models could have a big potential to develop a new model with a highly interesting industrial application. In the stochastic model developed it was considered the spill of wind generation in order to avoid overload of transmission network, however when dealing with hydro power plants with pumped storage, there is the possibility of using the wind generation to store energy by pumping water on hydro plants, which may significantly change the power flow in power networks, possibly affecting the optimal location of FACTS. This is a very interesting approach, however it requires a significant development of the work performed.

- Regarding the heuristic methods adopted, further research need to be done on the application of DEEPSO algorithm. This new method was successfully applied in this work, however it is important to evaluate its behavior when solving other kinds of problems in other to formulate a general opinion concerning the potential of DEEPSO.

Appendix A

Publications

A.1 "Differential Evolutionary Particle Swarm Optimization (DEEPSO): a successful hybrid"

The following paper was submitted to the "1st BRICS Countries & 11th Brazilian Congress on Computational Intelligence" with a major contribution of the work developed in this thesis.

Differential Evolutionary Particle Swarm Optimization (DEEPSO): a successful hybrid

Vladimiro Miranda, *Fellow, IEEE* and Rui Alves, *Student Member IEEE*

***Abstract* — This paper explores, with numerical case studies, the performance of an optimization algorithm that is a variant of EPSO, the Evolutionary Particle Swarm Optimization method. EPSO is already a hybrid approach that may be seen as PSO with self-adaptive weights or an Evolutionary Programming approach with a self-adaptive recombination operator. The new hybrid DEEPSO retains the self-adaptive properties of EPSO but borrows the concept of rough gradient from Differential Evolution algorithms. The performance of DEEPSO is compared to a well-performing EPSO algorithm in the optimization of problems of the fixed cost type, showing consistently better results in the cases presented.**

***Index Terms* — Evolutionary Particle Swarm Optimization, Differential Evolution, fuzzy clustering, unit commitment, PAR location.**

I. Introduction

THIS paper presents a new approach to build a hybrid between Evolutionary Programming, Particle Swarm Optimization and Differential Evolution. The reason behind the search for hybrid algorithms is that each "pure" method exhibits some characteristics that push the search for the optimum in a globally right direction. However, each method also displays its own difficulties. The hope is that, by suitably blending methods, a more robust and general method may be derived.

The work reported in this paper departed from an algorithm denoted EPSO, for Evolutionary Particle Swarm Optimization. The basic version of this algorithm was presented in 2002 [1] and introduced as a way "to join together the exploratory power of PSO (Particle Swarm Optimization) with the self-adaptation power of Evolutionary Algorithms (EA) and have as a result the *best of two worlds*". The results obtained in competition with classical versions of PSO were indeed promising and this was demonstrated by several authors and in several publications. Early reports as well as more recent works [2]-[16] confirmed the quality and reliability of the algorithm as well as its good performance in a diversity of domains.

The EPSO algorithm received further improvement and the latest version is available from [17], where examples and a source code are made public.

In a parallel path, the Differential Evolution concept (DE), early proposed in [18][19], has motivated many proposals for improvement and variants. A comprehensive survey may be found in [20]. In this survey, the allegations that DE is a fast and general optimization method for any kind of objective function are substantiated, although the authors caution against a hasty conclusion, reminding the reader of the No Free Lunch theorem.

In particular, the attempts to generate a synergy of DE with PSO are well documented in this survey. Many of the proposed hybrid models adopt a form of alternate use of DE and PSO iterations or DE and PSO operators [21][22] or even some mixture of operators [23][24]. These references are just examples and not to be taken as exhaustive and the reader is directed to the survey referred to above for further examples.

Self-adaptive versions of DE have been attempted also with many variations [25][26]. The pursuit for successful self-adaptive schemes is justified by the desire to achieve some algorithmic form close to a non-parametric or parameter-free definition. This search is also the motivation behind the inception of the EPSO algorithm.

The advanced version of the EPSO algorithm included the positive effect of a probability of communication among particles, implementing the scheme of the "stochastic star". Its success reinforced the idea that a degree of controlled random variation is beneficial to the search for the optimum. Therefore, one came up with the idea that some noise could be added to the EPSO search by embedding a DE operator in the global mechanism of the generation of new particles.

This paper presents a new hybrid DE-EA-PSO, which will be denoted DEEPSO. As in many other cases, there is no deductive demonstration of superiority over other options but illustration by example. A didactic and a complex study case will be presented, in the domain of power systems, to put in evidence the strong points of the new approach.

II. Basic models

A. PSO as a recombination process

The PSO – Particle Swarm Optimization [27] does not rely on a selection operator as its driving force: it depends on a *movement rule* that generates new individuals in space from a set of known alternatives, called a swarm (the same as population). Several variants have been proposed but the basic movement rule, producing a new individual **X** for iteration (k+1) is based on

This work is partially funded by the ERDF from the EU through the Programme COMPETE and by the Portuguese Government through FCT - Foundation for Science and Technology, project ref. LASCA PTDC/EEA-EEL/104278/2008.

V. Miranda (vmiranda@inescporto.pt) and R. Alves (ee08272@fe.up.pt) are with INESC TEC (INESC Technology and Science, coordinated by INESC Porto) and also with FEUP, Faculty of Engineering of the University of Porto, Portugal.

$$\mathbf{X}^{(k+1)} = \mathbf{X}^{(k)} + \mathbf{V}^{(k)} \quad (1)$$

where **V** is called the particle velocity and is defined by

$$\mathbf{V}^{(k+1)} = \mathbf{A}\mathbf{V}^{(k)} + \mathbf{B}(\mathbf{b}_i - \mathbf{X}^{(k)}) + \mathbf{C}(\mathbf{b}_G - \mathbf{X}^{(k)}) \quad (2)$$

where $\mathbf{b}_G$ is best point so far found by the swarm and $\mathbf{b}_i$ is the best past ancestor in the direct life line of the particle, with $\{\mathbf{b}_i, i = 1,\ldots,\text{no. particles}\} = \mathbf{P}_b$ forming the set of the historical past best ancestors of each particle. Of course, $\mathbf{b}_G \in \mathbf{P}_b$.

The parameters **A, B, C** are diagonal matrices with weights defined in the beginning of the process. In a classical formulation, the parameter **A** is affected by a decreasing value with time (iterations), while the parameters **B** and **C** are multiplied by random numbers sampled from a uniform distribution in [0,1].

If we examine this scheme, we conclude that a new particle $\mathbf{X}^{(k+1)}$ is formed as a combination of four other points:

- Its direct ancestor $\mathbf{X}^{(k)}$
- The ancestor of its ancestor $\mathbf{X}^{(k-1)}$
- A (possibly) distant past best ancestor $\mathbf{b}_i$
- The current global best of the swarm $\mathbf{b}_G$.

We can give a different aspect to the movement rule:

$$\mathbf{X}^{(k+1)} = (1 + \mathbf{A} - \mathbf{B} - \mathbf{C})\mathbf{X}^{(k)} - \mathbf{A}\mathbf{X}^{(k-1)} + \mathbf{B}\mathbf{b}_i + \mathbf{C}\mathbf{b}_G \quad (3)$$

In this expression, the sum of the parameters multiplying the four contributors to generate the offspring is equal to 1. It is therefore tempting to identify this expression with an intermediary recombination in EA with $\mu = 4$ and a special rule to determine who the parents are (they are not randomly selected). This means that we are considering an *enlarged population* including not only the active particles but also the immediate ancestors and the set of the past best ancestors.

B. *EPSO as an evolutionary adaptive recombination*

The idea behind the EPSO algorithm was to provide adaptive capability to this recombination operator. To achieve this, the parameters in (2) are subject to mutation and selection in order to try to achieve a higher progress rate.

Given a population with a set of particles, the general scheme of EPSO became:

```
REPLICATION - each particle is replicated
 (cloned) r times [usually r = 1]
MUTATION - all r particles have their A,B,C
 parameters mutated
REPRODUCTION - each of the r+1 particles
 (original and clones) generate an offspring
 through recombination, according to the
 particle movement rule (2) or (3)
EVALUATION - the offspring have their fitness
 evaluated
SELECTION - by stochastic tournament or other
 selection procedure (among siblings), the best
 child from each ancestor survives to form a new
 generation - every individual in the previous
 generation has one descendant.
```

The mutation of a parameter w = A,B,C is ruled by multiplicative Lognormal random numbers such as in $w_i^* = w_i\,[\log N(0,1)]^\tau$ or by additive Gaussian distributed random numbers such as in $w_i^* = w_i + \sigma N(0,1)$. The learning parameter (τ or σ) must be fixed externally. The recombination operator is defined by the set (A,B,C). The scheme results in an adaptive recombination operator.

The EPSO algorithm was further improved in efficiency by the introduction of two additions. In early versions, it was shown that noise affecting the exact location of $\mathbf{b}_G$ was beneficial, so a forth parameter or weight in the form of a diagonal matrix $\mathbf{w}_G$ was introduced, such that

$$\mathbf{b}_G^* = \mathbf{b}_G(1 + \mathbf{w}_G N(0,1)) \quad (4)$$

This weight is also subject to mutations of the kind referred to above, so it also enters in the self-adaptive model.

Finally, in the most recent and efficient version, the Communication Factor **P** was introduced, creating a Stochastic Star communication topology among the swarm.

The recombination (or movement) rule for EPSO becomes

$$\mathbf{X}^{(k+1)} = \mathbf{X}^{(k)} + \mathbf{V}^{(k)} \quad (5)$$

$$\mathbf{V}^{(k+1)} = \mathbf{A}\mathbf{V}^{(k)} + \mathbf{B}(\mathbf{b}_i - \mathbf{X}^{(k)}) + \mathbf{P}[\mathbf{C}(\mathbf{b}_G^* - \mathbf{X}^{(k)})] \quad (6)$$

P is a diagonal matrix affecting all dimensions of an individual, containing binary variables of value 1 with probability p and value 0 with probability (1-p); the p value (communication probability) controls the passage of information within the swarm and is 1 in classical formulations (this the *star*).

This stochastic scheme conceptually oscillates between the star arrangement and a selfish version called *cognitive model* in [28], where no communication exists. In fact, the stochastic star causes that some components of the global best become "known" by a particle while other components are ignored, so that the production of a new particle is affected in different ways in its distinct dimensions. This favors the uncoupling of the evolution for all the dimensions.

Experiments in a diversity of problems made it quite clear that one could achieve a fine tuning of the convergence of EPSO by adequately setting a value for p, the communication probability [13].

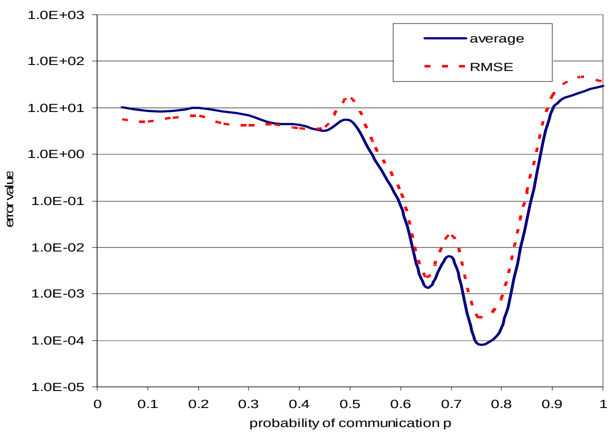

Fig. 1. Rosenbrock function in 30 dimensions after 100000 fitness function evaluations – average and RMSE of achieved error values for 20 runs with EPSO, as a function of the communication probability p.

In many problems, p = 0.75 seems a very good option but in some problems a much lower value favors the convergence. Figure 1 from [13] illustrates the sharp tuning in error, achieved for p = 0.75 in the Rosenbrock function problem in 30 dimensions (note the logarithmic scale).

C. Differential Evolution

The original idea behind DE, given a population (swarm) of individuals (particles, vectors), is to generate a new solution from an existing individual by adding some fraction of the difference between two other points $\mathbf{X}_{r1}$ and $\mathbf{X}_{r2}$ sampled from the population or swarm. Then, having a new population generated, some further recombination ensures more diversity and a selection procedure produces a new generation. This selection is elitists and one-on-one based, meaning that each parent competes for survival directly with its single offspring and the best is retained.

There are many variations to this scheme. One interesting case is the one that was denoted DE2 in [18], DE/rand-to-best/1 in [19] and DE/target-to-best/1 in [20], where the generation of a new individual may be written as

$$\mathbf{X}^{(k+1)} = \mathbf{X}^{(k)} + \mathbf{V}^{(k)} \tag{7}$$

$$\mathbf{V}^{(k+1)} = \mathbf{B}(\mathbf{X}_{r1}^{(k)} - \mathbf{X}_{r2}^{(k)}) + \mathbf{C}(\mathbf{b}_G^* - \mathbf{X}^{(k)}) \tag{8}$$

A notation slightly distinct from the usually seen in the DE literature is adopted here to enhance the similarities with (1) and (2), i.e. between DE and PSO in the process of generating new individuals. The canonic version of DE makes **C = 0**; the canonic DE/target-to-best/1 version makes **B** = **C**.

Neglecting recombination, DE then proceeds with a *parent selection* (choosing the next generation from both the parent and offspring populations) of a special type – each parent competes only with its offspring – while PSO adopts in a way a trivial *survivor selection* (the next generation is chosen among the offspring only).

EPSO has also a special survivor selection procedure where competition is established only among the direct descendants of each particle.

III. The DEEPSO alternative

The DE scheme, in a way, makes a sample of a local macro-gradient of the objective function by picking up two random individuals from the population. The same kind of sampling is produced by the PSO movement equation, but picking up the current position and the particle past best. So, it is natural to ask if the DE scheme would not work also when inserted in the PSO equation.

Also, the DE scheme is usually based on fixed B parameter values in [0.1, 1]. One must refer that in [8] the authors claimed to have a self-adapting process for this parameter; however, its value would only change with a certain probability (0.1), remaining fixed most of the time, so it must be seen as a quite modest effort into self-adaptation. But the EPSO scheme is truly self-adaptive, so it is natural to wonder if the EPSO scheme would not work also when acting over the DE parameter.

This reasoning led to the proposal of the model that will be denoted DEEPSO to clearly express its hybrid character. The DEEPSO algorithm is equal to the EPSO sequence; however, to grasp the flavor of DE, the following general equation should now express the movement rule:

$$\mathbf{V}^{(k+1)} = \mathbf{A}\mathbf{V}^{(k)} + \mathbf{B}(\mathbf{X}_{r1}^{(k)} - \mathbf{X}_{r2}^{(k)}) + \mathbf{P}[\mathbf{C}(\mathbf{b}_G^* - \mathbf{X}^{(k)})] \tag{9}$$

where $\mathbf{b}_G^*$ is given by (4). In (9), $\mathbf{X}_{r1}^{(k)}$ and $\mathbf{X}_{r2}^{(k)}$ should be any pair of distinct particles, in principle belonging to the set $\mathbf{P}_C$ of the particles in the current generation. But extensive testing led to an improved proposal, which regains back the spirit of PSO and also retains the spirit of DE. First of all, PSO relies on macro-gradients being sensed by a particle. So, these particles should be ordered such that, for minimization,

$$f(\mathbf{X}_{r1}^{(k)}) < f(\mathbf{X}_{r2}^{(k)}) \tag{10}$$

Then, one may enlarge the definition of which set must these particles be sampled from: this may be the set $\mathbf{P}_C$ of particles from the current generation or the set $\mathbf{P}_b$ of historical past best particles. Finally, the DEEPSO model defines that $\mathbf{X}_{r2}^{(k)}$ equal to $\mathbf{X}^{(k)}$ so only $\mathbf{X}_{r1}^{(k)}$ is sampled.

To complete the model, the sampling of $\mathbf{X}_{r1}^{(k)} (= \mathbf{b}_{r1}^{(k)})$ among $\mathbf{P_b}$ may repeated for each component of **V** to be calculated. This means that one is, in fact, calculating $\mathbf{X}_{r1}^{(k)}$ from a uniform recombination of all the particles in $\mathbf{P}_b$. The equations regulating DEEPSO are, therefore,

$$\mathbf{X}^{(k+1)} = \mathbf{X}^{(k)} + \mathbf{V}^{(k)} \tag{11}$$

with $\mathbf{V}^{(k)}$ in 4 versions:

1. **DEEPSO Sg** (sampling in the same generation):
$$\mathbf{V}^{(k+1)} = \mathbf{A}\mathbf{V}^{(k)} + \mathbf{B}(\mathbf{X}_{r1}^{(k)} - \mathbf{X}^{(k)}) + \mathbf{P}[\mathbf{C}(\mathbf{b}_G^* - \mathbf{X}^{(k)})] \tag{12}$$
with $\{\mathbf{X}_{r1}^{(k)}, \mathbf{X}^{(k)}\}$ ordered according to (10) and $\mathbf{X}_{r1}^{(k)}$ sampled once from the current generation.
2. **DEEPSO Sg-rnd**: the same but with $\mathbf{X}_{r1}^{(k)}$ re-sampled in the current generation for each component of **V**.
3. **DEEPSO Pb** (sampling from the past bests):
$$\mathbf{V}^{(k+1)} = \mathbf{A}\mathbf{V}^{(k)} + \mathbf{B}(\mathbf{b}_{r1}^{(k)} - \mathbf{X}^{(k)}) + \mathbf{P}[\mathbf{C}(\mathbf{b}_G^* - \mathbf{X}^{(k)})] \tag{13}$$
with $\{\mathbf{b}_{r1}^{(k)}, \mathbf{X}^{(k)}\}$ ordered according to (10) and $\mathbf{b}_{r1}^{(k)}$ sampled once from $\mathbf{P}_b$.
4. **DEEPSO Pb-rnd**: the same but with $\mathbf{b}_{r1}^{(k)}$ re-sampled among $\mathbf{P}_b$ for each component of **V**.

In the following sections, some examples will be presented to ilustrate the virtues of the DEEPSO scheme.

IV. DEEPSO vs. EPSO

A. Fuzzy clustering

The first example concerns an application to fuzzy clustering with the fuzzy c-means algorithm [30]. It is an example of a continuous function where EPSO is expected to behave well.

The fuzzy c-means algorithm minimizes the following function:

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \| \mathbf{X}_i - \mathbf{V}_j \|^2 \quad (14)$$

where $\mathbf{X}_i$ is a member of the set of d-dimensional data, m is any real number greater than 1, u_{ij} is the degree of membership of $\mathbf{X}_i$ in the cluster j, $\mathbf{V}_j$ is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between data and the centroids.

A comparative test has been done in a 2-dimension problem depicted in Fig. 2. Fig. 3 makes it evident that the DEEPSO concept seems to bring value to the swarm optimization. It displays the value of the objective function (14), on an average of 20 runs, for three experiments, using a swarm of 8 particles, and with the best tuned parameters for each model:

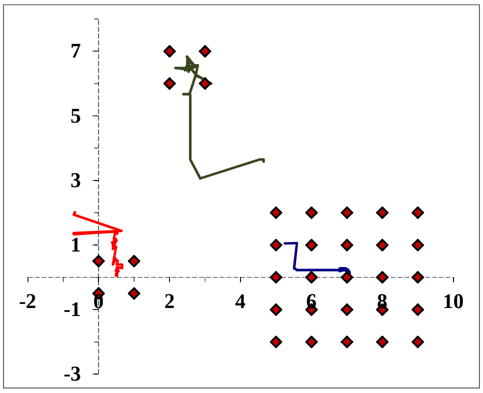

Fig. 2. Three clusters and the trajectory of the centroids during one run of the optimization process with EPSO.

- EPSO with p = 0.1 (best value)
- DEEPSO Sg-rnd as in (12), i.e. sampling $\mathbf{X}_{r1}^{(k)}$ in the current generation $\mathbf{P}_C$
- DEEPSO Pb-rnd as in (13), sampling in the set of past bests of the particles $\mathbf{P}_b$.

This example is interesting because it convincingly argues for the advantage of sampling within the population instead of using the canonic PSO choice.

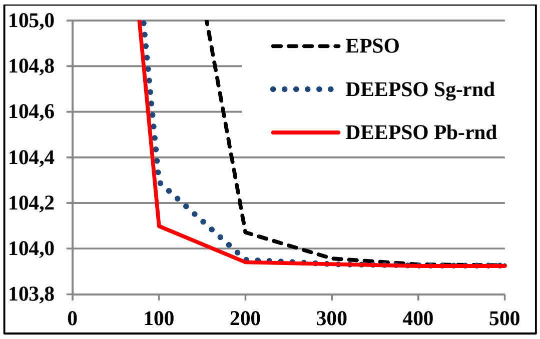

Fig. 3. Value J of the fuzzy c-means function plotted against the number of generations for EPSO and 2 versions of DEEPSO.

B. *Unit commitment*

The problem of unit commitment in power systems is mathematically defined as a fixed cost problem or a mixed-integer non-linear programming problem: given a set of generators and their generation cost curves, define which generators should be shut down and which should be in service and at which loading level, in order to minimize the overall cost (start up costs plus operation costs).

Because of technical limits, the domain of a generator is not connected – there is a point (0,0) corresponding to generator shut down and then there is a gap until a point (P_{min}, $c(P_{min})$) corresponding to the technical minimum of the machine. This general shape of the cost functions implies that the problem has a non-convex nature – therefore, many local optima may appear.

An illustrative problem of this type was included in [31], where a preliminary suggestion for a DEPSO algorithm was formulated. The data are:

- the number of generators – ngen = 5
- the parameters of the cost function of each generator – this function is assumed to be a cubic polynomial, with 4 parameters a_i, i=1 to 4: $C = a_0 + a_1 P + a_2 P^2 + a_3 P^3$ where C is the generation cost in \$/hour and P is the generator output in MW.
- the technical minimum and maximum of each generator P_{min} and $P_{max.}$
- the load, located at a single bus (transmission system neglected): L = 15 MW (see[31]).

The objective is to minimize the sum of the costs for the five generators, noting that the domain of each variable is not continuous.

The cost curves and technical limits are given as:

Generator	a_0	a_1	a_2	a_3	Pmin	Pmax
g1	1	0,5	0,1	0,03	0 or 1	10
g2	2	0,4	0,2	0	0 or 2	10
g3	4	0,3	0,3	0	0 or 7	10
g4	6	1,5	0,15	0	0 or 2	10
g5	0	4	0	0	0 or 1	10

The optimal solution is

g1	g2	g3	g4	g5	Cost
3.414	4.586	7	0	0	33.9068

Adopting a swarm of 16 particles, in 100 trials with random initialization and 1000 iterations, the number of times the optimal solution was discovered is indicated in the following table:

EPSO	DEEPSO Sg-rnd	DEEPSO Pb-rnd
46%	71%	81%

The same conditions were kept for all experiments – namely initializing the weights with A = 0.1, B = C = 0.5, w_G = 0.1, σ = 0.1 and p = 0.3. For less iterations or smaller populations, the same difference in performance was observed.

This seems to confirm the superior performance of the DEEPSO versions, with advantage to DEEPSO Pbest.

C. *PAR/PST location and sizing in power grids*

A Phase Angle Regulating (PAR) transformer of a Phase Shifting Transformer (PST) is a special arrangement of power transformers used to control the flow of active power in meshed three phase power system transmission grids. Because the power through a line is roughly proportional to the sine of the angle between voltages at the sending and receiving ends of a line, the control of such angle may re-route power through alternative paths in the system, preventing overloads and giving better use to the transmission capacity available.

This comes at a high capital cost per device but it may be compensated by avoiding costly line reinforcements or allowing a more flexible operation with higher security and reduced operation costs.

Given a set of load scenarios as well as wind power scenarios, a system operator may be faced with the need to curtail wind generation (at a cost) and replace it by conventional generation (at a cost) or, in more severe cases, to curtail load (at the highest cost of power not supplied). Instead, the suitable location of PAR transformers and their optimal dimensioning (in terms of the maximum angle they may inject in a line, admitting that they are of the variable phase shift type) may serve to reduce or eliminate such curtailment needs.

The capital cost of each PAR may be modeled as being composed of a fixed cost plus a non-linear variable cost which is a function of the maximum angle that the PAR may inject. Some candidate locations in the power network must be specified and, in each location, a tentative device allocation may be defined. This forms a possible solution to the problem, which must be evaluated by solving the power flow equations in all scenarios considered and deciding if and how much power must be curtailed and of what nature: wind generation or load.

Furthermore, each scenario may have a probability of occurrence associated. The problem becomes of the type of stochastic optimization. In the following paragraphs we will describe a model for this problem and its application to a realistic problem built around the IEEE RTS 24 bus system.

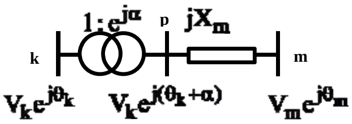

Fig. 4. Equivalent circuit for a PAR

The equivalent circuit for a PAR is in Fig. 4. Its effect is to force to a power flow from node k to node m:

$$P_{pm} = \frac{\theta_p - \theta_m}{X_{km}} = \frac{(\theta_k - \alpha) - \theta_m}{X_{km}} = \frac{\theta_k - \theta_m}{X_{km}} - \frac{\alpha}{X_{km}} \quad (15)$$

So this is equivalent to having a series reactance X_{km} plus a power injection which will be a load in node k and a generation in node m. This allows a network power flow model to be written, as a function of α.

Given a specific set of N candidate locations to install a PAR and considering a generation system composed only of conventional units, the allocation and sizing of PAR is defined by the following

$$\min J_k = \sum_{i=1}^{N} u_i (A + B(\alpha_i^{Max})^2) + \text{Penalties} \quad (16)$$

where u_i is a binary variable representing the installation of a PAR on location i, A and B are cost constants and α_i^{Max} is the maximum angle introduced by the device at location i. The constraints are the usual power flow equations of the DC model, incorporating eq. (15), plus limits on generation and on line flows and limits on the PAR angles:

$$\alpha_i^{min} \le \alpha_i \le \alpha_i^{max} \quad (17)$$

These constraints may be transformed into penalties, in eq. (16), when adopting a meta-heuristic as the solver. Finally, the penalty term will include if necessary the cost for load curtailment, which is usually modeled as fictitious generators by the loads with generation cost equal to the usually high cost of power not supplied.

The objective function is further modified when in the presence of wind power, because there is also the possibility to spill wind (disconnect wind generation) if necessary, to assure the network security described by the constraints. This may be represented as a negative load which is supplied at the cost associated with wind curtailment (compensation to wind power producers).

The wind power resource may be represented by a set of S scenarios stratified according to a Weibull distribution, associating each scenario k with a probability value p_k. This allows a stochastic optimization model to be built where a solution is evaluated in all S scenarios:

$$\min J = \sum_{k=1}^{S} p_k J_k \quad (18)$$

A chromosome for an EPSO algorithm will have a length of N and each component i is a proposal for α_i^{max} at location i.

This model was applied to the IEEE RTS 24-bus test system[32], with 8 possible locations for PAR. This is a realistic power system; data have been adjusted to fit in the problem of optimal PAR location. A comparison among EPSO and DEEPSO variants is presented in Fig. 5 for 100 runs of each algorithm, with a swarm of 30 particles.

The figure counts how many times each algorithm reached the optimum, in 100 runs, with varying number of generations. The DEEPSO Pb-rnd algorithm displays remarkable superiority: at 60 generations it had already reached a 96% efficiency in finding the optimum. In second place, we meet the DEEPSO Pb and the original EPSO algorithms with similar development. The algorithm using the DE trick with particles in the same generation lags definitely behind.

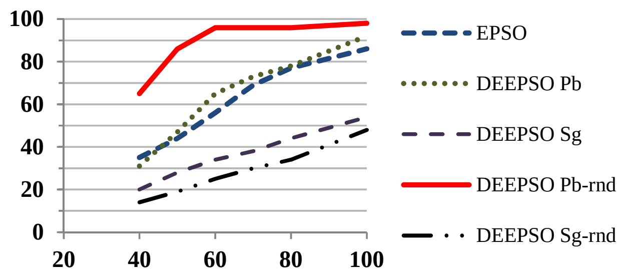

Fig. 5. Number of hits on the optimum (y-axis) vs. number of generations (x-axis) in 100 runs for EPSO and 4 DEEPSO variants.

V. Conclusion

The examples shown, selected among many other tested by the authors, illustrate that a successful hybrid between the evolutionary particle swarm algorithm and the differential evolution algorithm concept, deemed DEEPSO, leads to better performance in the optimization of problems with a fixed-cost mixed-integer objective function. These problems display generally a deceptive landscape which makes it difficult to discover the optimal solution in many cases.

The advantage of having an adaptive recombination scheme associated to the PSO logic had already been demonstrated. With the DEEPSO Pb-rnd formulation, one now suggests that the recombination scheme should be enlarged to the set of particle past bests with solid advantage.

References

[1] V. Miranda and N. Fonseca, "EPSO – Best-of-Two-Worlds Meta-Heuristic Applied to Power System Problems", Proceedings of WCCI/CEC – World Conf. on Computational Intelligence, Conf.on Evolutionary Computation, Honolulu (Hawaii), USA, June 2002

[2] V. Miranda and N. Fonseca, "Reactive Power Dispatch with EPSO - Evolutionary Particle Swarm Optimization", Proceedings of PMAPS – International Conference on Probabilistic Methods Applied to Power Systems, Naples, Italy, Set 2002

[3] I. M. S. Dias, N. Fonseca, H. M. Salgado and V. Miranda, "Optical Fibre Bragg Gratings Synthesis by Evolutionary Particle Swarm Optimization", Proceedings of the Portuguese Physics Conference FISICA 2002, Évora, Portugal, Sep 2002.

[4] V. Miranda and N. Fonseca, "EPSO - Evolutionary Particle Swarm Optimization, a New Algorithm with Applications in Power Systems ", Proceedings of IEEE/PES Transmission and Distribution Conference and Exhibition 2002: Asia Pacific, vol.2, pp.745-750, October, 2002

[5] H. Mori and Y. Komatsu, "A Hybrid Method of Optimal Data Mining and Artificial Neural Network for Voltage Stability Assessment", Proc. IEEE St. Petersburg PowerTech, St. Petersburg, Russia, June 2005

[6] V. Miranda, "Evolutionary Algorithms with Particle Swarm Movements", Proceedings of the 13th International Conference on Intelligent Systems Application to Power Systems - ISAP 2005, pp. 6-21, Arlington (VA), USA, 6-10 Nov. 2005

[7] N. W. Oo and V. Miranda, "Multi-energy Retail Market Simulation with Intelligent Agents", Proceedings of IEEE St. Petersburg Power Tech, St. Petersburg, Russia, Jun 2005

[8] N. W. Oo and V. Miranda, "Evolving Agents in a Market Simulation Platform – A Test for Distinct Meta-Heuristics", Proceedings of the 13th International Conference on Intelligent Systems Application to Power Systems ISAP 2005, pag. 482–487, Arlington (VA), USA, Nov. 2005

[9] Mehdi Eghbal, E.E.El-Araby, Naoto Yorino and Yoshifumi Zoka, "Application of Metaheuristic Methods to Reactive Power Planning: A Comparative Study for GA, PSO and EPSO", Proceedings - IEEE International Conference on Systems, Man and Cybernetics 2007 , pp. 3755-3760, Montreal (Quebec), Canada, Oct 7-10,2007

[10] P. Hilber, V. Miranda, M. Matos and L. Bertling, "Multiobjective Optimization Applied to Maintenance Policy for Electrical Networks", IEEE Trans. on Power Systems, Volume 22, No. 4, November 2007.

[11] "Advances in Evolutionary Computing for System Design", Series Studies in Computational Intelligence, Eds. L. C. Jain, V. Palade, D. Srinivasan, Volume 66, 2007, pp 139-167

[12] "Modern Heuristic Optimization Techniques – Theory and Applications to Power Systems", Eds. Kwang Y. Lee and Mohamed A. el-Sharkawi, IEEE Press series on Power Engineering, John Wiley and Sons Inc., Hoboken, New Jersey, 2008

[13] V. Miranda, H. Keko, Á. J. Duque, "Stochastic star communication topology in Evolutionary Particle Swarms (EPSO)", Intern. Journal of Computational Intelligence Research, vol.4, no.2, pp. 105-116, 2008

[14] V. Miranda, L. Carvalho, M. Rosa, A. M. Leite da Silva, C. Singh, "Improving Power System Reliability Calculation Efficiency With EPSO Variants", IEEE Transactions on Power Systems , vol. 24, no. 4, pp. 1772-1779, 2009

[15] H. Leite, J. Barros, V. Miranda, "The evolutionary algorithm EPSO to coordinate directional overcurrent relay", 10th IET International Conference Developments in Power System Protection (DPSP 2010) Managing the Change, pp. 1–5 (2010)

[16] D. L. Souza, O. N. Teixeira, D. C. Monteiro, R. C. L. Oliveira, "A New Cooperative Evolutionary Multi-Swarm Optimizer Algorithm Based on CUDA Architecture Applied to Engineering Optimization", in Combinations of Intelligent Methods and Applications - Proceedings of the 3rd International Workshop, CIMA 2012, Montpellier, France, August 2012, book series on Smart Innovation, Systems and Technologies, no.23, pp 95-115, Springer Berlin Heidelberg, 2013

[17] EPSO Home Page – http://epso.inescporto.pt

[18] R. Storn, and K. Price, "Differential Evolution - a Simple and Efficient Adaptive Scheme for Global Optimization over Continuous Spaces", Technical Report TR-95-012, ICSI, March 1995

[19] R. Storn, and K. Price, "Differential Evolution – A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces", Journal of Global Optimization no. 11, pp. 341–359, 1997

[20] S. Das and P. N. Suganthan, "Differential Evolution: A Survey of the State-of-the-Art", IEEE Transactions on Evolutionary Computation, vol. 15, no. 1, pp. 4-31,February 2011

[21] T. Hendtlass, "A combined swarm differential evolution algorithm for optimization problems," Lecture Notes in Computer Science, vol.2070, pp.11-18, 2001

[22] W.-J. Zhang and X.-F. Xie, "DEPSO: Hybrid particle swarm with differential evolution operator," in Proc. IEEE Int. Conf. Syst. Man & Cybernetics, pp. 3816–3821, 2003

[23] B. Liu, L. Wang, Y. H. Jin, and D. X. Huang, "Designing neural networks using hybrid particle swarm optimization," Lecture Notes in Computer Science, vol.3469, pp.391-397, 2005

[24] P. W. Moore and G. K. Venayagamoorthy, "Evolving digital circuit using hybrid particle swarm optimization and differential evolution," Int. J. Neural Syst., vol. 16, no. 3, pp. 163–177, 2006

[25] X. Xu, Y. Li, S. Fang, Y. Wu, and F. Wang, "A novel differential evolution scheme combined with particle swarm intelligence," IEEE Congress in Evolutionary Computation. (CEC08), pp.1057-1062, 2008

[26] M. G. H. Omran, A. P. Engelbrecht, and A. Salman, "Bare bones differential evolution," Eur. J. Oper. Res., vol. 196, no. 1, pp. 128–139, Jul. 2009

[27] J. Kennedy and R. C. Eberhart, "Particle Swarm Optimization", *Proceedings of the 1995 IEEE International Conference on Neural Networks*, pp. 1942-1948, Perth, Australia, 1995

[28] J. Kennedy, "The Particle Swarm: Social Adaptation of Knowledge", *Proceedings of the 1997 International Conference on Evolutionary Computation*, pp. 303-308, IEEE Press, 1997

[29] J. Brest, S. Greiner, B. Boskovic, M. Mernik, and V. Zumer, "Self-adapting control parameters in differential evolution: a comparative study on numerical benchmark problems," IEEE Trans. Evolutionary Computing, vol. 10, no. 6, pp. 646–657, Dec. 2006.

[30] J. C. Bezdek, "Pattern Recognition with Fuzzy Objective Function Algoritms", Plenum Press, New York, 1981

[31] V. Miranda and Naing Win Oo, "New experiments with EPSO – Evolutionary Particle Swarm Optimization", Proceedings of the IEEE Swarm Intelligence Symposium 2006, Indianapolis (Indiana), USA, May 2006

[32] IEEE RTS Task Force of APM Subcommittee, "IEEE Reliability Test System", *IEEE Transactions on PAS*, Vol-98, No. 6, pp 2047-2054, Nov/Dec. 1979.

Vladimiro Miranda (M'90, SM'04, F'05) received his B.Sc. and Ph.D. degrees from the Faculty of Engineering of the University of Porto, Portugal (FEUP) in 1977 and 1982 in Electrical Engineering. In 1981 he joined FEUP and currently holds the position of Full Professor. He is also a researcher at INESC since 1985 and is currently Director at INESC Porto, the leading institution of INESC TEC – INESC Technology and Science, an advanced research network in Portugal. He is also the President of INESC P&D Brasil, in São Paulo, Brazil. He has authored many papers and been responsible for many projects in areas related with the application of Computational Intelligence to Power Systems. He is the recipient of the 2013 IEEE PES Ramakumar Family Renewable Energy Excellence Award.

Rui Alves (StM'12) is a MSc. student in Power Systems at FEUP and junior researcher at INESC TEC.

A.2 "Stochastic Location of PAR in Power Networks with Wind Power"

The following long abstract is intended to be submitted to a power systems periodical.

Stochastic Location of PAR in Power Networks with Wind Power

Vladimiro Miranda, *Fellow, IEEE* and Rui Alves, *Student Member IEEE*

***Abstract*-- This paper presents a new model to locate PAR transformers in power systems with wind power integration. A stochastic programming based model is proposed to optimally locate PAR devices given a set of load and wind scenarios with associated probabilities of occurrence. The model is based on a heuristic method, and the performance of EPSO and DEEPSO is evaluated.**

A case study is presented where successful results are obtained on a IEEE 24-bus RTS, showing the accuracy of the developed model. The DEEPSO algorithm has proven to be a more efficient method than EPSO in this specific problem.

***Index Terms*--Differential Evolutionary Particle Swarm Optimization, PAR location, Stochastic optimization, Wind power.**

I. Introduction

PHASE Angle Regulating (PAR) transformers are effective devices in controlling active power flow in meshed three phase power networks and may be crucial in resolving congestion problems. The capital cost of each device is significant, but this can be balanced by delayed construction of new transmission infrastructures and improved system operation with increased security and reduced operation costs.

In the daily operation of power systems, a system operator may be forced to curtail wind generation in order to satisfy the network constraints. This may result in replacement of curtailed wind generation by conventional generation, with considerable incremental costs, due to the higher cost of conventional generation as well as to the need to compensate wind producers for the wind generation curtailed. Furthermore, in critical situations, the need to curtail load may arise, resulting in the highest associated costs of power not supplied.

Given a set of load and wind scenarios, an appropriate location of PAR devices and their optimal sizing is of extreme importance to consent a more flexible operation of the system, allowing the system operator to minimize curtailment needs.

In this paper, a stochastic model to optimally locate PAR transformers in power networks with wind power integration is proposed. The optimal location and sizing of these devices is achieved through the utilization of two distinct heuristic methods - EPSO and DEEPSO - with their relative performance being analyzed.

II. Phase Angle Regulating Transformers

Phase Shifting Transformers (PST) have been extensively used in transmission systems to provide active power flow control. A proper control of the amount and direction of active power exchanged over transmission lines may avoid congestion problems.

The active power transported over a transmission line is a function of three main network parameters: voltage magnitude at both sending and receiving ends, line reactance and voltage angle difference.

The Phase Angle Regulating transformer is a special arrangement of PST, which controls the active power by modifying the voltage angle difference. It can be modeled as a reactance and a phase shift in series with the transmission line where it is installed:

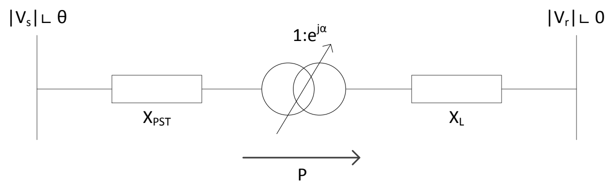

Fig. 1. PAR equivalent circuit.

The active power flowing through the line can be altered by adding a phase shift angle α. Changing the angle amplitude, within PAR limits, enables the control of the amount of power transported over the line.

III. EPSO and DEEPSO Algorithms

The utilization of heuristic methods to solve optimization problems with a combinatorial nature has been a common practice. The Evolutionary Particle Swarm Optimization (EPSO) and a new hybrid method identified as Differential Evolutionary Particle Swarm Optimization (DEEPSO) are proposed to optimize the location and sizing of PAR transformers in power networks.

A. Evolutionary Particle Swarm Optimization - EPSO

The Evolutionary Particle Swarm Optimization puts together concepts from both Evolutionary Algorithms (EA) and Particle Swarm Optimization (PSO). It was firstly introduced by Miranda et al. [1], using search capabilities of EA and the aptitudes of PSO in exploring the search space around the optimum value [2]. This hybrid method has proven to be a successful optimization algorithm, having very interesting convergence properties.

In the EPSO algorithm, considering a particle X_i, a new particle X_i^{New} is obtained by the following rule:

$$X_i^{New} = X_i + V_i^{New} \tag{1}$$

$$V_i^{New} = w^*_{i0} V_i + w^*_{i1}(b_i - X_i) + w^*_{i2} P(b^*_g - X_i) \tag{2}$$

The first term of V_i^{New} represents the inertia of the particle, making it to move in the direction it had previously moved. The second term represents the memory of the particle, making its movement being attracted to the best point found by the particle in its past life, b_i. The last term denotes cooperation, with the particles exchanging information to define the current best point found by the swarm, b_g, and moving in that direction. The communication factor P introduces a stochastic star communication topology to randomly control the information exchanged within the swarm. The parameters w^*_{ik} are the weights of each term, that should be subject to a mutation procedure.

The approach of EPSO consists of a replication process where each particle is replicated r times, originating identical particles, followed by the mutation of the weights of each particle. Then, a reproduction process of the particles is performed, based on the movement rule previously described, generating a set of offspring. Each offspring is subsequently evaluated by a fitness function and selected based on its fitness, forming a new generation of particles. This process is repeated for several generations until a certain stop criterion is reached [1].

B. Differential Evolutionary Particle Swarm Optimization – DEEPSO

The Differential Evolutionary Particle Swarm Optimization presents a new way to create a hybrid between EPSO and Differential Evolution (DE). DEEPSO is based on EPSO sequence, keeping its self-adaptive characteristics, but uses the concept of rough gradient from DE [3]. Consequently, the memory term of the movement rule of DEEPSO is modified according to:

$$V_i^{New} = w^*_{i0} V_i + w^*_{i1}(X_{r1} - X_{r2}) + w^*_{i2} P(b^*_g - X_i) \tag{3}$$

In a first version, closer to DE, X_{r1} and X_{r2}, correspond to two distinct individuals sampled from the current population. However, further improvements have been made, leading to a new proposal, preserving some basis of the DE but closer to PSO. It defines the enlargement of the set of particles from which X_{r1} should be sampled. Instead of sampling X_{r1} only from the particles of the current generation, the set may be extended in order to include all the historical past best particles. Moreover, in the DEEPSO method, X_{r2} is defined as being equal to X_i and only X_{r1} is randomly selected [3].

Four distinct versions of DEEPSO can then result, based on the methodology stated, depending on how X_{r1} is sampled:

- **DEEPSO Sg** (same generation): the particle X_{r1} is sampled **once** from the current generation [3].

$$V_i^{New} = w^*_{i0} V_i + w^*_{i1}(X_{r1} - X_i) + w^*_{i2} P(b^*_g - X_i) \tag{4}$$

- **DEEPSO Sg-rnd**: the same as previously, but with X_{r1} being re-sampled in the current generation for **each component** of V. In this case, X_{r1} is calculated from a uniform recombination of all the particles from the current generation [3].
- **DEEPSO Pb** (past bests): the particle b_{r1} is sampled **once** from the set of historical past best particles, b_i [3].

$$V_i^{New} = w^*_{i0} V_i + w^*_{i1}(b_{r1} - X_i) + w^*_{i2} P(b^*_g - X_i) \tag{5}$$

- **DEPSO Pb-rnd**: the same as previously, but with b_{r1} being re-sampled in the set of historical past best particles for **each component** of V. In this case, b_{r1} is calculated from a uniform recombination of all the historical past best particles [3].

C. Particles Structure and Fitness Function

Each particle of the swarm represents a possible solution to the PAR location problem. The length of a particle is defined by the number of candidate locations in the power network where a PAR can be installed. Every component of the particles denotes the placement of a PAR in a certain line, as well as the maximum angle the PAR may inject in that line.

α_1^{Max}	α_2^{Max}	...	...	...	α_{N-1}^{Max}	α_N^{Max}

Fig. 2. Particle Structure.

Given a set of N candidate locations to install a PAR, a particle will have a length of N and each component i is a proposal for the maximum angle introduced by the device at location i, α_i^{Max}. Each possible solution is then evaluated by a fitness function which values three factors, the capital cost of PAR, the need to curtail wind generation and to curtail load.

The capital cost of a PAR is considered as being composed of a fixed cost plus a non-linear variable cost which is a function of the maximum angle introduced by the PAR. Regarding the curtailment needs, they must be evaluated, for each possible solution, by solving the DC Optimal Power Flow (OPF) problem.

The allocation and sizing of PAR transformers is, therefore, defined by the following minimization:

$$\min J = \sum_{i=1}^{N} u_i \left(A + B(\alpha_i^{Max})^2\right) + Pen_{load} + Pen_{wind} \tag{6}$$

Where u_i is a binary variable representing the installation of a PAR in location i, A and B are the cost constants and α_i^{Max} is the maximum angle introduced by the device at location i. The penalty terms will be included if the optimal power flow problem results in the need to curtail wind generation, load or both.

IV. PAR Modelling on DC OPF

In order to evaluate the load and wind generation curtailment needs it is necessary to include the effect of a PAR in power networks, modelling its influence in power flow equations. Considering the equivalent circuit of a PAR, and the DC Power Flow formulation, the active power transported over a line with an installed PAR is given by:

$$P_{sr} = \frac{\theta_{sr} - \alpha}{X_{sr}} = \frac{\theta_{sr}}{X_{sr}} - \frac{\alpha}{X_{sr}} \qquad (7)$$

This is equivalent to have a power injection resulting from the utilization of a PAR, which is a load on sending bus, s, and a generation on the receiving bus, r. In consequence, the influence of a PAR can be directly represented in the vector of bus active power injections of the classic DC Power Flow formulation, allowing the power flow model to be written as a function of α.

The DC OPF should aim the minimization of wind generation and load curtailments for each possible solution. The evaluation of the load curtailed is possible to achieve through a fictitious generators based model. The constraints regarding the limits on generation and on line flows as well as the limits on PAR angles have to be considered. This will allow an appropriate quantification of the power not supplied and the wind generation curtailed for each possible solution, in order to apply the respective penalties in eq. 6.

V. Wind Power Integration Through Stochastic Programming

The evaluation of power systems with high degree of wind power integration has to consider the intermittence associated to the wind resource, responsible for wind power variations. In order to evaluate the influence of the wind power in power systems performance, the probabilistic behavior of wind speed characteristic has to be properly modeled.

Due to the probability of occurrence of a set of load and wind scenarios, the optimal PAR location with wind power integration becomes a stochastic optimization problem.

A. Wind Speed Model

Wind resource availability depends on geographical characteristics, varying from site to site, where the wind speed fluctuates randomly with time. An appropriate probabilistic representation of the wind speed is extremely important to accurately model the predictable output power from wind turbine generators. Commonly, wind speed probability distributions are represented by a Weibull distribution, which is widely accepted and recognized in the wind energy industry as an appropriate technique to represent wind speed variations.

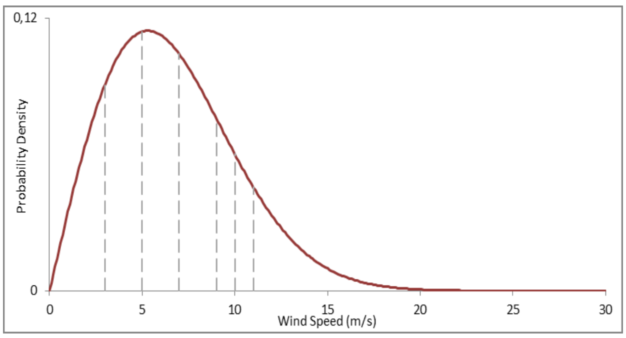

Fig. 3. Wind speed model – Stratification of Weibull distribution.

Having the wind resource represented by a Weibull distribution it is possible to represent a set of S wind scenarios with an associated probability of occurrence. In practice, the Weibull distribution is discretized and distributed in a set of intervals, each of them representing a wind scenario, having an associated probability of occurrence, which can be calculated through the integral of the Weibull density probability function. This approach is of extreme importance to allow the evaluation of power system behavior when dealing with different wind conditions.

B. Wind to Power Model

An efficient model to estimate the electric power generated by a wind turbine at a specific site can be determined by combining an accurate characterization of the wind speed, as presented before, and the information regarding its power curve. A typical power curve of a wind turbine generator is presented:

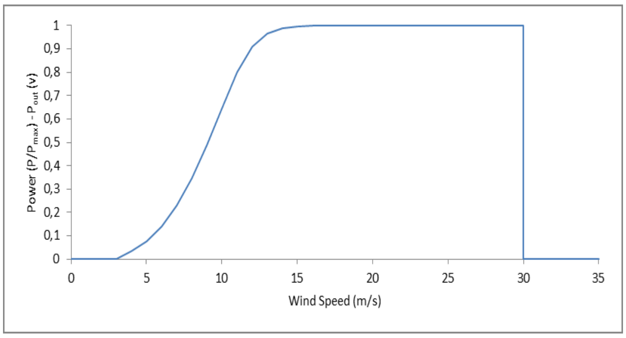

Fig. 4. Typical power curve of a wind turbine generator.

Having defined the wind speed model as well as the power curve of a wind turbine, its output power model can be obtained. The probability associated to a certain output power range will correspond to the probability of occurrence of the wind speed range that originates that produced power, accordingly to the power curve of the generator. This can be easily made if the wind speed Weibull distribution is stratified as demonstrated.

The power generation model of a wind turbine with a power curve as presented in figure 4, considering a wind scenario corresponding to the figure 3, is presented below:

TABLE I
Wind to Power Model

Wind Scenario	Wind Speed (m/s)	Power (P/Pmax)	Probability
1;8	[0;3] U [30;>30[	0	0.148
2	]3;5[	]0;0.076[	0.211
3	[5;7[	[0.076;0.2285[	0.223
4	[7;9[	[0.2285;0.489[	0.182
5	[9;10[	[0.489;0.648[	0.063
6	[10;11[	[0.648;0.799[	0.053
7	[11;30[	[0.799;1[	0.116

Therefore, the combination of a wind speed model with the output power curve of a wind turbine allowed the determination of a simplified wind power model of a wind turbine generator.

C. Stochastic Programming Model

Considering the wind power model as explained above, where the wind resource is represented by a set of S wind scenarios stratified according to a Weibull distribution, associating each scenario h with a probability value p_h, a stochastic programming based model can be implemented to properly evaluate each possible solution in order to optimally locate PAR transformers in all the S scenarios.

In eq. 6, the penalty terms should be applied taking into account the probability p_h of each wind scenario:

$$Pen_{load} = k_1 \left(\sum_{h=1}^{S} p_h PNS_h \right) \tag{8}$$

$$Pen_{wind} = k_2 \left(\sum_{h=1}^{S} p_h Pwc_h \right) \tag{9}$$

Where PNS_h is the power not supplied and Pwc_h stands for the wind generation curtailed on wind scenario h. Constant values k_1 and k_2 introduces the penalties given to load and wind generation curtailment. The constant k_1 should have a considerably higher value than k_2 in order to penalize much more the solutions leading to load curtailment.

VI. Case Study

Different simulations have been carried out on the IEEE 24-bus RTS in order to validate the proposed model as well as to compare the performance of the optimization algorithms applied to solve the optimal PAR location problem.

A. EPSO vs. DEEPSO

An extensive comparison between the classical EPSO and all the different variants of the DEEPSO method has been performed. The presented results are for the simulation of 100 runs of each algorithm.

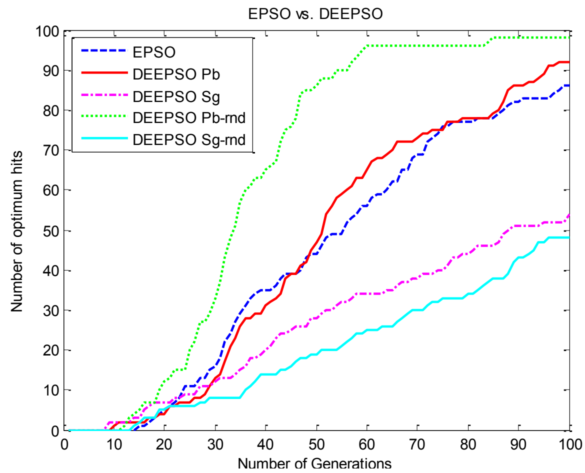

Fig. 5. Evolution of the number of hits on the optimum for 100 runs .

The figure above displays the number of hits on the optimum value with varying number of generations. The DEEPSO Pb-rnd has a superior behavior, showing considerable supremacy over all the other methods, reaching 96% of efficiency in finding the optimum only at 60 generations.

B. Location of PAR

A multiple load and wind scenarios approach was considered to optimally locate PAR transformers. A progressive increase of the wind power installed capacity was considered in order to evaluate the optimal location of PAR transformers for different levels of wind power integration. The following results were achieved:

TABLE II
OPTIMAL PAR LOCATION FOR 8 CANDIDATE LOCATIONS

Load (MW)	Wind Power Capacity (MW)	No. Device	Max. Angle (Deg)	Capital Cost ($)	Pwc (MW)	PNS (MW)
3277.5	0	2	5;10	178.75	-	0
	720	2	5;15	253.75	10.28	0
	1260	3	5;15;5	372.5	121	0
	1539	4	5;15;5;5	441.25	123.96	0
	1926	7	5;15;5;10;5;5;10	781.25	132.74	8.42

From these results, it is clear that the increase of wind power installed capacity, and the subsequent need to guarantee the maximum wind generation, has led to an increased number of PAR transformers to be placed, as well as their maximum angle injected.

VII. Conclusions

The stochastic method implemented to locate PAR transformers in a system with wind power has been successfully applied, showing consistent results. The integration of wind power had considerable influence the optimal PAR location.

Furthermore, a new heuristic method has shown great potential, specifically the DEEPSO Pb-rnd, proving to have better convergence capabilities than the classic EPSO, showing that for some specific problems the DEEPSO method can be advantageously used.

VIII. References

[1] V. Miranda and N. Fonseca, "EPSO - best-of-two-worlds meta-heuristic applied to power system problems," in *Evolutionary Computation, 2002. CEC '02. Proceedings of the 2002 Congress on*, 2002, pp. 1080-1085.

[2] H. Keko, A. J. Duque, and V. Miranda, "A Multiple Scenario Security Constrained Reactive Power Planning Tool Using EPSO," in *Intelligent Systems Applications to Power Systems, 2007. ISAP 2007. International Conference on*, 2007, pp. 1-6.

[3] V. Miranda and R. Alves, "Differential Evolutionary Particle Swarm Optimization (DEEPSO): a successful hybrid," 2013.

References

[1] Lina B. Tjernberg and Tuan A. Le. *Power Market Management*. Chalmers University of Technology, 2011.

[2] M. Saravanan, S. M. R. Slochanal, P. Venkatesh, and P. S. Abraham. Application of pso technique for optimal location of facts devices considering system loadability and cost of installation. In *Power Engineering Conference, 2005. IPEC 2005. The 7th International*, pages 716–721 Vol. 2.

[3] S. Gerbex, R. Cherkaoui, and A. J. Germond. Optimal location of multi-type facts devices in a power system by means of genetic algorithms. *Power Systems, IEEE Transactions on*, 16(3):537–544, 2001.

[4] F. G. M. Lima, F. D. Galiana, I. Kockar, and J. Munoz. Phase shifter placement in large-scale systems via mixed integer linear programming. *Power Systems, IEEE Transactions on*, 18(3):1029–1034, 2003.

[5] J. J. Paserba. How facts controllers benefit ac transmission systems - phases of power system studies. In *Transmission and Distribution Conference and Exposition, 2010 IEEE PES*, pages 1–1.

[6] Enrique Acha and Hugo Ambriz-Perez Cesar Angeles-Camacho, Claudio R. FuerteEsquivel. *FACTS Modelling and Simulation in Power Networks*. John Wiley & Sons, LTD, 2004.

[7] M. Santiago-Luna and J. R. Cedeno-Maldonado. Optimal placement of facts controllers in power systems via evolution strategies. In *Transmission & Distribution Conference and Exposition: Latin America, 2006. TDC '06. IEEE/PES*, pages 1–6.

[8] N. G. Hingorani. High power electronics and flexible ac transmission system. *Power Engineering Review, IEEE*, 8(7):3–4, 1988.

[9] S. N. Singh and A. K. David. Congestion management by optimising facts device location. In *Electric Utility Deregulation and Restructuring and Power Technologies, 2000. Proceedings. DRPT 2000. International Conference on*, pages 23–28.

[10] D. Van Hertem, J. Verboomen, K. Purchala, R. Belmans, and W. L. Kling. Usefulness of dc power flow for active power flow analysis with flow controlling devices. In *AC and DC Power Transmission, 2006. ACDC 2006. The 8th IEE International Conference on*, pages 58–62.

[11] L. Ippolito and P. Siano. Selection of optimal number and location of thyristor-controlled phase shifters using genetic based algorithms. *Generation, Transmission and Distribution, IEE Proceedings-*, 151(5):630–637, 2004.

[12] P. Paterni, S. Vitet, M. Bena, and A. Yokoyama. Optimal location of phase shifters in the french network by genetic algorithm. *Power Systems, IEEE Transactions on*, 14(1):37–42, 1999.

[13] S. Gerbex, R. Cherkaoui, and A. J. Germond. Optimal location of facts devices to enhance power system security. In *Power Tech Conference Proceedings, 2003 IEEE Bologna*, volume 3, page 7 pp. Vol.3.

[14] Tjing T. Lie and Wanhong Deng. Optimal flexible ac transmission systems (facts) devices allocation. *International Journal of Electrical Power & Energy Systems*, 19(2):125–134, 1997.

[15] G. I. Rashed, H. I. Shaheen, and S. J. Cheng. Optimal location and parameter setting of tcsc by both genetic algorithm and particle swarm optimization. In *Industrial Electronics and Applications, 2007. ICIEA 2007. 2nd IEEE Conference on*, pages 1141–1147.

[16] H. Mori and Y. Maeda. A hybrid method of epso and ts for facts optimal allocation in power systems. In *Systems, Man and Cybernetics, 2006. SMC '06. IEEE International Conference on*, volume 3, pages 1831–1836.

[17] Vladimiro Miranda. *Computação Evolucionária: Uma Introdução*. 2005.

[18] V. Miranda and N. Fonseca. Epso - best-of-two-worlds meta-heuristic applied to power system problems. In *Evolutionary Computation, 2002. CEC '02. Proceedings of the 2002 Congress on*, volume 2, pages 1080–1085.

[19] Vladimiro Miranda, Dipti Srinivasan, and L. M. Proença. Evolutionary computation in power systems. *International Journal of Electrical Power & Energy Systems*, 20(2):89–98, 1998.

[20] J. Kennedy and R. Eberhart. Particle swarm optimization. In *Neural Networks, 1995. Proceedings., IEEE International Conference on*, volume 4, pages 1942–1948 vol.4.

[21] H. Keko, A. J. Duque, and V. Miranda. A multiple scenario security constrained reactive power planning tool using epso. In *Intelligent Systems Applications to Power Systems, 2007. ISAP 2007. International Conference on*, pages 1–6.

[22] Vladimiro Miranda and Nuno Fonseca. New evolutionary particle swarm algorithm (epso) applied to voltage/var control.

[23] Vladimiro Miranda, Hrvoje Hrvoje, and Álvaro Jaramillo Duque. Stochastic star communication topology in evolutionary particle swarms (epso). *International Journal of Computational Intelligence Research*, 4(2), 2008.

[24] V. Miranda and R. Alves. Differential evolutionary particle swarm optimization (deepso): a successful hybrid. 2013.

[25] Rainer Storn and Kenneth Price. Differential evolution – a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11(4):341–359, 1997.

[26] P. M. Subcommittee. Ieee reliability test system. *Power Apparatus and Systems, IEEE Transactions on*, PAS-98(6):2047–2054, 1979.