Universitat de Girona

OPTIMISATION METHODS MEET THE SMART GRID. NEW METHODS FOR SOLVING LOCATION AND ALLOCATION PROBLEMS UNDER THE SMART GRID PARADIGM

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PhD Thesis

Optimisation methods meet the smart grid

New methods for solving location and allocation problems under the smart grid paradigm

Ferran Torrent Fontbona

2015

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Ferran Torrent Fontbona

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Supervised by:

Dr. Beatriz López

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Dr. Beatriz López from Universitat de Girona.

DECLARE

That the work entitled *Optimisation methods meet the smart grid. New methods for solving location and allocation problems under the smart grid paradigm* presented by *Ferran Torrent Fontbona* to obtain the degree in Doctor of Philosophy has been developed under our supervision and complies with the requirements needed to obtain the International Mention.

Therefore, in order to certify the aforesaid statement, we sign this document.

Girona, April 2015.

Agraïments

Aquesta tesi és el resum de la feina feta durant els últims 3 anys, que a més, m'ha servit per conèixer un magnífic grup de persones del PIV, i especialment del grup eXiT, que m'han ajudat a assolir la fita que representa aquesta tesi.

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- **Ferran Torrent-Fontbona**, Víctor Muñoz and Beatriz López. Solving large immobile location-allocation by affinity propagation and simulated annealing. Application to select which sporting event to watch. *Expert Systems with Applications* Vol. 40(11), pp. 4593-4599. September 2013. DOI:10.1016/j.eswa.2013.01.065. ISSN: 0167-9236. Elsevier. Impact Factor: 1.965 (Q1).

Conferences

- **Ferran Torrent-Fontbona**, Albert Pla and Beatriz López. Using Mutli-Attribute Combinatorial Auctions for Resource Allocation. In *Multiagent System Technologies. 12th German Conference (MATES2014). Proceedings published at Lecture Notes in Computer Science*, Vol. 8732, pp. 57-71. September 2014. Stuttgart.

- **Ferran Torrent-Fontbona**, Albert Pla and Beatriz López. A new perspective of trust through multi-attribute auctions. In *AAAI 2015 Workshop in Incentives and Trust in E-Communities (WIT-EC15)*. January 2015. Austin.

- **Ferran Torrent-Fontbona**, Víctor Muñoz and Beatriz López. Solving large location-allocation problems by clustering and simulated annealing. In 2*nd International Conference on Applied and Theoretical Information Systems Research*. December 2012. Taipei.

Acronyms

APR Accumulated Power Rights. 63, 66

B&B Branch and Bound. 9, 10, 21, 25, 26, 37, 38, 68, 99–101, 139

CFP Call For Proposals. 41, 48

CHP Combined Heat and Power. 19, 122–125, 127, 130, 131

DER Distributed Energy Resource. 1–5, 16, 17, 19–25, 27, 69, 70, 72–80, 83–89, 92–94, 96, 97, 122–125, 127, 130–134, 136, 139–141, 144, 145, 152–155

DG Distributed Generation. 1–5, 16, 19, 22–25, 27, 69, 86, 87, 89, 90, 92, 93, 97, 132, 133, 135, 136

DGLS Distributed Generation Location & Sizing. 21–25, 27, 84, 85, 87, 89, 92, 93, 95, 134, 138, 139, 141, 142, 144–146

DSM Demand Side Management. 17, 18, 30, 67, 139, 141

e-MPSP energy-aware multi Mode Project Scheduling Problem. 30–32, 34, 36–38, 40, 67, 68, 98–101, 106, 114, 139, 140, 143–145, 147

GA Genetic Algorithm. 12, 13, 21–23, 26, 27, 37–39, 44, 68, 85, 89, 92–96, 99, 101, 105, 106, 109, 114, 115, 135, 136, 138–141, 144

LRS Linear Random Search. 92, 96, 134

MACA Multi-Attribute Combinatorial Auction. 41, 48, 50, 107–110, 115, 140, 143

MPSP multi Mode Project Scheduling Problem. 30–32, 34, 37, 99–101

PRA Power Re-Allocation. 54, 57, 58, 61, 62, 64–67, 117–120, 140, 141, 144

PSO Particle Swarm Optimisation. 12, 13, 18, 22, 23, 26, 27, 37, 85, 89, 92, 94–96, 135, 136, 138, 141, 145

PSP Project Scheduling Problem. 18, 37

PV Photo-Voltaic. 20, 23, 24, 84, 122–125, 131, 133, 136

RAP Received Amount Priority. 66, 67, 117, 120, 122

RES Renewable Energy Sources. 1, 16, 20, 69

RFP Received Frequency Priority. 66, 67, 117, 120, 122

SA Simulated Annealing. 11, 13, 14, 85, 89–92, 94–96, 132, 134–136, 138, 141

trust-MACA Multi-Attribute Combinatorial Auction with Trust. 48–50, 115, 140, 143–145

VCG Vickrey-Clark-Groove. 45, 50

VPP Virtual Power Plant. 16, 19–21, 58, 69, 70, 72–78, 80, 97, 123, 124, 127, 141, 145, 152, 153

WDP Winner Determination Problem. 43, 44, 48, 115

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Abstract

The currently energy system is changing, mainly, due to the rise of global energy consumption and the depletion of fossil energy sources. Regarding the electric power system, this change comes on the heels of the *smart grid*, an electric smart network capable, among other things, to monitor individual energy consumptions, to support communication channels which enable the use of demand management techniques, like variables prices, and to integrate a significant use of renewable energy sources reducing our dependency on fossils fuel resources. In other words, smart grid offers an infrastructure for the management of energy demand and generation towards a sustainable future.

Accordingly, there is the objective to provide consumers with a response capacity to stimuli of the electricity market aiming at an adjustment of the energy consumption to match the generation capacity, and at the same time, to efficiently manage the generation system which tends to a diversification of the generators and of the energy sources. Therefore, a system with many more generators, but smaller and not only based on fossil fuels. These objectives can be interpreted as optimisation problems and this thesis is committed to the development of optimisation tools or methods for tackling such problems.

For that purpose, this thesis is first focused on providing to consumers methods for managing their energy consumption and then reducing costs according to their production activities. Thus it formalises the problem of assigning resources to activities and scheduling them taking into account energy consumptions, variable energy prices and an agreed load shape besides other typical aspects of resource allocation such as the requirements of the activities of the abilities of the resources. Furthermore, it presents methods for solving this problem considering an inner implementation or an outsourcing of their activities. For the latter case, new auction mechanisms are proposed. The presented resource allocation methods are complemented with a method that takes advantage of the creation of coalitions of consumers to reduce costs derived from their peaks of demanded power.

Next, this thesis focuses on electricity generation, tackling the problem of how to share out

energy production among a set of distributed generators. As the number of distributed generators is becoming large, other approaches than centralised control should be explored. In this dissertation a method based on self-organisation which does not need any organisation of control is proposed. Besides, aiming at achieving a fair, but also efficient share of the production outcomes, the presented method is based on different concepts of justice which enable the attainment of the fair and efficient objectives and, at the same time, give it the capacity to adapt itself to new situations or to the incorporation of a new generator.

However, the performance of a group of generators is limited to the composition of the group and the localisation of the generators. Therefore, the connection of new generators to a given grid is also addressed in this thesis to support the planning of placing new generators (how many, where, which kind, etc.). To tackle such a quandary, different methods based on meta-heuristics are proposed, analysed and compared.

Resum

Últimament s'està albirant un canvi en el sistema energètic actual degut, principalment, a l'augment del consum mundial d'energia i l'esgotament dels recursos fòssils del planeta. Pel que fa al sistema elèctric, aquest canvi ve de la mà de la *smart grid*, una xarxa elèctrica *intel·ligent* capaç, entre altres coses, de monitoritzar els consums elèctrics individuals, suportar canals de comunicació que habilitin l'ús de tècniques de gestió de la demanda, com els preus variables, i integrar l'ús significatiu d'energies renovables que redueixin la nostra dependència en les energies fòssils. En altres paraules, la *smart grid* ofereix una infraestructura per a la gestió de la demanda i generació d'electricitat cap a un futur més sostenible.

En aquest sentit, hi ha l'objectiu de proveir els consumidors de capacitat de reacció davant d'estímuls del mercat elèctric perquè modifiquin el seu consum i l'ajustin a la generació, i al mateix temps, gestionar de forma eficient un sistema de generació que tendeix cap a una diversificació de generadors i del tipus de recursos utilitzats. És a dir, un sistema amb molts més generadors, però més petits i que no estaran basats, només, en les energies fòssils. Aquests objectius es tradueixen en a problemes d'optimització i aquesta tesi està compromesa amb el desenvolupament d'eines o tècniques d'optimització per a resoldre aquests problemes nous.

Amb aquest objectiu, aquesta tesi primer es centra a desenvolupar mètodes perquè els consumidors puguin gestionar els seus consums i així també reduir-ne els costos d'acord amb les seves activitats de producció. D'aquesta manera es formalitza el problema d'assignar recursos a activitats i programar aquestes activitats tenint en compte els consums energètics, els preus variables de l'energia i una corba de consum acordada, a més d'aspectes clàssics en l'assignació de recursos a activitats com els requisits de les activitats o les habilitats dels recursos. A més, es presenten mètodes per resoldre aquest problema considerant un context de realització interna de les activitats o d'externalització d'aquestes. Per al darrer cas, es proposen nous mètodes de subhasta. Els mètodes presentats són complementats amb la proposta d'un mètode que s'aprofita de l'organització de consumidors en grups per reduir els costos derivats dels seus pics de potència.

Posteriorment, la tesi es centra en la generació elèctrica i ho fa abordant el problema de com repartir la producció d'energia d'entre un conjunt de diferents generadors distribuïts. A causa de l'augment del nombre de generadors distribuïts, és necessari explorar altres mètodes que no proposin un control centralitzat. En aquesta tesi es proposa un mètode basat en auto-organització, de manera que no necessita cap organisme de control. A més, i amb l'objectiu d'aconseguir un repartiment just de la generació, però alhora eficient, el sistema està basat en diferents principis de justícia que li permeten assolir els objectius de justícia i eficiència, però alhora li proporcionen capacitat per adaptar-se a noves situacions o noves incorporacions de generadors.

A banda dels mètodes que es desenvolupin per determinar la generació d'energia que li pertoca a cada generador, els resultats d'aquests mètodes estan limitats per la composició del grup de generadors i la localització d'aquests. Per tant, la realització d'una bona planificació sobre quins generadors serien els més adequats i quina seria la seva ubicació òptima és essencial abans de decidir si connectar nous generadors a una xarxa elèctrica i on s'haurien de connectar. Per abordar aquesta problemàtica es proposen, s'analitzen i es comparen diferents mètodes metaheurístics.

Resumen

Últimamente se está vislumbrando un cambio en el sistema eléctrico actual, debido principalmente al aumento del consumo mundial de energía y al agotamiento de los recursos fósiles del planeta. En cuanto al sistema eléctrico, este cambio viene de la mano de la *smart grid*, una red *inteligente* capaz, entre otras cosas, de monitorizar los consumos energéticos individuales, soportar canales de comunicación que habiliten el uso de técnicas de gestión de la demanda, como los precios variables, e integrar el uso significativo de energías renovables que reduzcan nuestra dependencia en las energías fósiles. En otras palabras, la *smart grid* ofrece una infraestructura para la gestión de la generación y demanda de electricidad hacia un futuro más sostenible.

Por este motivo el objetivo es proveer a los consumidores de capacidad de reacción ante estímulos del mercado eléctrico para que modifiquen su consumo y lo ajusten a la generación y, paralelamente, gestionar de manera eficiente un sistema de generación que tiende hacia una diversificación de generadores y del tipo de recursos utilizados. Es decir, un sistema con muchos más generadores, pero más pequeños y no solamente basados en energías fósiles. Estos objetivos se traducen como problemas de optimización, y esta tesis está comprometida con el desarrollo de técnicas o métodos para resolver estos problemas.

Con este objetivo, esta tesis primero se centra en el desarrollo de métodos para que los consumidores puedan gestionar sus consumos y así también reducir sus costes según sus actividades de producción. De este modo se formaliza el problema de asignar recursos a actividades y programar éstas teniendo en cuenta los consumos energéticos, precios variables de la energía y una curva de consumo acordada, además de aspectos clásicos en la asignación de recursos a actividades como los requisitos de éstas y las habilidades de los recursos. Además, se presentan métodos para resolver este problema considerando un contexto de realización interna de las actividades o de externalización de éstas. Para el último caso se presentan nuevos métodos de subasta. Los métodos presentados son complementados con la propuesta de un método que se aprovecha de la organización de los consumidores en grupos para reducir los costes

derivados de los picos de potencia demandada.

Posteriormente, la tesis se centra en la generación eléctrica y lo hace abordando el problema de cómo repartir la producción de energía entre un conjunto de diferentes generadores distribuidos. Debido al aumento de generadores distribuidos, es necesario investigar otros métodos a parte de los que proponen sistemas de control centralizado. En esta tesis se propone un método basado en autoorganización, de modo que no necesita ningún organismo de control. Además, y con el objetivo de conseguir un reparto justo de la generación, pero a la vez eficiente, el sistema está basado en diferentes principios de justicia que le permiten alcanzar los objetivos, pero al mismo tiempo le proporcionan capacidad para adaptarse a nuevas situaciones o nuevas incorporaciones de generadores.

A parte de los métodos que se desarrollen para determinar la generación de energía que le toca a cada generador, los resultados de estos métodos están limitados por la composición del grupo de generadores y la localización de éstos. Por lo tanto, la realización de una buena planificación sobre qué generadores serían los más adecuados y cuál sería su ubicación óptima es esencial antes de decidir si conectar nuevos generadores a una red eléctrica y dónde se tendrían que conectar. Para resolver esta problemática se proponen, analizan y comparan diferentes métodos metaheurísticos.

CHAPTER 1

INTRODUCTION

This chapter presents an overview with the motivations of this dissertation. It also describes the antecedents and hypothesis which this thesis is based on, presents the objectives and determines the scope it is framed in.

1.1 Motivations

The rapid development of the global economy has notably increased energy requirements, especially in emerging countries. The scarcity of fossil fuel resources and evidences linking carbon emissions and global warming have raised the interest in energy saving and environmental protection. To reduce our dependence on fossil fuels, two strategies are being followed:

1. Integrating renewable energy resources fostering their implantation and usage, as well as, adapting electricity demand to new supply conditions.
2. Reducing energy consumption through energy saving programs focused on energy demand reduction and energy efficiency in domestic and industrial fields.

Regarding the first point, technological advances have made available small power plants of different types (photovoltaic, wind turbines, fuel cells, co-generation plants, etc.) from 10KW to several MW, leading a diversification of the energy sources and energy generators. This combined with incremental demand for electrical energy and possible benefits of Distributed Generation (DG), has led a growth of the prevalence of distributed generators as, also, a way to integrate Renewable Energy Sources (RES) in the power grid. The integration of renewable Distributed Energy Resources (DERs) requires dealing with the uncertainty derived from RES such as wind, but also requires dealing with the complexity to deal with many generators of different types. Thus, questions such as where to place new generators, which technology should be used or how much energy each DER should produce become complex optimisation problems.

Furthermore, the difficulties of storing large amounts of electricity imply a constant balance between electricity production and consumption. This has not been an obstacle when carbon-based energy sources, i.e. gas, oil and coal, were used to produce electricity because they can be easily stored in large amounts. However, many renewable energy resources are characterised by not being storable. Hence, the integration of renewable energy sources requires the use of strategies, such as variable electricity prices, to adapt the demand to the new supply conditions. In this scenario, for consumers, energy efficiency becomes a matter of a smart usage of the energy instead of only a matter of increasing the yield of engines and devices. This smart usage implies a need to be aware and take account of the energy prices, the limitations of energy sources and the used utilities when switching them on/off or scheduling a set of energy-consumer tasks, what is known as demand response.

Given the objectives for the energy-related future, the smart grid is thought to be, regarding electrical energy, the base on which to build new systems and carry out new methodologies for meeting these objectives. Then, the smart grid brings a new scenario into the fields of electricity generation and consumption where different disciplines, such as electrical engineering, computer science, telecommunications, architecture, etc., are called to face new problems.

Considering that, the smart grid offers a new infrastructure for energy demand and generation control. This dissertation aims to study synergies between energy demand and generation using optimisation techniques taking as hypothesis that *optimisation methods can be used as support tools for cost reduction and solving new problems posed by the smart grid*. Specifically, it means that using optimisation methods with energy-related information provides decision support tools for:

- analysing energy consumption and reducing its derived costs.
- determining the energy generation in a DG context for improving system sustainability.
- planning the power network including new DERs

Therefore, this dissertation studies new problems posed by the smart grid which can be modelled as optimisation problems and brings, adapts and analyses methodologies to solve them. In particular, this thesis is focused on solving location and allocation problems under the context of the smart grid paradigm.

1.2 Contributions

This dissertation has the objective of providing optimisation methodologies that can be used as decision support tools for demand-response mechanisms, allocating energy demand and planning and designing the power network in a DG context. Thus, the contributions of this dissertation are summarised as follows:

- Demand response methods for reducing costs.
  - Formulation and presentation of an energy-aware project scheduling problem to reduce energy consumption and costs with the proposal of single-agent and multi-agent methods for solving it.
  - Development of a new methodology for reducing power related costs based on power re-allocation among coalitions of consumers.
- Self-organising energy demand allocation based on distributive justice to determine energy production of each generator in a DG context assuring system sustainability and general satisfaction among other objectives.
- Adjustment and application of optimisation techniques for determining optimal location of DERs as well as their size and type in a power grid.

Beyond these three main contributions, this dissertation presents two new methods for solving the energy-aware project scheduling problem, based on auctions (a well-known mechanism for resource allocation) that merge multi-attribute auctions, combinatorial auctions and trust, for first time in the literature.

1.3 Thesis outline

- **Chapter 1:** ***Introduction.*** This chapter offers an overview of this thesis, its motivations, contributions, methodology and the outline of the individual chapters.
- **Chapter 2:** ***Optimisation methods for solving location and allocation problems.*** This chapter offers a review of the literature needed to understand this thesis. Within this chapter, previous existing optimisation methods are described and analysed with criticism of their strengths and weaknesses.

- **Chapter 3:** ***Demand response: Resource Allocation on the Smart Grid*** This chapter addresses energy cost reduction managing and scheduling tasks of factories that need to be done, and power-related costs reduction using power re-allocation among coalitions of consumers. It presents the formulation of the problems and explains the methodologies proposed to solve the problems.

- **Chapter 4:** ***Energy Demand Allocation.*** Within this chapter the problem of determining energy production of each DER in a DG context is formulated. It also proposes the use of self-organisation to address the problem.

- **Chapter 5:** ***Planning of new generators based on new renewable energy sources.*** This chapter analyses the problem of determining the optimal location to place new DERs and their most appropriate type and size. Then it proposes and adapts different optimisation techniques for solving the problem.

- **Chapter 6:** ***Experimentation and Results.*** In this chapter the methods presented in chapters 3 to 5 are tested and analysed. It also provides a discussion about the performance of all of them.

- **Chapter 7:** ***Conclusions.*** This chapter summarizes and discusses the research conducted in this thesis. In addition, it suggests future research and improvements in systems which can be derived from this work.

CHAPTER 2

BACKGROUND AND RELATED WORK

This chapter provides some background regarding optimisation problems and techniques. It also presents an overview of optimisation methods used to tackle the problems posed by the smart grid and studied throughout this dissertation.

2.1 Introduction

Every day, engineers and decision makers have to deal with problems of growing complexity, which emerge in diverse technical sectors such as operations research, mechanical systems, image processing, etc. These problems are usually expressed as *optimisation problems*, defined by one (or several) objective function(s) sought to be minimised or maximised. Usually, they are not able to solve problems in one step, but they follow some methodology which guides them through problem solving. For example, common steps of the problem solving are recognising and defining problems, constructing and solving models, and evaluating and implementing solutions.

This dissertation aims to provide and present optimisation methodologies for solving optimisation problems to support decision making about energy management under the smart grid paradigm. Thus, the purpose of this chapter is first, to set the stage and give an overview of properties of optimisation problems that are relevant throughout this dissertation. Second, this chapter presents a brief overview of the current optimisation techniques and third, the chapter presents a survey of the relevant research done regarding optimisation methodologies related to the smart grid. In particular, it focuses on demand-response or consumer oriented solutions, on determining the generation schedule under a DG context and on renewable DERs planning.

2.2 Optimisation problems

Optimisation problems have been a focal point in operations research for over fifty years. They are concerned with the efficient allocation of limited resources to meet desired objectives. In such problems, different alternatives exist and a user or an organisation has to select one of these. The selection of one available alternative has some impact on the user, which can be measured or described by some kind of evaluating function. Furthermore, users cannot freely choose from all available alternatives since they have to fit some constraints that restrict them. Common restrictions come from technical limitations, interpersonal relations between humans or law. Hence, these problems are made up of a set of decision variables and additional constraints that limit the number of alternatives. Each decision alternative can have a different effect and it can be evaluated through an objective function. The final goal is to find the decision alternative that maximise/minimise the objective function.

To achieve the goal, it is necessary to follow a systematic and rational process able to analyse and provide an optimal (or near-optimal) decision alternative. Such process consists of several steps [Rothlauf, 2011]:

1. **Recognising the problem**. First, to recognise the existence of an optimisation problem, users or organisations must become aware that there are different alternatives for doing a particular resource allocation. This situation often occurs as a result of external pressure or changes in the environment (i.e. new technology, new requirements, etc.).

2. **Defining the problem**. Once the problem is identified, it can be described and defined. For doing so, the different decision alternatives must be formulated, it must be ascertained whether there are any additional constraints to be considered, and evaluation criteria must be selected as well as the goals of the process. An important aspect of the problem definition is the selection of the relevant decision alternatives, since usually there is a trade-off between the number of decision alternatives and the difficulty of the resulting problem.

3. **Constructing a model**. The problem model is usually a simplified representative of the real world. Mathematical models describe reality by extracting the most relevant relationships and properties of a problem and formulating them using mathematical expressions. Therefore, when constructing a model, there are always aspects of reality that are idealised or neglected.

4. **Solving the model**. After the model of the problem is defined, it can be solved by some

kind of *algorithm*[1] (usually an optimisation algorithm). The goal of this step is to find a solution with minimal or maximal evaluation value.

When problems become too complex for traditional optimisation techniques, artificial intelligence provides methods for solving them.

5. **Validating solutions**. Once optimal solutions are given, they must be evaluated to determine how they depend on variations of the model.

6. **Implementing solutions**. The solution found is ready to be implemented after it is validated.

2.2.1 Notions of optimality

This subsection provides a brief explanation of optimality concepts relevant within this dissertation.

Problem model. The problem model is a mathematical description of the problem. The model describes the different decision variables $\{x_1, \ldots, x_n\}$, the restrictions that hold for the different decision variables and the objective function f. Decision variables can be represented using the vector $(x_1, \ldots, x_n)$ and an assignment of specific values to it becomes a solution $\mathbf{x}$ and the set of feasible solutions is denoted as X. The restrictions can be expressed by constraints, i.e. $x_1 \in \{0, 1\}$ or $x_2 + x_3 \leq 5$. The objective function $f : X \longrightarrow \mathbb{R}$ assigns a real value to each possible solution and measures its quality.

An instance of a problem is a specific problem described by the model with specific input data. Usually each instance has a collection of solutions X where each solution $\mathbf{x} \in X$ satisfies the constraints of the problem. The goal associated with each instance is to find the feasible solution $\mathbf{x} \in X$ that minimises (or maximises) the objective function.

Solution space. The solution space, alternatively called search space, X is implicitly defined by the definition of the decision variables $(x_1, \ldots, x_n)$ of the optimisation problem. It contains the set of feasible solutions of the problem and it can define the relationships, such as distances, between them.

Depending on the structure of the solution space, it is usually described as the convexity of the solution space. It is said that the space is convex if a line segment connecting any two

[1]Procedure with a finite set of well-defined instructions for accomplishing some task.

feasible solutions is contained in the solution space. This conveys that any local optimum will also be a global optimum, and thus the optimisation problem will be easier to solve.

Neighbourhood. A neighbourhood determines which solutions are similar to each other. A neighbourhood is a mapping that assigns to each solution $\mathbf{x} \in X$ a set of solutions Y that are neighbours of $\mathbf{x}$. Usually, the neighbourhood $N(\mathbf{x})$ defines a set of solutions $Y \subset X$ which are in some sense similar to $\mathbf{x}$.

Optimal solution. An optimal solution or globally optimal solution is defined as the solution $\mathbf{x}^* \in X$, where $f(\mathbf{x}^*) \leq f(\mathbf{x})$ for all $\mathbf{x} \in X$ (in case of minimisation problem). For the definition of a globally optimal solution, it is not necessary to define the structure of the search space.

Local optima. A local optimal solution is a feasible solution $\mathbf{x}' \in X$ which is the best solution inside a neighbourhood $N(\mathbf{x}')$ of the solution space. For a minimisation problem, a local optima is defined as follows

$$f(\mathbf{x}') \leq f(\mathbf{x}) \quad \forall \mathbf{x} \in N(\mathbf{x}') \tag{2.1}$$

It is said that an optimisation algorithm performs a global search of the optimal solution when it is capable to avoid getting stuck on local optima.

Pareto optimality. Some problems require optimisation considering several objectives. In this situation, all objectives can be aggregated into the objective function with information about the decision maker's preference. However, when this information is not available, problems are solved in terms of Pareto optimality. To explain this concept, let us consider two solutions $\mathbf{x}_1$ and $\mathbf{x}_2$ and that $\mathbf{x}_1$ is better or equal than $\mathbf{x}_2$ in all the objectives, with at least one strictly better. Then it is said that $\mathbf{x}_1$ *dominates* $\mathbf{x}_2$ in the Pareto sense. A Pareto optimal solution is one solution that cannot be dominated.

Computational complexity. The complexity of an optimisation problem is the *minimum amount of effort* (in terms of time or memory) necessary to solve a particular problem. The effort depends on the size of the problem and the mostly used measure is the worst case of the problem solving.

2.3 Optimisation methods

There are many optimisation methods in the literature and their use depends on the solution space and the complexity of the optimisation problem to solve. This section provides a brief overview of the main optimisation methods.

2.3.1 Exact methods

Exact methods, alternatively called complete methods, are those capable of finding an optimal solution to a problem. They range from very general techniques (useful to solve a great variety of optimisation problems) such as Branch and Bound (B&B) [Apt, 2003], to problem dependent algorithms such as Dijkstra's algorithm [Dijkstra, 1959].

General exact optimisation methods can be classified among the following paradigms (see also Figure 2.1):

Heuristic (A*). A* [Hart et al., 1968, Lerner et al., 2009] is an extension of Dijkstra's algorithm. It is a goal-directed graph traversal strategy capable of finding the least-cost path (optimal solution) from a given source node to a target node. It consists of ordering the different possible paths (solutions) and first exploring the most promising one. The algorithm estimates the quality of each path using a knowledge-plus-heuristic cost function, where the knowledge part is the cost of going from the source node to the current node, and the heuristic is an estimation of the cost of going from the current node to the target node. The heuristic has to fulfil a set of requirements to guarantee the optimal solution. A* has been the inspiration of many other variants such as D* [Stentz, 1994], IDA* [Korf, 1985], etc.

Branch and Bound. B&B was first proposed by Land and Doig in 1960 [Land and Doig, 1960]. A B&B algorithm consists of a systematic enumeration of candidate solutions through a rooted search tree. The algorithm explores the branches of the tree, which represent subsets of the solution set. While the algorithm explores the branches, it checks them against upper and lower estimated bounds on the optimal solution. Then the branches are discarded if they cannot produce a better solution than the best found so far by the algorithm.

Dynamic programming. Dynamic programming [Bradley et al., 1977, Jongen et al., 2004] consists of solving a complex problem by breaking it down into a sequence of smaller, and

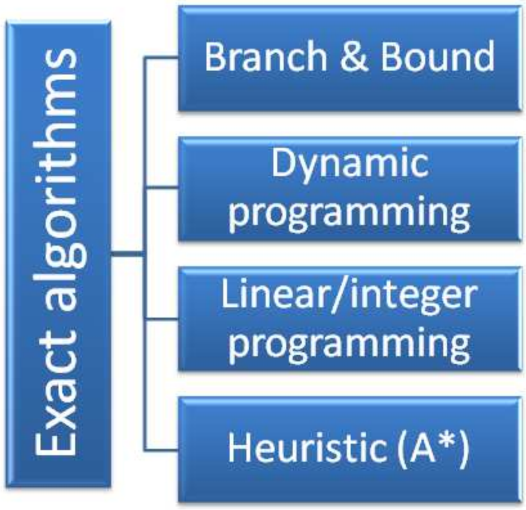

Figure 2.1: Paradigm based classification of exact methods.

therefore easier, sub-problems. Then the solution of the larger problem is discovered through solving the individual smaller problems.

Linear programming. Linear programming is used to solve optimisation problems which are represented by a linear objective function and linear inequality constraints. The solution space is a convex polygon delimited by several planes (constraints).

Integer programming is based on the concepts of linear programming. Unlike linear programming, integer programming admits that some or all the variables are restricted to be integer instead of real. Integer programming problems are usually solved using branch and cut algorithms [Mitchell, 2002]. These methods combine cutting plane methods with a B&B algorithm. They work by solving a sequence of linear programming[2] relaxations of the integer programming problem (relaxing the restriction of the variables to be integer). Cutting plane methods are used to add constraints to the initial problem to improve the relaxation of the problem to more closely approximate the integer programming problem. The B&B part of the algorithm is use to iteratively split the problem into multiple (usually two) versions and the new linear programming problems are then solved by the simplex method. During the B&B process, non-integer solutions to linear programming relaxations serve as upper bound and integer solutions as lower bounds (in case of a maximisation problem).

[2]Linear programming problems can be solved efficiently by the simplex method [Dantzig and Thapa, 1997].

2.3.2 Inexact methods

There would be no need of any other kind of method if there were no problems that exact methods cannot solve with feasible resources. Since this is not the case, a great range of methods exists in the literature that are capable of providing satisfactory enough solutions in reasonable amounts of time and memory. The methods proposed in this dissertation are mostly inexact methods because the problems posed, especially large instances of them, cannot be solved efficiently using exact methods.

Inexact methods include those algorithms that return a feasible solution in finite time with absent accuracy of such solution (it is not known if the returned solution is optimal, good or bad), and those capable to return a solution with an estimation of the accuracy of such solution. These latter algorithms are usually called approximate algorithms. Other classifications about inexact methods are available in the literature [Paquete, 2006, Luke, 2013]. Figure 2.2 provides a classification according to the paradigms used by inexact methods to perform the *search*. In this regard it can be distinguished among:

Deterministic search. These algorithms rely heavily on linear algebra since they are commonly based on the computation of the gradient of the objective function [Cavazzuti, 2013, Luke, 2013]. Usually the convergence of such algorithms is very fast (requires to evaluate a low number of alternative solutions), especially compared with stochastic search algorithms. Deterministic methods look for stationary points of the response variables (i.e. points where the gradient is zero), and thus, the optimal solution eventually found might be a local optimum instead of the global optimum. Most common deterministic search algorithms are greedy algorithms [Gonzalez, 2007, Pirsiavash et al., 2011], but also other algorithms such as guided local search [Glover and Kochenberger, 2003] and variable neighbourhood search algorithms [Hansen and Mladenović, 2001] are examples of deterministic search methods.

Stochastic search. Stochastic search algorithms search for solutions using the local knowledge provided by the definition of a neighbourhood or a set of partial solutions. Since they are based on a randomised search process, they are not expected to return the same outcome for different runs with different random seeds. Some examples are Simulated Annealing (SA) [Kirkpatrick et al., 1983, Luke, 2013, Russell et al., 2010, Torrent-Fontbona, 2012, Torrent-Fontbona et al., 2013, Černý, 1985], iterated local search [Glover and Kochenberger, 2003] or tabu search [Glover, 1989, Glover, 1990].

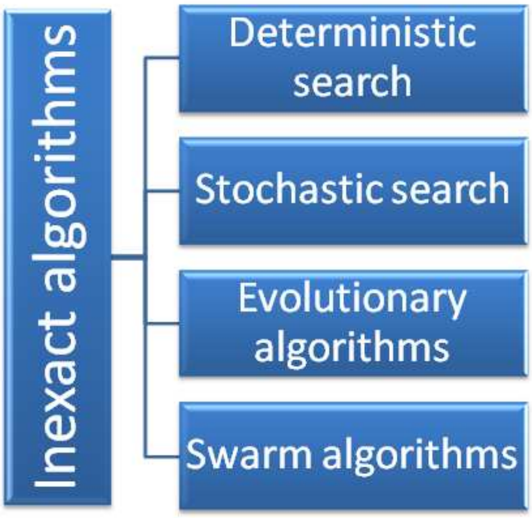

Figure 2.2: Paradigm based classification of inexact methods.

Evolutionary algorithms. Evolutionary algorithms employ principles of biological evolution to solve optimisation problems. They start with a population of solutions which evolve, improving the quality of the solutions, throughout a finite number of iterations. Most popular examples are Genetic Algorithm (GA) [Haupt and Haupt, 2004, Holland, 1975, Mitchell, 1998, Torrent-Fontbona, 2012], memetic algorithms [Moscato et al., 2004] and immune algorithms [Cai and Gong, 2004, de Castro, 2002].

Swarm algorithms. These algorithms are inspired by the *collective intelligence*. They are represented as decentralised systems of simple homogeneous systems interacting locally with the environment and with each other. Despite the absence of a centralised agent-control structure, local interaction between them results in global behaviour of the system as a whole. Some examples are ant colony optimisation [Dorigo, 1992], Particle Swarm Optimisation (PSO) [Kennedy, 2010, Poli et al., 2007], firefly algorithm [Yang, 2010], etc.

Despite the classification provided by Figure 2.2, some algorithms use two or more of the paradigms mentioned in the figure. For example, stochastic search is used by many swarm or evolutionary algorithms such as PSO or GA. Others, like variable neighbourhood search algorithms, combine stochastic search and deterministic search which a priori may be thought of as opposite. Thus, Figure 2.2 should not be seen as a strict classification of the algorithms, but as a representation of the paradigms used by inexact methods.

Stochastic, evolutionary and swarm algorithms are also known as meta-heuristics. The term meta-heuristics is used to refer to general algorithms (they make a few assumptions about the problem to be solved) that employ some degree of randomness to find optimal or near-optimal solutions to complex problems [Luke, 2013]. The methods presented within this dissertation are mostly based on meta-heuristics, and therefore this section provides a deeper overview of them. They can be also classified according to the following criteria:

Nature-inspired vs. non-nature inspired. Depending on their origins, meta-heuristics can be tagged as nature-inspired algorithms, like GA and SA, or non-nature-inspired algorithms like tabu search or iterated local search. Although this seems an easy classification of meta-heuristics, there are many algorithms that fit both classifications, since they are based on nature and non-nature inspired concepts. Furthermore, being a nature-(or non-nature-)inspired algorithm do not represent any particular advantage or disadvantage when solving an optimisation problem. Thus, this classification is useless when deciding the most appropriate algorithm to tackle a particular problem [Birattari et al., 2001, Blum and Roli, 2003].

Population-based vs. single point search. Depending on the number of solutions the algorithm manages at the same time, meta-heuristics can be classified as population-based algorithms, like PSO and GA, or single point search algorithms, like SA. Whilst algorithms working on single solutions describe a trajectory in the solution space, population-based algorithms work with sets of solutions that interact between themselves. Using a population-based algorithm provides a convenient way for the exploration of the search space. However, the final performance depends strongly on the way the population is manipulated [Birattari et al., 2001, Blum and Roli, 2003, Luke, 2013].

Dynamic vs. static objective function. Most meta-heuristics keep the objective function given in the problem representation invariable along the whole search process. Nevertheless, other meta-heuristics, like guided local search, modify the objective function during the search in order to escape from local optima [Birattari et al., 2001, Blum and Roli, 2003].

One vs. various neighbourhood structures. In general meta-heuristics work on a single neighbourhood structure. But, some algorithms use a set of neighbourhood structures. Its objective is the same as using dynamic objective functions or working with a population of solutions, to avoid or to escape from local optima [Birattari et al., 2001, Blum and Roli, 2003].

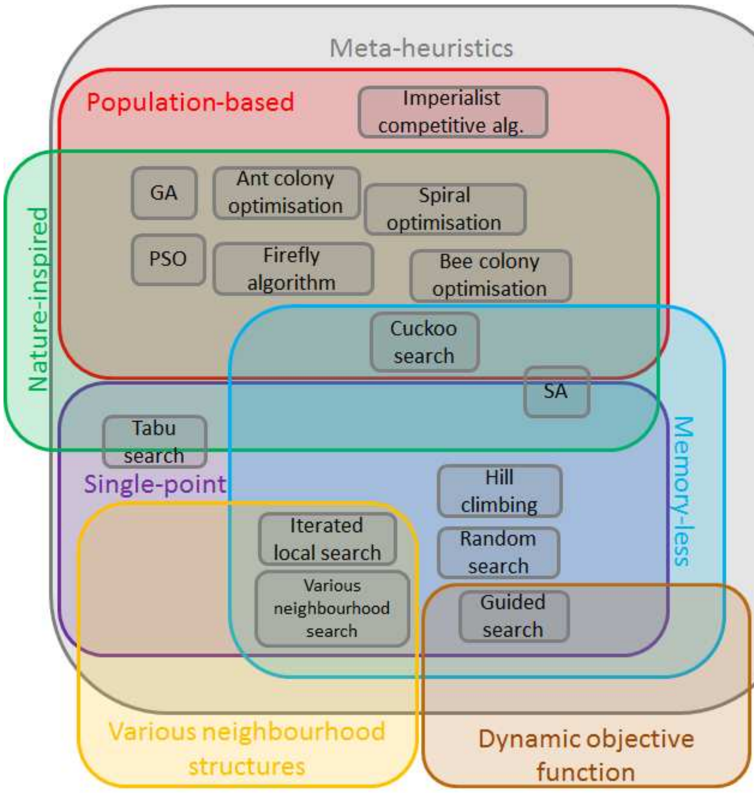

Figure 2.3: Classification of meta-heuristics

Memory usage vs. memory-less methods. Memory-less algorithms perform a Markov process, as the information they use to determine the next action is the current state of the search process. But other algorithms take advantage of using information of past states of the algorithms. For example, the use of short-term memory usually consists of keeping track of recently performed moves or checked solutions; and long-term memory is usually an accumulation of synthetic parameters about the search [Birattari et al., 2001, Blum and Roli, 2003].

Figure 2.3 illustrates a classification of meta-heuristics according to the concepts posed above and locating popular algorithms within the classification (the reader can find them in [Beheshti et al., 2013, Dréo et al., 2006, Glover and Kochenberger, 2003, Gonzalez, 2007, Luke, 2013, Torrent-Fontbona, 2012]). Nevertheless, the classification of some algorithms depends on the implementation. For example SA is usually considered a single-point algorithm, but some implementations of the algorithm work with a set of solutions, and thus it can be considered a population-based algorithm. On the other hand, the classification of other algorithms is not clear, especially in terms of nature or non-nature inspired algorithms. For example, one might ask the question if the use of memory in tabu search is not nature-inspired. Therefore,

Figure 2.3 should not be considered as a definitive or unequivocal classification.

2.3.3 Organisational aspects

Advances in communications technology, especially the Internet, have made possible to solve optimisation problems through multi-agent systems [Shoham and Leyton-Brown, 2009, Weiss, 1999]. Some of these systems use other optimisation methods, like those previously explained, but at the same time allow coordination among different resources (owned and controlled by different agents or organisations) in order to achieve the objectives. Furthermore, multi-agent systems are very useful in situations where there already are independent resources with their own objectives but with the need to be coordinated.

Many of the multi-agent systems are centrally coordinated by a single agent with most of the decision power. An example is auctions where a set of agents sends offers to another agent (auctioneer) which decides what offer is the most appropriate [Pla Planas, 2014].

However, there are also many multi-agent systems that are self-organised, and therefore not centrally coordinated. In these systems all agents participate in the decision-making and usually there is not a hierarchy among them [Ostrom, 1990, Pitt et al., 2012].

2.4 Optimisation on the smart grid

We are living a transition age regarding energy generation, consumption and management, due to the depletion or price rising of the traditional energy sources, like fossil fuels; due to environmental problems, such as the greenhouse effect; and due to social repudiation of some energy sources, such as nuclear power. Regarding electric energy, the transition is based on the implantation of a smart network, called smart grid, which enables a flexible management of the energy resources and demand. This section provides an overview of the state-of-the-art of the main features of the smart grid, namely, demand response, energy generation management and network planning. The state-of-the-art is preceded by a brief explanation of some basic electric concepts.

2.4.1 Some electrical concepts

This subsection provides a brief explanation of some energy-related concepts relevant throughout this dissertation.

Renewable energy resources. According to the International Energy Agency, RES are defined as resources that are generally not subject to depletion, such as heat and light from the sun, the force of wind, organic matter (biomass), falling water, ocean energy and geothermal heat [International Energy Agency, 1997]. Renewable energy does not include energy resources derived from fossil fuels, waste products from fossil fuels sources, or waste products from inorganic sources. Despite this definition, there is some debate about how to strictly define and distinguish renewable energy from non-renewable. For example, in some regions (i.e. most US states) there is a strong debate about whether hydroelectric power is a renewable or not (or if hydro-power plants should benefit from renewable energy policies) because of the air emissions produced during the building of reservoirs or their impact in the local ecosystems and wildlife.

Distributed generation. Although there is not a consistent definition of DG in the current literature, in general it can be defined as electric power generation within distribution networks on the customer side of the network. In Europe and parts of Asia it is also known as *decentralised generation* and in Anglo-American countries as *embedded generation* or *dispersed generation*. [Ackermann et al., 2001] discusses the relevant issues regarding DG and provides some general definitions of the term.

Distributed energy resources. DERs are DG units and they are characterised by being small power generators that can be aggregated to provide power necessary to meet regular demand [Ackermann et al., 2001]. In some cases the definition of DERs includes energy storage systems [Schienbein and Dagle, 2001]. Deploying DERs in a widespread, efficient and cost-effective manner requires complex integration with the existing electricity grid. Nevertheless, they can contribute to enhance the performance and control of the grid.

Virtual power plant. A Virtual Power Plant (VPP) is a cluster of DERs that behave as a single entity. The formation of VPPs responds to the need of alternative control strategies to the increased number of DG units and to the need of DG units to participate in electricity markets competing with big generators. The reader can find further information about VPPs in [Bakari and Kling, 2010, Pudjianto et al., 2007].

Micro-grid. A micro-grid is a group of interconnected loads and DERs with clearly defined physical and electrical boundaries that act as a single controllable entity with respect to the main grid. Micro-grids can be isolated but also connected to the main grid with the capacity to connect or disconnect from it to enable itself to operate in both connected or island mode. Micro-grids can support the integration of renewable energy sources and DERs market participation by clustering and controlling small generators that, behaving as a single entity, can participate in the energy markets and offer ancillary services to the main grid operator such as voltage control [Perea et al., 2008, Wang et al., 2014].

2.4.2 Demand-response

Matching demand to supply is one of the key features of the smart grid infrastructure and it is the central objective of Demand Side Management (DSM) techniques. DSM encourages energy consumers to change their behaviour or power profile according to stimuli like price in order to keep energy generation under a certain threshold.

In this regard, significant research efforts have been directed towards studying consumers' behaviour and how they respond in front of DSM strategies [Brounen et al., 2013, Gottwalt et al., 2011, Jia et al., 2012, Mohsenian-Rad et al., 2010]. Furthermore, over the past years, new DSM schemes or techniques have been proposed [Kota et al., 2012, Li et al., 2011, Mohsenian-Rad et al., 2010, Nguyen et al., 2012] or even frameworks or simulators, like [Faria et al., 2011], to test those DSM techniques. Generally, DSM techniques are based on game theory concepts and seek that a collection of consumers behave in a certain way, i.e. minimising the consumption during the peak hours, cooperating with other consumers, reporting true estimations of their expected consumption, etc. Each contribution in the literature focuses on achieving some of these objectives. For example, [Kota et al., 2012] and [Mohsenian-Rad et al., 2010] emphasise the importance of having mechanisms that incentivise the formation of coalitions of consumers that cooperate and jointly respond to DSM strategies. Usually, DSM strategies seek that consumers report their expected energy consumption, to the system operator [Li et al., 2011, Nguyen et al., 2012] or to the coalition of consumers [Kota et al., 2012, Mohsenian-Rad et al., 2010], in order to act in consequence (modify prices or consumptions). Then, [Kota et al., 2012, Li et al., 2011] focus on incentivising consumers to be honest and report the true expected consumption. Despite not all the presented DSM techniques having the same objectives, they all seek to minimise the energy consumption during the peak hours. Finally, it is worth mentioning the overview of DSM techniques provided by [Saad et al., 2012], and the discussion of [Vale et al., 2010] about the problem of energy resources management in the context of smart grids focusing on the importance of DSM strategies and mechanisms and intelligent applications that offer consumers a certain demand-response capacity.

Nevertheless, DSM is based on the capacity to send stimuli to clients with the hope that these clients will respond to such stimuli. Demand-response refers to those techniques or applications aimed to provide some response capacity to the clients when facing DSM techniques.

When consumers face DSM strategies, a demand-response method capable of controlling electric appliances and providing an optimal work schedule can reduce electricity costs. Most researchers have focused their efforts on providing centralised scheduling methods for reducing electricity costs of household appliances meeting the time and comfort requirements of the users. Then [Boutaba and Won-Ki Hong, 2010] presents a specific algorithm for reducing electricity consumption during the peak hours, [Kishore and Snyder, 2010] proposes to solve the appliances scheduling problem by decomposing the problem into sub-problems using dynamic programming, and [Ha et al., 2006] and [Pedrasa et al., 2010] present approaches based on tabu search and PSO respectively. Furthermore, some methods take advantage of a good price prediction to improve the quality of the solutions [Mohsenian-Rad and Leon-Garcia, 2010, Molderink et al., 2010]. On the other hand, [Erol-Kantarci and Mouftah, 2011] proposes a decentralised approach capable of achieving near-optimal solutions through wireless sensor networks. These approaches model the control and scheduling of appliances as optimisation problems consisting of scheduling of tasks, taking account of a variable price of the electricity.

Despite the research on household demand-response, only a few works take into account the energy consumption and variable electricity prices in a business process context or in the Project Scheduling Problem (PSP) which consists of scheduling tasks given a set of resources. Indeed, even the survey of the types of PSP presented in [Hartmann and Briskorn, 2010] does not mention any variant or extension of the PSP that considers the energy consumption. On those works that consider energy consumption in the business process, it is worth mentioning [Bose and Pal, 2012] which highlights the importance of considering energy issues for organisations, [Lopez et al., 2014, Rózycki and Weglarz, 2012] which propose formal models for energy-aware scheduling problems and methods for tackling it, and [Simonis and Hadzic, 2011] which explores the use of new constraints to tackle the problem with exact optimisation methods. This dissertation, especially Chapter 3, aims to complement these works and to fill the literature gap regarding energy-aware PSPs, formulating the problem and proposing different approaches to solve it.

Demand-response methods do not only gather methods to control and schedule tasks and appliances to reduce costs. Some authors take advantage of the opportunities derived from coalitions to explore new methods to respond to DSM strategies. Thus, [Rose et al., 2012, Veit et al., 2013, Vinyals et al., 2012] propose the formation of coalitions with methods and metrics for determining the best coalitions. The objective of forming coalitions is to create bigger entities with more flexibility in order to gain access to electricity markets for buying energy at better prices or offering services for revenue. However, these works only consider the creation of coalitions to minimise costs derived from energy consumption. In this regard, Chapter 3 presents a method for reducing costs derived from peak power demand through coalitions of consumers.

2.4.3 Energy demand allocation

The smart grid fosters DG, and therefore, poses the problem of determining the amount of energy each generator has to produce at each time given an energy demand, or what is known as the energy demand allocation. In other words, the problem consists of determining the portion of energy demand each generator has to cover. However, the complexity of working out the amount of energy each generator should produce at each time grows with the number of DERs. Then, the presence of a great number of DERs may become an unfeasible problem, leading to an under-utilisation and reducing the efficiency of the power system. In this regard, [Pudjianto et al., 2007] highlights the importance of VPPs as tools to increase the visibility and control of DERs, and thus, to exploit their potential benefits.

VPPs are thought to be formed by a collection of DERs and/or controllable loads, but that are seen as a single entity from the main grid. Since not all loads or generators in a VPP have to be ruled by the same entity, [Dimeas and Hatziargyriou, 2007] exposes the possible advantages of using multi-agent systems to operate VPPs. Following this line, [Chalkiadakis et al., 2011] and [Robu et al., 2012] propose mechanisms, mainly payment mechanisms, to encourage independent DERs to cooperate with others in order to create bigger entities to allow them to participate in electricity markets and therefore, increase their revenue.

Despite this, most research regarding VPP management is based on developing methods that optimise VPP operation, assuming that DERs can be controlled by a single and central entity. In this regard, [Oyarzabal et al., 2009] proposes a system to control grid voltage taking advantage of the presence of DERs and their reactive power production. In [Wille-Haussmann et al., 2010], the authors propose a method for managing VPPs with Combined Heat and Power (CHP) generators and thermal storages. In particular they propose to rely the VPP management on forecasting the load and production capacity of DERs using multiple linear regression. They then model the energy demand allocation problem as an integer linear programming and propose to solve the problem relaxing the integer conditions and running the simplex algorithm. Note that relaxing the integer conditions conveys finding out approximate solutions but not the optimal unless a branch and cut algorithm is used. Besides, this optimisation problem is too complex to use exact methods for solving large instances. Finally, the authors realise that electricity and heat demand are barely simultaneous, and so they propose the use of thermal storage to decouple the production of heat and electricity. [Wang et al., 2014] proposes a management scheme to optimise the operation of a VPP where renewable energies constitute a significant portion of the power resources. In particular, the authors propose the use of robust optimisation[3] and convert the problem into an integer quadratic programming problem[4] in order to solve it using branch and cut algorithms.

It is worth pointing out that the presence of RESs conveys an important uncertainty regarding electricity production due to the random availability of the energy sources (i.e. solar radiation or wind speed). Therefore, keeping the reliability of the system becomes a challenge. To tackle the uncertainty derived from RESs, some works, such as [Kongnam and Nuchprayoon, 2010, Zhang et al., 2013], take advantage of considering a single type of generators and then provide very good models and forecasting methods to optimise the VPP management.

On the other hand, some researchers bet for the use of electricity storage systems to minimise the effect of randomness of energy generation by RESs. An example is [Li et al., 2013], which proposes a method to aggregate and coordinate geographically dispersed Photo-Voltaic (PV) generators and batteries to participate in the electricity markets as a single entity. Note that the capacity to accurately estimate the capacity of generation is a key aspect when an entity participates in the electricity market. However, the construction of large storage systems of electricity is a technological challenge not yet solved. But electric vehicles are forecast to have a high penetration in society in the coming years. Thus, many people think that electric vehicles will play an important role in the future smart grid as storage systems. In this regard, [Binding et al., 2010] explains a system to optimise the coordination between electric vehicles in the context of the Danish EDISON project, which investigates how to integrate great fleets of electric vehicles in such a way as to give support to the electricity network.

The aggregation of DERs into VPPs is not only about facilitating the control of DERs, but also about giving them the opportunity to participate in electricity markets and increase their revenue. Accordingly, [Mashhour and Moghaddas-Tafreshi, 2011, Peik-Herfeh et al., 2013, You et al., 2010] propose methods and strategies for VPPs with RES to participate in electricity

[3]Robust optimisation is a field of the optimisation theory in which a measure of robustness is sought against uncertainty; i.e. [Wang et al., 2014] uses robust optimisation to confine the renewable generation in a pre-defined uncertainty set containing the worst-case scenario

[4]Integer quadratic programming is an type of optimisation problem where the objective function is quadratic, the constraints are linear inequalities and some or all variables are restricted to be integers.

markets and maximise their benefits taking into account the uncertainty in the energy generation. Once the VPP knows the amount of energy it has to produce, then comes the problem of deciding how to allocate the production among its DERs. The final problem to solve is an optimisation problem, usually a non-linear integer programming problem. Hence [Mashhour and Moghaddas-Tafreshi, 2011] proposes the use of GA to solve it and [Peik-Herfeh et al., 2013, You et al., 2010] propose B&B methods. Although VPPs are usually formed by a collection of DERs and loads, the presence of both is not necessary. In this regard, a collection of controllable loads can form a VPP and participate in electricity markets, offering load curtailing. For example [Ruiz et al., 2009] presents methods for scheduling loads. Although it can be classified as demand response, the truth is that it is not, because demand response methods are thought to provide consumers with the ability to modify its consumption responding to stimuli. Also, on the other hand, what [Ruiz et al., 2009] proposes is that all the centrally controlled loads offer to modify their consumption as a service to the system operator. Finally, [Ausubel and Cramton, 2010] analyses the energy markets which VPPs usually participate in.

This dissertation contributes to the literature about energy demand allocation, with Chapter 4 presenting a self-organised method to determine the amount of energy each DER has to produce at each time. This contribution aims to fill the gap in energy demand allocation problems tackled by self-organised methods instead of single agent approaches or centralised multi-agent systems.

2.4.4 Network planning

The potential benefits that can be achieved with the presence of DERs in a smart grid can become disadvantageous if there is not an appropriate planning. The potential advantages mainly depend on the visibility of the generators and the ability to control them. But also, these potential benefits are conditioned by the location where DERs are connected, their capacity of generation and the type of energy source they use. For example, if it is sought to control the voltage at an end point of the grid, the best option could be to connect a generator to this end point with the capacity to control the voltage. On the other hand, if it is sought to minimise the power losses, usually the best option will consist of placing the generators as close as possible to the loads so that these generators can produce electricity when there is a demand for electricity. Network planning is a wider problem involving problems from many disciplines. However, this thesis is focused only on the problem of locating and sizing generators.

The problem of locating and sizing generators in a power grid, Distributed Generation Location & Sizing (DGLS), seeks to answer the questions that Figure 2.4 illustrates. These are how

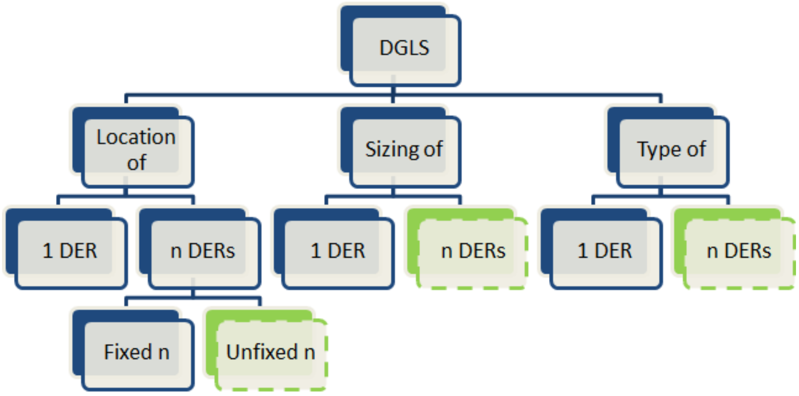

Figure 2.4: Classification of the issues tackled by the DGLS problem. In green, the issues tackled in this paper.

many generators should be placed [Moradi and Abedini, 2012], which type of generators they should be [Nerves and Roncesvalles, 2009], how big these generators should be and where is the most appropriate location to place them [Aman et al., 2014, Ameli et al., 2014, Helal et al., 2012, Martín García and Gil Mena, 2013, Moradi and Abedini, 2012, Nerves and Roncesvalles, 2009, Pisica et al., 2009], in order to optimise a set of objectives that are usually power losses, the voltage throughout the grid and the economical benefits or costs. This problem is very complex to solve and, thus it is usually simplified by, for example, not considering the variation of the load and generation throughout time, or solving the problem only for a given number of generators or for a single type of generator. Table 2.1 summarises which questions of the DGLS problem are tackled and which are omitted in the literature reviewed in this section.

Moreover, to avoid simplifying the problem in excess, many researchers opt for the use of methods based on meta-heuristics that are able to find good solutions in feasible time but in exchange for a guarantee of finding the optimal solution. For example [Moradi and Abedini, 2012] presents an approach based on the combination of GA for locating DERs and PSO for determining their sizes. The authors formulate the problem as a non-linear problem with an objective function that aggregates power losses, voltage profile index and voltage stability index. The proposed algorithm is able to find the optimum number of DG units, assuming that they are the same type (i.e. they use the same technology and their parameters are identical). Moreover, the authors do not consider the variation of the load and generation throughout time. Other GA based algorithms are presented in [Helal et al., 2012] and [Pisica et al., 2009], but both need the number of DERs to locate from beforehand. They differ in the objective function they use, i.e. [Helal et al., 2012] only minimises power losses while keeping an acceptable voltage profile and [Pisica et al., 2009] minimises power losses and investment costs of the DERs. Like [Helal et al., 2012] and [Pisica et al., 2009], the algorithm presented in [Martín García and Gil Mena, 2013] needs, from the beginning, the number of DG units to locate. However, conversely to [Helal et al., 2012, Pisica et al., 2009], this approach is based on the teaching-learning algorithm, which is a meta-heuristic algorithm similar to PSO. Another meta-heuristic approach is presented in [Ameli et al., 2014] where the authors use a multi-objective PSO to determine the optimal location and size of a set of DG units. Authors of [Pisica et al., 2009] and [Ameli et al., 2014] take into account not only power losses and grid voltages but also the economic implications of installing new DG units. Another work that takes advantage of the PSO properties is [Aman et al., 2014] which presents a hybrid PSO approach for placing and sizing distributed generators. Nevertheless [Aman et al., 2014] aims the approach to take account of the penetration level of the distributed generators (usage of DERs) besides other objectives such as the voltage stability index. All these works share the assumption that all generators are equal except for their size and they do not consider the variation of the load and generation over time. Not considering the variation of the load and generation may not be a critical issue if the generators are capable to produce when it is required. However, in case of renewable generators, generation and consumption may not be simultaneous (i.e. residential peak demand usually occurs on low radiation times).

A work where the variation of the generation and load over time is considered is [Nerves and Roncesvalles, 2009] where the authors present an evolutionary programming-based approach to solve the DGLS problem considering different types of DG, the availability of the resource used by DG units (wind, solar radiation) and a load profile. However, their approach needs the number of DERs to locate from beforehand.

Other authors also focus on developing methods for the size of generators but not taking into account the electric grid or the electric load. For example [Emami and Noghreh, 2010, González et al., 2010] use GA to distribute wind turbines in a wind farm. Therefore, they focus on placing the wind turbines in order to not disturb each other and to maximise the electricity production from the wind. Note that they seek the size of a wind farm and other parameters (like the distribution of the wind turbines) but not the location of the farm. Other examples are [Kornelakis and Marinakis, 2010, López et al., 2008, López and Galán, 2008] which use PSO to determine the size and other parameters of PV and biomass generators respectively.

	One or some DERs	DER location	Type of DER	Size of DER	Number of DERs
[Moradi and Abedini, 2012]	Some	√		√	√
[Aman et al., 2014] [Ameli et al., 2014] [Helal et al., 2012] [Martín García and Gil Mena, 2013] [Pisica et al., 2009]	Some	√		√	
[Atwa and El-Saadany, 2010] [Nerves and Roncesvalles, 2009]	Some	√	√	√	
[Elnashar et al., 2010] [Gautam and Mithulananthan, 2007] [Ghosh et al., 2010] [López et al., 2008] [López and Galán, 2008]	One	√		√	
[Emami and Noghreh, 2010] [González et al., 2010] [Kornelakis and Marinakis, 2010]	One			√	

Table 2.1: Parts of the DGLS problem tackled by the state-of-the-art

All previously presented papers simplify the DGLS problem and take advantage of the properties of meta-heuristic algorithms. However, a key work is [Atwa and El-Saadany, 2010] which provides a methodology to determine the number, location, size and type of DERs. For doing so, it models the PV and wind generation at each time as probabilistic functions and formulates the problem as a mixed integer non-linear. It proposes to solve the problem on a GAMS (General Algebraic Modelling System) environment. It takes into consideration the hourly variation of the generation and load. For formulating the problem, [Atwa and El-Saadany, 2010] divides all possible combinations of wind and PV output powers into states with their according probability. Then it solves the optimal power flow problem for each state and builds the final solution aggregating the partial results using the probabilities.

In addition, there are other papers in the literature that tackle the DGLS problem but do not use meta-heuristic algorithms. Some examples are [Elnashar et al., 2010, Gautam and Mithulananthan, 2007, Ghosh et al., 2010], which propose different approaches for locating and sizing a single DG unit in a given power distribution grid. For example, [Elnashar et al., 2010] presents a visual optimization approach to determine the optimal size and location of a single DG unit; [Gautam and Mithulananthan, 2007] solves the location and sizing problem of a single DG unit by identifying the different candidate locations on the basis of locating the marginal price and the load at each bus; conversely to this dissertation, and specially Chapter 5, [Gautam and Mithulananthan, 2007] considers different electricity prices at each bus; and [Ghosh et al., 2010] implements a conventional iterative method combined with the Newton-Raphston method for the load flow analysis. Nevertheless, most works that do not use meta-heuristics, solve the DGLS problem for a single DG unit due to its complexity.

Chapter 5 completes the literature regarding the DGLS problem, proposing and analysing approaches based on meta-heuristic algorithms capable of working out the near-optimal number, location, size and type of generators for a given power grid and electricity demand. Chapter 5 differs from [Atwa and El-Saadany, 2010] for the use of meta-heuristics and for optimising other objectives beyond power losses. Furthermore, the fact of using meta-heuristics allows the use of an easier formulation of the problem.

2.5 Summary

This Chapter has presented a background regarding optimisation and smart grid concepts needed throughout the reading of this dissertation. It has also presented different classifications of optimisation methods according to different paradigms or concepts that the algorithms are based on. Next, the chapter has presented a review of the literature regarding smart grids and the problems they posed related to demand response, energy demand allocation and the planning of placing new DERs in a given power grid.

According to this literature review, Table 2.2 exposes the optimisation methodologies chosen in the different works. In demand response and energy demand allocation problems (which are similar resource allocation problems), it is common to simplify the model in such a way that it can be solved using linear programming techniques. Usually the constraints and the objective function are linearized and the constraints of integer variables are relaxed. Then, the problem model can be solved to the optimality, but this optimality is *virtual* due to a possible excess of idealisation or simplification of the problem.

On the other hand, as Table 2.2 shows, meta-heuristics are widely chosen methods for solving the optimisation problems posed by the smart grid, especially for solving the DGLS problem. This dissertation also proposes to solve the posed complete DGLS problem, and not only parts of it (see Table 2.1), using different meta-heuristics. Then it provides a comparison of their performance.

The use of B&B for solving smart grid problems may seem appropriate to its capacity to

Optimisation method	Demand response	Energy demand allocation	DGLS	
Linear programming or convex optimisation	[Li et al., 2011] [Mohsenian-Rad et al., 2010] [Mohsenian-Rad and Leon-Garcia, 2010] [Nguyen et al., 2012] [Vinyals et al., 2012]	[Binding et al., 2010] [Oyarzabal et al., 2009] [Wang et al., 2014] [Wille-Haussmann et al., 2010]	[Atwa and El-Saadany, 2010]	
B&B	[Rózycki and Weglarz, 2012] [Simonis and Hadzic, 2011]	[Oyarzabal et al., 2009] [Peik-Herfeh et al., 2013] [You et al., 2010]	[Atwa and El-Saadany, 2010]	Exact
Dynamic programming	[Kishore and Snyder, 2010] [Molderink et al., 2010]			
GA and other evolutionary algorithms		[Li et al., 2013] [Mashhour and Moghaddas-Tafreshi, 2011]	[Emami and Noghreh, 2010] [González et al., 2010] [Helal et al., 2012] [Moradi and Abedini, 2012] [Nerves and Roncesvalles, 2009] [Pisica et al., 2009]	
PSO and other swarm algorithms	[Pedrasa et al., 2010]	[Kongnam and Nuchprayoon, 2010] [Zhang et al., 2013]	[Aman et al., 2014] [Ameli et al., 2014] [Kornelakis and Marinakis, 2010] [López et al., 2008] [López and Galán, 2008] [Martín García and Gil Mena, 2013] [Moradi and Abedini, 2012]	Inexact
Stochastic methods	[Ha et al., 2006]			
Deterministic methods	[Boutaba and Won-Ki Hong, 2010]			
Game theoretic games	[Kota et al., 2012] [Robu et al., 2012]	[Chalkiadakis et al., 2011]		

Table 2.2: Utilisation of optimisation methods

tackle any kind of model, but in practice, its use is restricted to solving small instances of the problems due to their complexity. This dissertation also explores the utilisation of B&B for scheduling tasks as a mean of demand response, but due to the complexity of the problem, it explores the utilisation of GA for solving large instances of the problem.

Furthermore, this dissertation also focuses on the development of multi-agent methods for tackling demand response and energy demand allocation problems. In this regard it contributes in the development of mechanisms to incentivise the involved agents to behave in a certain way that seeks the general well-being. Some examples are promoting to reveal and report the truth or a mechanism of fairness that merges different concepts of justice. Besides, when these multi-agent mechanisms implicitly have an optimisation problem to solve, i.e. determining the winner of an auction, this dissertation proposes the use of meta-heuristics to solve it.

Summing up, it can be said that, in general, there is a trend to simplify smart grids' problems, either by simplifying the model for them using exact algorithms, or by using meta-heuristics able to provide good, but not optimal, solutions to complex models. Regarding meta-heuristics, there is a clear trend on using population-based algorithms such as PSO and GA.

In addition, some authors bet for the use of multi-agent systems to tackle demand response and energy demand allocation problems. These systems are capable to model the presence of independent organisations involved in the problem context. Usually, these methods are based on game theory and use mechanisms to incentivise agents to behave in a certain way.

Beyond the literature review presented in this chapter, it is worth pointing out the review provided in [Baños et al., 2011] which surveys optimisation methods applied for solving problems related to the design, planning (i.e. determining the location, size and type of new DERs) and control of renewable DERs. Thus, [Baños et al., 2011] may be useful to the reader to complete the literature review provided in this chapter regarding other problems related to renewable energy resources. Additionally, [Baños et al., 2011] shows a clear trend on using meta-heuristics, especially GA and PSO, for solving DGLS and energy demand allocation problems.

In conclusion, from the literature review several gaps have been found that this thesis aims to cover. First, there are many works regarding household demand response, but only a few tackling demand response problems (or energy issues) in business processes. Moreover, there is no work proposing demand response methods to reduce peak power related costs and not only energy related costs. Regarding energy demand allocation, most research is focused on developing centralised optimisation methods, but no research explores the use of self-organised methods to tackle this problem. That, added to the significant presence of DERs in contexts of DG makes the exploration of self-organised methods an interesting line of research. Finally, the DGLS problem has been generally tackled in parts, and no works analyse the performance of meta-heuristic algorithms to solve the complete DGLS problem.

CHAPTER 3

DEMAND RESPONSE: RESOURCE ALLOCATION ON THE SMART GRID

In this chapter we address demand response methodologies for reducing costs derived from the electricity tariff. First, we tackle the energy-aware resource allocation problem formalising it and presenting some techniques to solve it. In particular, the problem is tackled from two perspectives: a single-agent context and, a multi-agent context where independent agents that manage resources are ordered to perform tasks. Second, it proposes a new methodology based on power re-allocation among coalitions of consumers for reducing demand peaks and thus, power related costs.

3.1 Introduction

The future smart grid provides a new scenario in which demand for electricity could be made more adaptive to supply conditions, what is known as demand response. Demand response involves utility strategies that influence the end use of energy according to the desired changes in the pattern and magnitude of an energy load, known as load shape [Gellings, 2009].

One of the strategies for demand response handling is to promote time-dependent rates; thus, energy demand peaks can be softened as a consequence of users shifting their consumption to the energy cheapest hours. However, it is not only a case of shifting energy consumption but, due to sustainable issues, it is important to reduce the amount of energy consumed, in what is called energy efficiency. In this regard, the ISO50001:2011 standard considers the definition of energy plans, so that companies can compromise to move from a current energy load shape to a lower one. The fulfilment of this standard regarding the consequent contribution of the companies to the reduction of emissions will be as important as ISO:9000 has been for quality.

Another DSM strategy used is maximum power dependent pricing, which highly penalises the customer when they exceed the contracted power, even if they do so for a short period of time.

This dissertation contributes with two demand-response methods to deal with these DSM strategies. The first, a method regarding how to schedule the activities inside a company so that it becomes energy efficient. The second method provides a cooperation framework among different entities such that they can share their contracted power, tackling the maximum power dependent prices and helping to fulfil the companies' local profile, contributing to energy efficiency too.

3.2 Energy aware project scheduling problem

Energy-related aspects affect the scheduling of resources in companies, since the energy consumption of the resources in either their production or service activities should follow the load shape agreed and when there is some margin for scheduling the use of one resource inside a time window, companies would be more interested in using the resource on the cheapest energy hours. Nowadays scheduling tools are mainly based on the makespan and costs. However, in the coming years, it will become crucial to incorporate energy issues in business process management to make them adaptive to the changes smart grids will bring about [Bose and Pal, 2012, Lopez et al., 2014].

The problem of assigning resources to tasks considering resources abilities, and scheduling the execution of these tasks optimising a particular objective is known as the multi Mode Project Scheduling Problem (MPSP) [Hartmann and Briskorn, 2010]. MPSP incorporates the possibility of executing tasks in different modes, which are usually determined by the resource in charge of carrying it out, defining the parameters of the performance. Thus, this section extends the MPSP, becoming the energy-aware multi Mode Project Scheduling Problem (e-MPSP) for incorporating compromised load patterns as well as time-dependent energy prices whilst minimising not only the makespan, but also production costs (including energy-related costs) and energy consumption.

3.2.1 Problem statement

The e-MPSP extends the MPSP and basically consists of working out a schedule to execute a group of tasks forming a project, and determining which resources will carry out the tasks in order to optimise some objectives. Tasks T_i, $i \in \{1,\ldots,N\}$ forming a project are linked by a classical end-to-start precedence relationship, which means that a task i cannot start before all its predecessor $\mathscr{P}_i$ tasks have finished. On the other hand, each resource R_m, $m \in \{1,\ldots,M\}$, masters one or more skills among all the skills S_k, $k \in \{1,\ldots,K\}$, existing in the project. Skills determine whether a resource is able to execute a task or not depending on the requirements of such task and the resource in charge of a task determines the execution mode of the task defining the processing time $p_{i,m}$, the resource cost $c_{i,m}$ and the energy consumption $e_{i,m}$.

Therefore, the resolution of the e-MPSP is given for a set of variables s_i which indicates the start time of each task i, and another set of binary variables $z_{i,m}$ which determines which resource m is in charge of the execution of each task i, and so, determines the execution mode of each task. Hence, an assignment of values to these variables $\mathscr{S} = \{s_0,\ldots,s_N\}$ and $\mathscr{Z} = \left\{z_{1,1},\ldots,z_{i,m},\ldots,z_{N,M}\right\}$ define the scheduled starting time and execution mode of the tasks of the project. Then, for the sake of simplicity a schedule is denoted as $(\mathscr{S},\mathscr{Z})$.

Given the common description of the e-MPSP and MPSP and the involved variables and parameters, the end-to-start precedence relationship is fulfilled if

$$s_i \geq \sum_{j=1}^{N} s_j + \sum_{k=1}^{M} z_{j,m} p_{j,m} \quad \forall j \in \mathscr{P}_i \tag{3.1}$$

Additionally, start and end times must be within the start $\left[\underline{s_i}, \overline{s_i}\right]$ and end $\left[\underline{et_i}, \overline{et_i}\right]$ time intervals specified by the task:

$$\underline{s_i} \leq s_i \leq \overline{s_i} \tag{3.2}$$

$$\underline{et_i} \leq s_i + \sum_{m=1}^{M} z_{j,m} p_{j,m} \leq \overline{et_i} \tag{3.3}$$

Similarly, task execution must be within the project time interval defined by ST and ET:

$$ST \leq s_i \leq s_i + \sum_{m=1}^{M} z_{j,m} p_{j,m} < ET \tag{3.4}$$

Furthermore, the specification that each task has to be performed by a single resource is formalised as follows:

$$\sum_{k=1}^{M} z_{i,m} = 1 \quad \forall i \tag{3.5}$$

As has been remarked previously, the e-MPSP extends the MPSP to take account of the energy consumption and its consequences under the smart grid paradigm. Then, the energy consumption derived from a schedule $(\mathscr{S}, \mathscr{Z})$ at a given time t is defined by $\rho_t(\mathscr{S}, \mathscr{Z})$, also called load profile. As Equation (3.6) formalises, it consists of the sum of the energy consumptions (second summation) of all active tasks at time t (first summation)

$$\rho_t(\mathscr{S}, \mathscr{Z}) = \sum_{\forall i | s_i \leq t < s_i + \sum_{l=1}^{M} z_{i,l} p_{i,l}} \sum_{m=1}^{M} z_{i,m} \cdot e_{i,m} \tag{3.6}$$

This load profile $\rho_t \ \forall t$ has to fit a compromised load shape Σ which is loosely defined within a set of boundaries as follows:

$$\Sigma = \left\langle \underline{P_t}, \overline{P_t}, \underline{\rho_t}, \overline{\rho_t} \right\rangle_{\forall t} \tag{3.7}$$

where $\underline{P_t}$ and $\overline{P_t}$ are the minimum and maximum allowed energy consumption at time t, and $\underline{\rho_t}$ and $\overline{\rho_t}$ are the lower and upper bounds of the compromised energy load. An organisation with a compromised energy profile Σ must keep its energy consumption ρ_t within the interval $\left[\underline{P_t}, \overline{P_t}\right]$, but also it is expected to keep ρ_t in the interval $\left[\underline{\rho_t}, \overline{\rho_t}\right]$ because consuming energy out of this interval would involve some economic consequences like augmented prices or fines. The economic agreement (energy tariff) an organisation is subject to, is defined as:

$$\Gamma = \left\langle \pi_t, \underline{\pi_t}, \overline{\pi_t}, \underline{f_t}, \overline{f_t} \right\rangle \tag{3.8}$$

where π_t is the time-dependent price of the energy when $\rho_t \in \left[\underline{\rho_t}, \overline{\rho_t}\right]$, $\underline{\pi_t}$ is the price when $\rho_t < \underline{\rho_t}$ and $\overline{\pi_t}$ the price when $\rho_t > \overline{\rho_t}$; $\underline{f_t}$ and $\overline{f_t}$ are fines applied when $\rho_t < \underline{\rho_t}$ and $\rho_t > \overline{\rho_t}$ respectively. Note that $\underline{f_t}$ and $\overline{f_t}$ are not per-energy-unit prices. Figure 3.1 shows a graphical representation of Γ and Σ.

The e-MPSP consists of determining a schedule $(\mathscr{S}, \mathscr{Z})$ that fits the time and energy constraints but that also minimises some objectives. This dissertation proposes to solve the e-MPSP optimising three objectives:

- Makespan: the processing time of the whole project. It is defined as the maximum difference between the start of one task and the end of another.

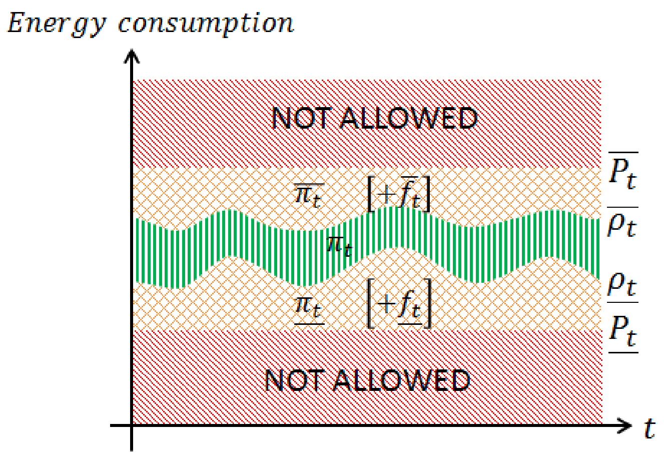

Figure 3.1: Load shape example. The green zone defines the gap $\left[\underline{\rho_t}, \overline{\rho_t}\right]$ where the energy consumption should be. Outside this gap, augmented prices, $\underline{\pi_t}$ or $\overline{\pi_t}$, and fines, $\underline{f_t}$ or $\overline{f_t}$, will be imposed by the electricity company. Red zone is the not allowed consumption due to, for example, physical features of the line.

$$C_T(\mathscr{S}, \mathscr{Z}) = \max_{i,j} \left(s_i + \sum_{m=1}^{M} z_{i,m} p_{i,m} - s_j \right), \quad \forall i, j \; 1 \leq i, j \leq N \tag{3.9}$$

Including a dummy start task and an end task, the makespan could be defined by the difference between the beginning and the end of the start and end tasks respectively.

- Energy consumption: sum of all the energy needed to execute tasks in the scheduled modes.

$$C_E(\mathscr{S}, \mathscr{Z}) = \sum_{t=1}^{T_{max}} \rho_t(\mathscr{S}, \mathscr{Z}) \tag{3.10}$$

- Economic cost: cost of the resources used to execute tasks plus the cost of the energy consumed. It is defined as follows:

$$C_M(\mathscr{S}, \mathscr{Z}) = \sum_{i=1}^{N} \sum_{m=1}^{M} z_{i,m} c_{i,m} + \sum_{t=1}^{T_{max}} \Phi(\rho_t(\mathscr{S}, \mathscr{Z}), \Sigma, \Gamma) \tag{3.11}$$

where

$$\Phi(\rho_t, \Sigma, \Gamma) = \begin{cases} \rho_t \pi_t + \left(\underline{\rho_t} - \rho_t\right) \underline{\pi_t} + \underline{f_t} & \rho_t < \underline{\rho_t} \\ \rho_t \pi_t & \underline{\rho_t} \leq \rho_t \leq \overline{\rho_t} \\ \rho_t \pi_t + (\rho_t - \overline{\rho_t}) \overline{\pi_t} + \overline{f_t} & \rho_t > \overline{\rho_t} \end{cases} \tag{3.12}$$

Observe then, that the second term related to energy cost depends on the time argument, leading the optimisation problem e-MPSP to be much more complex than the MPSP.

Given the objectives to minimise, the e-MPSP consists of finding the schedule $(\mathscr{S}, \mathscr{X})$ that minimises a weighted sum of them as follows:

$$\min_{\mathscr{S}, \mathscr{X}} \{\Psi(\mathscr{S}, \mathscr{X})\} \tag{3.13}$$

where

$$\Psi(\mathscr{S}, \mathscr{X}) = \{w_1 C_T(\mathscr{S}, \mathscr{X}) + w_2 C_E(\mathscr{S}, \mathscr{X}) + w_3 C_M(\mathscr{S}, \mathscr{X})\} \tag{3.14}$$

Weights values will depend on each application case and they should be used to tune the importance of each objective and, at the same time, to equilibrate the magnitude of the values resulting from each objective function. Additionally, it is worth pointing out that the complexity of the e-MPSP is higher than the MPSP, as the minimisation process depends on variables prices.

Next an example is provided of e-MPSP with different Σ and Γ that results in different optimal schedules.

Example 3.2.1. Illustrative example

Consider that there is a project to schedule that consists of a set of activities $\{T_1, T_2, T_3\}$. All tasks need to be performed by a resource with the same skill S_1 and the maximum time horizon considered is $T_{max} = 5$. Consider a discretionary interval of 1 unit.

Also consider having a set of resources $\{R_1, R_2\}$ which both have the skill S_1. Resources' energy consumptions are $e_{1,1} = 1$, $e_{1,2} = 5$, $e_{2,1} = 2$, $e_{2,2} = 3$, $e_{3,1} = 4$, $e_{3,2} = 2$ (kWh); the durations are $p_{1,1} = 3$, $p_{1,2} = 1$, $p_{2,1} = 2$, $p_{2,2} = 3$, $p_{3,1} = 2$, $p_{3,2} = 1$ (hours). Focusing on the time-dependent prices and their related cost, $\sum_{t=1}^{T_{max}} \Phi(\rho_t(\mathscr{S}, \mathscr{X}), \Sigma, \Gamma)$, which are the second component of C_M. Thus, the resources costs $c_{i,m}$ are considered negligible $(\sum_{i=1}^{N} \sum_{m=1}^{M} z_{i,m} c_{i,m} \approx 0)$, and $w_1 = w_2 = 0$ and $w_3 = 1$ in $\Psi(\mathscr{S}, \mathscr{X})$.

Finally, consider the three different scheduling scenarios with different load shapes and electric tariffs:

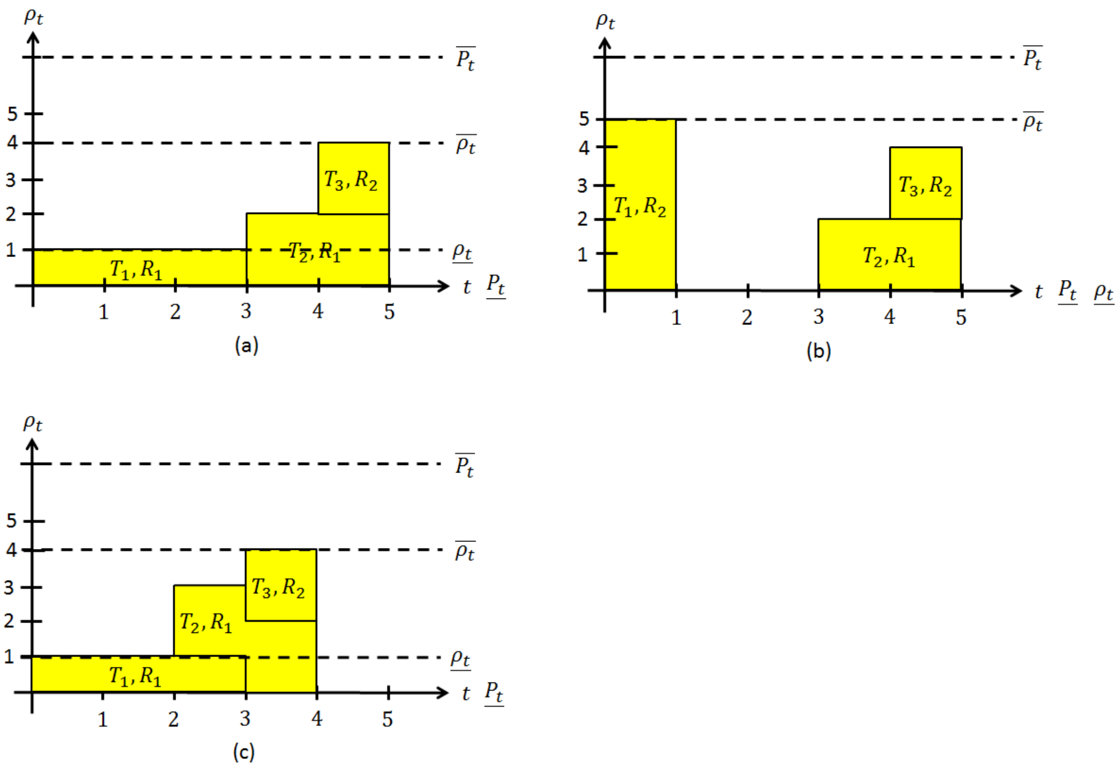

Figure 3.2: Examples of scheduling

Case (a):

$$\Gamma = \left\langle \begin{bmatrix}1\\2\\3\\2\\1\end{bmatrix}, \begin{bmatrix}2\\4\\6\\4\\2\end{bmatrix}, \begin{bmatrix}2\\4\\6\\4\\2\end{bmatrix}, \begin{bmatrix}1\\1\\1\\1\\1\end{bmatrix}, \begin{bmatrix}1\\1\\1\\1\\1\end{bmatrix} \right\rangle$$

$$\Sigma = \left\langle \begin{bmatrix}0\\0\\0\\0\\0\end{bmatrix}, \begin{bmatrix}10\\10\\10\\10\\10\end{bmatrix}, \begin{bmatrix}1\\1\\1\\1\\1\end{bmatrix}, \begin{bmatrix}4\\4\\4\\4\\4\end{bmatrix} \right\rangle$$

For $t = 0$, the allowed energy defined in case (a) is defined by $\underline{P_0} = 0$ and $\overline{P_0} = 10$, while the compromised energy consumption is within $\underline{\rho_0} = 1$ and $\overline{\rho_0} = 4$. That happens for all t. Regarding energy tariffs, for $t = 0$, $\pi_0 = 1$, $\underline{\pi_0} = 2$, $\overline{\pi_0} = 2$, $\underline{f_0} = 1$, and $\overline{f_0} = 1$; while for $t = 1$, $\pi_1 = 2$, $\underline{\pi_0} = 4$, $\overline{\pi_0} = 4$, $\underline{f_0} = 1$, and $\overline{f_0} = 1$.

Case (b): Same Γ as (a), but with a broader load shape Σ, as follows

$$\Sigma = \left\langle \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 10 \\ 10 \\ 10 \\ 10 \\ 10 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 5 \\ 5 \\ 5 \\ 5 \\ 5 \end{bmatrix} \right\rangle$$

$\underline{\rho_t}$ has been lowered from 1 to 0, and $\overline{\rho_t}$ has been increased from 4 to 5.

Case (c): Same Σ as (a), but with a different time-dependent tariff Γ, as follows

$$\Gamma = \left\langle \begin{bmatrix} 3 \\ 2 \\ 1 \\ 2 \\ 3 \end{bmatrix}, \begin{bmatrix} 6 \\ 4 \\ 2 \\ 4 \\ 6 \end{bmatrix}, \begin{bmatrix} 6 \\ 4 \\ 2 \\ 4 \\ 6 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \right\rangle$$

In this case, the prices behave in the opposite way to (a): when prices in (a) decrease, in (c) they increase, and vice-versa.

The resulting optimal schedules of each case are illustrated in Figure 3.2. This shows how optimal schedules try to keep the energy profile in the bounds defined by Σ while trying to perform most of the tasks in the cheapest time slots. Solutions for cases (a) and (b) fulfil the compromised load shape ($\rho_t \in \left[\underline{\rho_t}, \overline{\rho_t}\right]$). The optimal solution found in case (c) does not fulfil the load shape (there is no load for $t = 5$, so the minimum required load $\underline{\rho_5}$ is not reached) because, from the economic point of view, it is cheaper to break it down than to move one activity to the slot 4-5. Thus, it is necessary to work out if it is worthwhile to break down some soft-constraints and to face the involved penalty.

Assumptions and limitations

The presented formulation of the e-MPSP assumes that the energy price is known in advance as well as the energy consumption, processing time and the cost of using a resource for carrying out a particular task. It is also assumed that the tasks needed to execute are known.

3.2.2 Single-agent approaches

The e-MPSP, like the PSP or MPSP, is a very complex optimisation problem whose objective function is not derivable and whose solution space is not convex. Different methods have been proposed to tackle PSPs and MPSP. For example, some authors, like [Bellenguez-Morineau and Néron, 2007], propose exact methods such as B&B to solve small instances of scheduling problems, while, others bet for the use of meta-heuristic algorithms, such as tabu search [Yu et al., 2011], GA [Alcaraz and Maroto, 2001], or PSO [Jarboui et al., 2008], due to the complexity of the problem.

This chapter proposes the use of algorithms that can handle the objective function and the constraints posed in the previous section. In particular, it presents a B&B algorithm and a GA to tackle the problem and find good, even optimal, solutions. These algorithms consider that all resources are managed by a single agent (i.e. a corporation), the same one that needs to perform the tasks.

Branch and bound

B&B is a complete optimisation method able to handle any kind of objective function or constraint [Schneider and Kirkpatrick, 2006]. The proposed B&B approach seeks the optimal schedule by first building a tree-shaped graph where each depth level corresponds to an activity and each node corresponds to an activity executed by a particular resource with a particular start time. Therefore, each node corresponds to a specific pair $z_{i,m}$ and s_i and each branch of the tree corresponds to a particular schedule $(\mathscr{S}, \mathscr{Z})$.

Since all nodes in the same depth level correspond to the same task, nodes sharing the same level are not interconnected. Furthermore, for minimising the number of nodes, and therefore the search effort, depth levels are ordered into decreasing order of their number of nodes, meaning that activities with less available execution modes and possible start times, make up the top levels.

Algorithm 3.1 shows the recursive procedure of B&B for exploring the tree. Due to the size of the tree, B&B explores it in a depth-first-search way. It enables the algorithm to keep in memory only the best branch found and the current explored branch, reducing, thereby, the memory usage. Furthermore, to speed up the search time, the algorithm stops exploring a branch when it stops fitting the constraints (i.e. $\rho_t > \overline{P_t}$). Then it backtracks to the first node with an explored path. Nevertheless, constraint $\rho_t > \underline{P_t}$ cannot be checked before reaching the leaf node because all activities are energy consuming.

Algorithm 3.1 BB_expand(bag)

Require: bag of tasks modes (bag) grouped by tasks and ordered into a decreasing order

```
b ← choose(bag[0]) 'take a task mode from the corresponding task-level'
branch.add(b)
fits ← checkConstraints(branch) 'returns true if it fits.'
Aux ← remove_current_task_bids(bag) 'removes all bids related to the task done by b.'
if fits and not leaf node then
    BB_expand(Aux)
else
    value ← evaluate(branch) 'returns schedule's value and ∞ if it does not fit the constraints.'
    if value < bestValue then
        bestBranch ← branch
    end if
end if
branch.remove(b) 'remove b from the current explored branch.'
```

When B&B reaches a leaf node, it evaluates the branch (the schedule) according to Equation (3.14) and compares it with the past best branch found. If the current branch is better, the past best branch is replaced by it and backtracks to the first node with an available unexplored path. For the sake of simplicity, Algorithm 3.1 refers to a task to be executed by a particular resource at a particular start time as task mode.

Genetic algorithm

The complexity of e-MPSP rises exponentially with the number of possible task modes and possible task starting times. Then, sometimes, it becomes infeasible to find the optimal solution through complete methods. In these situations it becomes attractive to find, not the optimal solution, but a good one, in a feasible amount of time. This is the main raison d´être of meta-heuristic algorithms, the GA among them [Haupt and Haupt, 2004, Holland, 1975, Mitchell, 1998, Schneider and Kirkpatrick, 2006, Torrent-Fontbona, 2012]. This chapter presents a GA approach for solving the e-MPSP. GAs exploit the ability of the evolution operators to improve the quality of a collection of solutions, called population, generation after generation, in order to find the optimal solution to a given problem. However, GAs cannot guarantee that the solution they provide is the optimal one. Despite this, GAs are widely used to solve hard optimisation problems because they are very effective tools for performing a global search and their use does not involve many mathematical assumptions.

The proposed GA to solve the e-MPSP uses chromosomes which are strings of length N where each slot corresponds to an activity and each slot has the information regarding the scheduled mode (resource assigned to carry out the activity and the scheduled start time) used to perform the corresponding activity. Therefore, each chromosome represents a candidate schedule $(\mathscr{S}, \mathscr{X})$ to the problem. The GA starts computing an initial population (new random chromosomes) of size $popSize$. Then it determines the fitness values of the individuals of the initial population. The fitness function used is the following:

$$f(\mathscr{S}, \mathscr{X}) = \frac{1}{\Psi(\mathscr{S}, \mathscr{X})} \tag{3.15}$$

meaning that the higher the fitness the better. Note that zero values in the denominator are not expected. Once the initial population is made up, the GA carries out reproduction and elitism, generation after generation, to make the population evolve and to find better solutions.

Reproduction consists of 3 main steps:

- Selection of parents. At each generation the GA selects $\frac{popSize}{2}$ couples of parents to breed N_c couples of children. The selection of each couple is done using the 3-tournament selection rule, which consists of selecting randomly 3 random chromosomes and choosing the best as the first parent of the couple. The process is repeated to select the second parent. This rule has been selected because it tends to keep more diversity than the roulette wheel selection [Haupt and Haupt, 2004].

- Crossover. After selecting the parents, each couple of parents breeds a couple of children exchanging their *genetic information* using the 2-point crossover [Haupt and Haupt, 2004]. Thus, each child has two strings of information from one of the parents separated by a string of information from the other parent.

- Mutation. After each new child chromosome is created it mutates by randomly changing the execution mode of some of the activities. In particular, it changes the execution mode to another randomly selected one with a probability of 0.01.

After new chromosomes are created and added to the population, GA uses elitism to remove the worst members of the population and maintain the population size. Algorithm 3.2 summarises the procedure of the explained GA. The termination criterion is based on the number of generations because it prioritises the control over the search time instead of the quality of the solutions in the experimentation. However, a termination criterion based on how the best solution has improved in the last generations can be easily implemented as well as a mix of different termination criteria (number of generations, improvement in last generations, etc.).

Algorithm 3.2 Genetic Algorithm

Require: $N_g = 1000$, $popSize = 300$
1: $population \leftarrow initialize\_population(popSize)$
2: Compute the fitness of each chromosome using $f(\mathscr{S}, \mathscr{X})$
3: **for** $generation = 0$ **to** N_g **do**
4: Selection: selects $\frac{popSize}{2}$ couples of parents using 3 tournament selection
5: Crossover: creates each couple of parents creates a couple of children using 2 point crossover
6: Mutation
7: Compute the fitness of each new chromosome using $f(\mathscr{S}, \mathscr{X})$
8: Add new chromosomes to $population$
9: Elitism: remove the worst chromosomes from $population$ keeping only the best $popSize$ members
10: **end for**

3.2.3 Multi-agent approach - MACA

The problem of allocating resources to tasks often has to be solved under a dynamic environment where tasks are not known in advance, and therefore, the allocation has to be done under demand. Furthermore, tasks are usually carried out by a limited number of local resources, but sometimes by outsourcing them to external providers. As a consequence, the allocation of resources to tasks involves several independent organisations some of which offer their working capacity and others that offer jobs to execute. Then, the use of multi-agent systems is justified for solving the e-MPSP problem where resources are managed by different agents. To allocate resources in multi-agent systems, auctions have been proved as a useful mechanism [Pla Planas, 2014].

An auction is a method for buying and selling goods or items using a bid system in which the best bids obtain the sold items. In domains where the aim is to allocate or outsource tasks to third party companies it is common to follow a reverse auction schema: an auctioneer needs a task to be done and offers to pay an external provider for carrying it out (becoming the buyer who aims to buy a service at the cheapest price) whilst bidders offer their working capacity at a given price (becoming the sellers who compete to offer the best working conditions at the cheapest price). This reverse auction schema is the one followed in this research.

The auction approach is of particular interest when tackling the allocation of energy consuming tasks under variable energy costs. In this case, auctions offer bidders the chance to handle energy costs for tasks, leaving the assignment process to the auctioneer: bidders provide offers to deploy tasks at a given time, at a given price and with the energy costs they would incur; thus, no alternatives other than those provided in the bid would be considered by the auctioneer.

However, the management of multiple attributes other than price (i.e. energy consumption and delivery times) requires a multi-criteria decision. To that end, multi-attribute auctions as in [Pla et al., 2014] are required. Moreover, the dependencies between attributes and bidder's schedules (i.e. the time when a task is being performed conditions its costs due to variable energy prices) will push bidders to submit multiple bids with different attribute configurations. In consequence, a combinatorial multi-attribute auction mechanism, Multi-Attribute Combinatorial Auction (MACA), is used. The mechanism is described below, according to the four main steps of the protocol: call for proposals, bidding, determining the winner, and payment. Companies are considered as agents that act from self-interest in order to increase their own utility. They will aim to outsource tasks on the best possible terms (auctioneer agents) or they will aim to sell their services in order to perform tasks at the highest prices for the lowest effort (bidder agents).

Call for proposals

When an auctioneer needs to outsource a task it sends a Call For Proposals (CFP) indicating the different tasks constraints and the required skills $\mathbf{RQ}_i$ to all the bidders $(a_1 ... a_n)$ inside the market. Each set of tasks is defined as a set of independent tasks $\mathbf{T} = \{T_1 \dots T_N\}$. Each task is defined as follows:

$$T_i = \langle \left[\underline{s_i}, \overline{s_i}\right], \left[\underline{et_i}, \overline{et_i}\right], \mathbf{RQ}_i \rangle \tag{3.16}$$

where $\underline{s_i}$ is the task earliest start time , and $\overline{s_i}$ the latest start time; $\underline{et_i}$ the earliest end time and $\overline{et_i}$ the latest end time; and $\mathbf{RQ}_i$ is a list with the resource skills S_k required by the task. All these parameters ($\left[\underline{s_i}, \overline{s_i}\right], \left[\underline{et_i}, \overline{et_i}\right], \mathbf{RQ}_i$) constitute the constraints of the task. Bidders pursuing to perform a certain task need to have available resources with the required skills, otherwise they will be unable to perform the task. On the other hand, they should provide actual starting times for tasks and duration that agree with the task time windows $\left[\underline{s_i}, \overline{s_i}\right]$ and $\left[\underline{et_i}, \overline{et_i}\right]$.

Bidding

Once a bidder receives the auctioneer's proposal, if the bidder is interested in any of the auctioned tasks and is able to provide an offer according to the task's constraints, it offers a bundle of bids where each bid describes possible conditions (price, energy consumption and delivery time) under which the bidder can perform the task. It is worth noting that in doing so, each resource agent has its own energy constraints and resource capacity constraints, which are opaque to other agents, and which are summarised in the bids.

Every bidder can send several bids with different configurations for the same task, because (due to variable energy prices) the cost of performing a task may change depending on the time it is scheduled and on other tasks the bidder could be assigned to perform. This leads to combinatorial auctions, meaning that agents bid bundles of tasks at different prices and conditions. The kth bid proposed by the jth bidder to perform the ith task is defined as

$$B_{i,j,k} = \left\langle T_i @ s_{i,j,k} : \left(\mu_{i,j,k}, \epsilon_{i,j,k}, \delta_{i,j,k}\right), M_{i,j,k}, E_{i,j,k}, \Delta_{i,j,k} \right\rangle \tag{3.17}$$

where T_i is the ith task to which the bid is submitted, $s_{i,j,k}$ is the start time proposed by the bidder, $\mu_{i,j,k}$ is the price of the bid, $\epsilon_{i,j,k}$ is the energy consumption and $\delta_{i,j,k}$ is the duration; $M_{i,j,k}$, $E_{i,j,k}$ and $\Delta_{i,j,k}$ are $N \times 1$ vectors that indicate modifications on the price, energy consumption and duration (respectively) if the bid is accepted together with another bid of the same bidder. In this way $E_{i,j,k}(l)$ indicates a modification on the energy consumption of $B_{i,j,k}$ if the lth bid of bidder i is also accepted to perform its corresponding task. This notation is taken from [Lopez et al., 2014]

This approach considers three attributes: price, energy and duration. However, this can be generalised to apply more attributes according to the ethos suggested by [Pla et al., 2014].

Winner determination problem

Once the bidding period is over, the auctioneer must decide which bids maximise its expected utility. For that purpose it calculates the utility of each bid and seeks the optimal combination of bids with the highest utility. In general, the utility of the auctioneer derived from a task performed according a set of attributes $a_1, \ldots, a_n$ can be defined as follows:

$$u(T_0, a_1, \ldots, a_n) = v(T_0) - f(a_1, \ldots, a_n) \tag{3.18}$$

where T_0 is the auctioned task, $v(T_0)$ is the value the auctioneer gives for the task completed and $f(a_1, \ldots, a_n)$ is the valuation function which evaluates the bid attributes. Then, the utility of the auctioneer obtained for outsourcing a particular task T_i according to a specific bid $B_{i,j,k}$ which contains the information about the attributes can be defined as

$$u(T_i, B_{i,j,k}) = v(T_i) - f(B_{i,j,k}) \tag{3.19}$$

where $f(B_{i,j,k})$ represents the cost of bid $B_{i,j,k}$ for the auctioneer considering all the dimensions involved in the allocation (economic cost, ending time and energy consumption). Note that, given T_i, maximising $u(T_i, B_{i,j,k})$ is equivalent to minimising $f(B_{i,j,k})$. Thus, the Winner Determination Problem (WDP) is defined as:

$$\arg\min_{j,k} \sum_{i,j,k} x_{i,j,k} * f(B_{i,j,k}) \tag{3.20}$$

Subject to

- $x_{i,j,k} = 1$ if bid $B_{i,j,k}$ is selected; otherwise $x_{i,j,k} = 0$
- Each task is assigned to and executed by a single bidder/bid $\sum_{j,k} x_{i,j,k} = 1, \forall i$
- All tasks constraints are satisfied

However, this minimisation problem is not trivial due to the combinatorial values regarding $M_{i,j,k}$, $E_{i,j,k}$ and $\Delta_{i,j,k}$. One possible way to simplify the problem is to use auxiliary variables to express the final price $b_{i,j,k}$ of a bid, the final end time $t_{i,j,k}$, and the final energy consumption $e_{i,j,k}$:

$$b_{i,j,k} = \mu_{i,j,k} + \sum_{l=1}^{N_j} M_{i,j,k}(l) \cdot x_{i,j,l} \tag{3.21}$$

$$t_{i,j,k} = s_{i,j,k} + \delta_{i,j,k} + \sum_{l=1}^{N_j} \Delta_{i,j,k}(l) \cdot x_{i,j,l} \tag{3.22}$$

$$e_{i,j,k} = \epsilon_{i,j,k} + \sum_{l=1}^{N_j} E_{i,j,k}(l) \cdot x_{i,j,l} \tag{3.23}$$

where N_j is the number of bids sent by the jth bidder.

The WDP can be then reformulated as follows:

$$\arg\min_{j,k} \sum_{i,j,k} x_{i,j,k} * f(b_{i,j,k}, t_{i,j,k}, e_{i,j,k}) \tag{3.24}$$

Subject to the same constraints as above. Note that the minimisation problem considers all tasks ($\forall i$).

Therefore the problem of the determination of the auction winner(s) can be solved by minimising f, which combines the different attributes of bids (price, time and energy), becoming, by definition, a key issue for the WDP. For the mechanism to be feasible, V (a particular case of f) is considered as an aggregation function, which must be a real-valued monotonic bijective function [Pla et al., 2012b]. In particular, this thesis uses the weighted sum (see equation (3.14)) but other functions could be considered as well (see [Pla et al., 2012b] for alternative evaluation functions):

$$V(b_{i,j,k}, t_{i,j,k}, e_{i,j,k}) = w_0 \cdot b_{i.j,k} + w_1 \cdot t_{i,j,k} + w_2 \cdot e_{i,j,k} \tag{3.25}$$

$$\sum_k w_k = 1 \tag{3.26}$$

The complexity of solving the problem is exponential [Collins et al., 2002], and complete methods cannot provide a solution in a realistic amount of time when the number of tasks and bids increases. Therefore, the use of meta-heuristic methods is a good alternative to obtain near optimal solutions. As for the single-agent case, this chapter proposes the use of GA.

On the other hand, equation (3.25) is used as fitness function. The algorithm is explained in Algorithm 3.3, where N_g is the number of generations and N_p is the size of the population.

Algorithm 3.3 Genetic Algorithm

```
Require: N_g = 2000, N_p = 300
Create popSize random chromosomes
for g ← 1 to N_g do
    for i ← 1to N_p/2 do
        Select 2 parents using the 3 tournament selection
        Breed two new chromosomes using 2 cross-point crossover
        Apply mutation operator over the new chromosomes
        Compute fitness of the new chromosomes using V_0
    end for
    Elitism: remove all chromosomes except the N_p best
end for
select the best chromosome as solution
```

Payment

A payment rule is used to establish the economic amount that auctioneers must pay to the auction winner(s) for performing any task. In this regard, incentive compatibility[1] has special

[1] An auction system is said to be incentive compatible if the optimal behaviour of the bidders is to bid truthfully. Put in other words, agents best behaviour is to reveal the true attributes (price, processing time, energy consumption, etc.) of the tasks they will perform.

relevance. Given the multi-dimensional nature of the allocation problem, payment is not only conditioned by the bid economic amounts but also by other attributes. For instance, delivering a task later than agreed may involve receiving less money than the initial bid amount. Moreover, the auctioneer cannot assume that bidders will follow a truthful bidding strategy.

Concerning multi-attribute auctions and incentive compatibility, a key work is [Che, 1993] where the author describes different scenarios regarding the payment rule and demonstrates that to achieve incentive compatibility the payment should be derived by matching the evaluation of the payment and the provided attributes with the evaluation obtained by the second best bid. In a later work, [Parkes and Kalagnanam, 2005] proposes an adaptation of the Vickrey-Clark-Groove (VCG) method [MacKie-Mason and Varian, 1994] for multi-attribute auctions under an iterative schema (bidders are allowed to modify their bids in response to the bids from other agents). The approaches presented in this section are based on a similar methodology to determine the auction winner and its payment, however they do not allow iteration. In practice, bid iteration leads to a slower procedure due to the increase of communications and a possible loss of privacy for bidders, who may not want to reveal their offers to competitors. These drawbacks may be acceptable in cases where auctions appear only occasionally and where losing an auction might lead to a long period without workload for bidders. However, in the tackled problem the allocation of resources to tasks is performed on a continuous basis on the arrival of new tasks; therefore this section proposes the use of VCG auctions, which provide equivalent results in a more straight forward mechanism [Sandholm, 1996]. VCG payment considers that the payment $p_{i,j,k}$ to bidder j for performing task i according to bid $B_{i,j,k}$ will correspond to the difference of the welfare all bidders would have obtained if the winning bid had not been sent to the auction and the welfare they receive with the chosen allocation excluding the welfare for bid $B_{i,j,k}$. However, such a mechanism considers a single attribute, price, and does not guarantee that bidders deliver tasks to the terms agreed during the bidding process (i.e. due to estimation errors [Pla et al., 2014]). So the VCG payment mechanism is modified in order to reduce the auctioneer's utility loss when bidders do not deliver tasks to the agreed attributes.

The payment rule proposed is a two case method following [Pla Planas, 2014]: on the one hand, when winning bidders are successful (delivering the task as agreed) they receive a payment $p_{i,j,k}$ according to a classical VCG auction schema. On the other hand, if the bidder delivers a task in worse conditions than those agreed (i.e. $t^{'}_{i,j,k}, e^{'}_{i,j,k}$ instead of $t_{i,j,k}, e_{i,j,k}$), it will receive a smaller payment in such a way that the valuation of the obtained payment $p_{i,j,k}$ and the delivered attributes matches the valuation of the initially presented bid, as follows:

$$V(p_{i,j,k}, {t'}_{i,j,k}, {e'}_{i,j,k}) = V(b_{i,j,k}, t_{i,j,k}, e_{i,j,k}) \tag{3.27}$$

where $t'_{i,j,k}$ and $e'_{i,j,k}$ are the true delivery time and the final energy consumption. Therefore the payment is defined as follows:

$$p_{i,j,k} = \begin{cases} V^{-1}\left(\Phi_{i,j,k}, t'_{i,j,k}, e'_{i,j,k}\right) & \text{if } t'_{i,j,k} \prec t_{i,j,k}, e'_{i,j,k} \prec e_{i,j,k} \\ V^{-1}\left(V\left(b_{i,j,k}, t_{i,j,k}, e_{i,j,k}\right), t'_{i,j,k}, e'_{i,j,k}\right) & \text{otherwise} \end{cases} \tag{3.28}$$

where

$$\begin{aligned} \Phi_{i,j,k} = & \sum_{(l,m,n)\in G_{-(i,j,k)}} V\left(b_{l,m,n}, t_{l,m,n}, e_{l,m,n}\right) - \\ & \sum_{(x,y,z)\in G\setminus(x,y,z)\neq(i,j,k)} V\left(b_{x,y,z}, t_{x,y,z}, e_{x,y,z}\right) \end{aligned} \tag{3.29}$$

and $\prec$ means *worse than*, G is the set of winning bids, $G_{-(i,j,k)}$ is the set of bids that would have won the auction if bid $B_{i,j,k}$ had not been sent, $G\setminus(x,y,z) \neq (i,j,k)$ indicates the set of winning bids different to $B_{i,j,k}$ and where

$$V^{-1}\left(\Phi_{i,j,k}, t'_{i,j,k}, e'_{i,j,k}\right)$$

is the reverse function of $V(b_{i,j,k}, t_{i,j,k}, e_{i,j,k}) = v$ which given v, $t_{i,j,k}$, $e_{i,j,k}$ returns $b_{i,j,k}$. Note that for achieving the set $G_{-(i,j,k)}$, the WDP must be resolved without the bid $B_{i,j,k}$.

In this way bidders are encouraged to bid truthfully: on the one hand, if they underbid regarding any attribute, they do not increase their utility (and they could lose utility, because if they win they are forced to work under the bid conditions). On the other hand, overbidding will reduce their chances of winning the auction. Finally, misdelivering confers a payment reduction, which will reduce the bidder's utility (encouraging it to improve its attribute estimation) whilst avoiding a loss of utility from the auctioneer's side (for instance, paying less to the winning bidder will allow the auctioneer to hire better resources in future). The following example illustrates the payment methodology.

Example 3.2.2. Payment rule example

Consider the example of Table 3.1 where three different bidders have sent three bids each (for three tasks), and where the evaluation function V of the auctioneer is a weighted sum

	T_1				T_2				T_3			
	b	e	t	V_0	b	e	t	V_0	b	e	t	V_0
Bidder 1	**20**	**5**	**5**	**10**	10	7	7	8	**6**	**5**	**3**	**5**
Bidder 2	20	10	6	12	**7** (5)	**5** (4)	**3** (3)	**5** (4)	10	7	7	8
Bidder 3	25	10	10	15	8	8	5	7	15	10	5	10

Table 3.1: Example of 3 bidders bidding for 3 different tasks. It shows the values of the attributes and the global value of the bids considering the weighted sum (with all weights equal to $\frac{1}{3}$ in Equation 3.25). Winning bids are in bold face. Numbers in brackets correspond to the bid values (considering set-up costs) if tasks T_1 and T_2 are assigned to bidder 2.

with all the weights set to $w = \frac{1}{3}$. According to the values of Table 3.1, bidder 1 is the winner for performing tasks T_1 and T_3, and bidder 2 is the winner for T_2.

When a task is delivered in the agreed conditions, the payment to the bidder for performing a task according to a particular bid is computed according to Equations (3.28) and (3.29). First, the payment of bidder 1 is computed: $\Phi_{1,1,1}$ is the difference between the valuations of bids $B_{2,1,1}$, $B_{2,2,2}$ and $B_{3,1,3}$ (winning bids if bid $B_{1,1,1}$ had not been sent) and the valuations of bids $B_{2,2,2}$ and $B_{3,1,3}$ (winning bids except $B_{1,1,1}$). Thus, considering Table 3.1,

$$\Phi_{1,1,1} = (12 + 4 + 5) - (5 + 5) = 11 \tag{3.30}$$

Note that when bid $B_{1,1,1}$ is not sent, set-up costs of bid $B_{2,2,2}$ must be considered because T_1 would have been assigned to bidder 2. Then, $b_{2,2,2} = 5$, $t_{2,2,2} = 3$, $e_{2,2,2} = 4$ and $V(5,3,4) = 4$.

Then, the payment $p_{1,1,1}$ corresponding to bidder 1 for doing task 1 according to $B_{1,1,1}$ is calculated according to Equation (3.28) as follows:

$$p_{1,1,1} = \frac{\Phi_{1,1,1}}{w} - \left(t'_{1,1,1} + e'_{1,1,1}\right) = \frac{11}{0.33} - (5 + 5) = 23 \tag{3.31}$$

Similarly, payments corresponding to bids $B_{2,2,2}$ and $B_{3,1,3}$ are 13 and 16 respectively if the tasks are delivered in the agreed conditions.

However, assuming that bidder 2 does task T_2 with an energy consumption of $e'_{2,2} = 8$ instead of 5, the corresponding payment is calculated according the second branch of Equation (3.28). Thus,

$$p_{2,2,2} = \frac{V\left(b_{1,1,1}, t_{1,1,1}, e_{1,1,1}\right)}{w} - \left(t'_{1,1,1} + e'_{1,1,1}\right) = \frac{5}{0.33} - (3 + 8) = 4 \tag{3.32}$$

So, bidder 2 would receive a payment of 4 instead of 13 for not fulfilling the agreed energy consumption.

3.2.4 Multi-agent approach - Trust-MACA

Incentive compatible mechanisms encourage agents to reveal the attributes which they estimate as truthful. However, these mechanisms by themselves cannot know if such estimations are reliable or not due to uncertainty caused by the available data to bidders [Jurca and Faltings, 2003, Pla et al., 2014]. Under such circumstances, trust [Pinyol and Sabater-Mir, 2013], an index that reflects the expected reliability of a bidder, could complement incentive compatibility reducing the risk of losses by the auctioneer. Trust can be controlled if the auctioneer keeps a history of past interactions with bidders. Then, it is assumed that different auctions are summoned in different rounds to allocate different tasks, the results of these auctions (winner bids and delivered tasks) are stored and the auctioneer has access to such information.

This dissertation presents a new perspective on trust in a multi-attribute framework. The trust model is multi-faceted, so the auctioneer keeps track of each verifiable (i.e. traceable or checkable) attribute provided by bidders. Using separated trusts, it provides a higher flexibility [Pinyol and Sabater-Mir, 2013]. For instance, in a moment with a high work load with a tight schedule an auctioneer might be more concerned about delivery times than energy consumptions and therefore could give more importance to being reliable on delivering a task at the agreed time. Using a global trust, the agent would not be able distinguish between which agents are reliable in terms of time and which are reliable in terms of energy.

Conversely to other previous works where trust is only used in the WDP, the presented approach, called Multi-Attribute Combinatorial Auction with Trust (trust-MACA), uses trust both in deciding the winner of the auction and the payment to the corresponding bidder. Taking into account trust in the WDP and the payment reduces the losses of the auctioneer, defining positive synergies between truthful bidding and trust. Then the proposed auction protocol consists of 5 steps (CFP, bidding, WDP, payment and trust learning) where the CFP and bidding steps are identical to MACA. The other three steps are described as follows:

Winner determination problem

Once the period of receiving bids is closed, the auctioneer must decide who is the winner of the auction: the bidder who offered the bid that maximises the auctioneer's expected utility [Ramchurn and Mezzetti, 2009]. Similarly to MACA, the utility u of the auctioneer can be defined as follows for a given set of attributes $a_1, \ldots, a_n$ provided by the bid and the auctioneer:

$$u(T_0, a_1, \ldots, a_n) = v(T_0) - f(a_1, \ldots, a_n) \tag{3.33}$$

where T_0 is the auctioned task, $v(T_0)$ is the value the auctioneer gives for having the task completed and $f(a_1, \ldots, a_n)$ is the valuation function which evaluates the bid attributes.

In trust-MACA the attributes $a_1, \ldots, a_{n-k}$ are provided by the bidders, while the attributes $a_{n-k+1}, \ldots, a_n$ are trust attributes. $k < n$ is the number of checkable attributes, those that the auctioneer can check if are true, provided by the bidders.

In the particular case tackled here, $\tau^t_{j,r}$ and $\tau^e_{j,r}$ define the confidence the auctioneer has in bidder j at round r regarding time and energy attributes according to its past experience. Observe that time and energy are attributes that the auctioneer can check when receiving the tasks, while this is not the case with the economic cost of performing the task. The behaviour of the attributes regarding their traceability has been studied in [Pla et al., 2014], where attributes are distinguished among verifiable attributes (like delivery time and energy consumption), unverifiable attributes (like the economic cost), and auctioneer provided attributes (like trust). Therefore, more trust parameters could be added if more verifiable attributes were available. Both trust attributes, $\tau^t_{j,r}$ and $\tau^e_{j,r}$, are defined in $(0, 1]$, and the higher the trustee.

Therefore, it is proposed to maximise the expected utility with the chances the bidder has to fail delivering the task in the agreed conditions according to the following expression:

$$\overline{u}\left(T_i, b_{i,j,k}, t_{i,j,k}, e_{i,j,k}, \tau^t_{j,r}, \tau^e_{j,r}\right) = v(T_i) - V\left(b_{i,j,k}, \frac{t_{i,j,k}}{\tau^t_{j,r}}, \frac{e_{i,j,k}}{\tau^e_{j,r}}\right) \tag{3.34}$$

where $V\left(b_{i,j,k}, \frac{t_{i,j,k}}{\tau^t_{j,r}}, \frac{e_{i,j,k}}{\tau^e_{j,r}}\right)$ is the expected valuation that the auctioneer gives to the bid B_i. As stated above, the lowest delivery time and energy consumed the better outcome. Therefore, dividing the delivery time and energy consumed values provided by bidders by the corresponding trust value, results in an augmented value for untrusted agents, and thus a lower chance to become the winners. The new value can be seen as the value of the attribute plus a security margin for the auctioneer.

According to Equation 3.34, solving the winner determination problem means to minimise the value of V:

$$\arg\min_{j,k} \left\{ V\left(b_{i,j,k}, \frac{t_{i,j,k}}{\tau^t_{j,r}}, \frac{e_{i,j,k}}{\tau^e_{j,r}}\right)\right\} \tag{3.35}$$

As in the previous section, the weighted sum is proposed as evaluation function:

$$V\left(b_{i,j,k}, \frac{t_{i,j,k}}{\tau^t_{j,r}}, \frac{e_{i,j,k}}{\tau^e_{j,r}}\right) = w_0 b_{i,j,k} + w_1 \frac{t_{i,j,k}}{\tau^t_{j,r}} + w_2 \frac{e_{i,j,k}}{\tau^e_{j,r}} \tag{3.36}$$

subject to $\sum_k w_k = 1$.

Payment

The payment rule is used to establish the economic amount $p_{i,j,k}$ that the auctioneer must pay to the auction winner after performing a task. It is a key aspect for ensuring the incentive compatibility of an auction mechanism. Due to the multidimensional nature of the faced allocation problem, the payment is not only conditioned by the price of the bid but also by the value of the rest of the attributes.

In such situations, there are no mechanisms guaranteeing incentive compatibility beyond single shot auctions. But as the payment rule used by the approach MACA, trust-MACA uses a two case method depending on whether the bidder delivers the task as agreed or not, which minimises auctioneer losses in case of cheater agents participation. In case the task is successfully delivered, the payment will be carried out following a classical VCG schema as follows[2]:

$$V\left(\Phi_{i,j,k}, \frac{t_{i,j,k}}{\tau^t_{j,r}}, \frac{e_{i,j,k}}{\tau^e_{j,r}}\right) = \Phi_{i,j,k} \tag{3.37}$$

where

$$\begin{aligned}\Phi_{i,j,k} = &\sum_{(l,m,n)\in G_{-(i,j,k)}} V\left(b_{l,m,n}, \frac{t_{l,m,n}}{\tau^t_{m,r}}, \frac{e_{l,m,n}}{\tau^e_{m,r}}\right) - \\ &\sum_{(x,y,z)\in G\setminus(x,y,z)\neq(i,j,k)} V\left(b_{x,y,z}, \frac{t_{x,y,z}}{\tau^t_{y,r}}, \frac{e_{x,y,z}}{\tau^e_{y,r}}\right)\end{aligned} \tag{3.38}$$

and G is the set of winning bids, $G_{-(i,j,k)}$ is the set of bids that would have won the auction if bid $B_{i,j,k}$ had not been sent, $G\setminus(x,y,z) \neq (i,j,k)$ indicates the set of winning bids different to $B_{i,j,k}$.

[2]In case of a draw, a tie-breaking rule should be used. In such circumstance both, the best and the second best bidders, will obtain 0 pay-off [Maskin and Riley, 2003].

Given that in the winner determination problem, all the attributes including trust are evaluated together, the payment rule needs to use all these parameters in order to assess the payment corresponding to the auction winner. To this end, it is assumed that the auctioneer is not able to change (intentionally or not) the trust values assigned to each bid.

In the case that the bidder delivers the task in worse conditions, the bidder receives a smaller payment in such a way that the valuation of the initially presented bid matches with the valuation of the actual delivered task, as follows:

$$V\left(p_{i,j,k}, \frac{t'_{i,j,k}}{\tau^t_{j,r}}, \frac{e'_{i,j,k}}{\tau^e_{j,r}}\right) = V\left(b_{i,j,k}, \frac{t_{i,j,k}}{\tau^t_{j,r}}, \frac{e_{i,j,k}}{\tau^e_{j,r}}\right) \tag{3.39}$$

where $t'_{i,j,k}$ and $e'_{i,j,k}$ are the real delivery time and energy consumption respectively. This payment will avoid the auctioneer being harmed in case of receiving a task in worse conditions than its valuation during the winner determination problem.

The payment is defined as follows:

$$p_{i,j,k} = \begin{cases} V^{-1}\left(\Phi_{i,j,k}, \frac{t'_{i,j,k}}{\tau^t_{j,r}}, \frac{e'_{i,j,k}}{\tau^e_{j,r}}\right) & \text{if } t'_1 \leq t_1, e'_1 \leq e_1 \\ V^{-1}\left(V\left(b_{i,j,k}, \frac{t_{i,j,k}}{\tau^t_{j,r}}, \frac{e_1}{\tau^e_{j,r}}\right), \frac{t'_{i,j,k}}{\tau^t_{j,r}}, \frac{e'_{i,j,k}}{\tau^e_{j,r}}\right) & \text{otherwise} \end{cases} \tag{3.40}$$

where $V^{-1}(v, \ldots, a_n)$ is the reverse function defined previously.

Trust learning

After any bidder delivers a completed task, the auctioneer can collect information regarding the bidder's performance (i.e. delivery on time and appropriate energy consumption) and update its trust on the bidder. If the delivered task has been successful, the auctioneer increases trust in the corresponding bidder, but if the bidder delivers a task in bad conditions, the auctioneer reduces trust in the bidder. It is important to note that the sense of success or failure will be different in every domain (i.e. in certain domains a successful task will be delivered just at a certain moment while in others a task will be considered successful if it is delivered before the deadline).

The updating function proposed for each trust attribute is given by Equations (3.41) and (3.42).

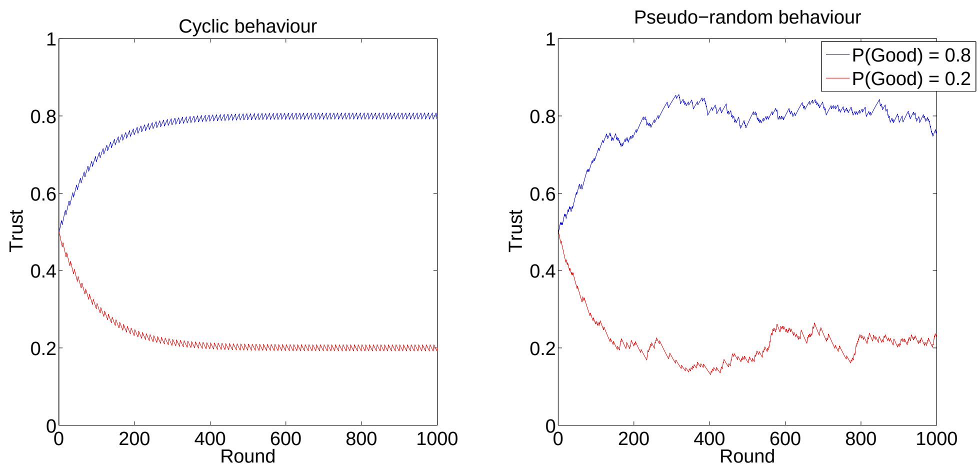

Figure 3.3: Illustration of different evolutions of the trust index with $alpha = beta = 0.01$ equal probabilities of good delivery ($P(Good)$). On the right, the good and bad deliveries are periodic. On the right the good and bad deliveries are random.

$$\tau^t_{1,r+1} = \begin{cases} \tau^t_{j,r} + \alpha_t \left(1 - \tau^t_{j,r}\right) & \text{if } t'_{i,j,k} \leq t_{i,j,k} \\ \tau^t_{j,r} - \beta_t \tau^t_{j,r} & \text{otherwise} \end{cases} \tag{3.41}$$

$$\tau^e_{1,r+1} = \begin{cases} \tau^e_{j,r} + \alpha_e \left(1 - \tau^e_{j,r}\right) & \text{if } e'_{i,j,k} \leq e_{i,j,k} \\ \tau^e_{j,r} - \beta_e \tau^e_{j,r} & \text{otherwise} \end{cases} \tag{3.42}$$

where α_t, β_t, α_e and β_e are coefficients in $[0, 1]$ which determine the rate of reinforcement.

The proposed model presents asymptotes on 0 and 1. This implies that, in case of a bad task delivery, agents with a trust close to 1 suffer a higher trust reduction than those agents with a trust close to 0. Similarly, in case of a successful delivery, low-trust agents are rewarded with a higher increase of trust than those agents with a high value of trust. Thus, high-trust agents need to successfully deliver several tasks to recover their trust value from a task delivered in bad conditions.

Furthermore, the trust value of an agent remains inside an interval which contains the real probability of the agent of successful delivery of tasks. The span and the precision of such interval depend on the values of the reinforcement coefficients. Small coefficients involve small and precise intervals but a slow convergence, whilst higher coefficients lead to a fast convergence at the expense of the interval's precision. Figures 3.4 and 3.3 illustrate examples of how the trust index evolves with different bidders' behaviours and reinforcement coefficients.

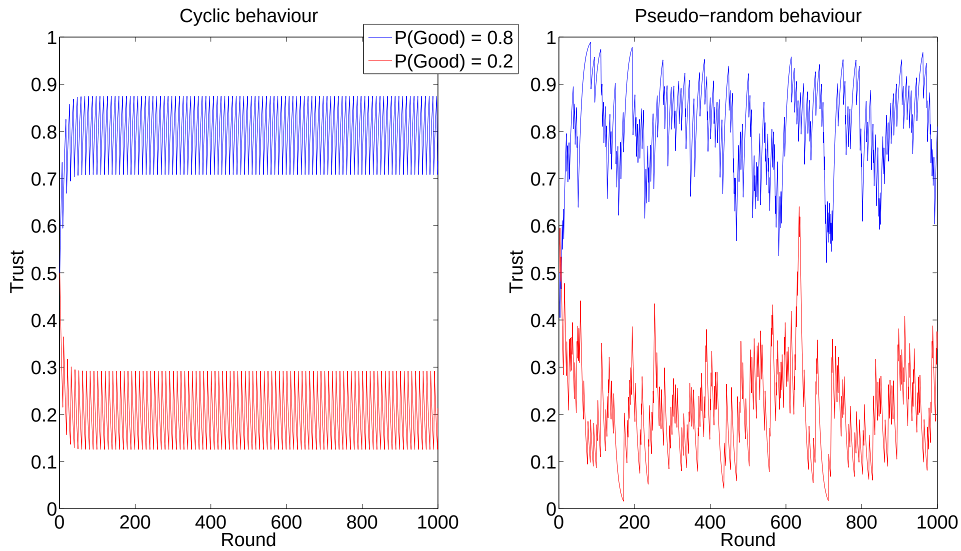

Figure 3.4: Illustration of different evolutions of the trust index with $alpha = beta = 0.1$ and equal probabilities of good delivery ($P(Good)$). On the right, the good and bad deliveries are periodic. On the right the good and bad deliveries are random.

3.3 Power re-allocation in coalitions of consumers

The second contribution of this dissertation regarding demand-response strategies consists of a new methodology for reducing power-related costs through power re-allocation among coalitions[3] of consumers.

Electric companies charge their customers for the amount of energy demanded and for the contracted power they have. Contracted power is supposed to be the maximum power at which the electric service will be interrupted (by some physical device) if the power required by the customer exceeds it. However, the popularisation of maximeters (devices that measure the maximum demanded power) has brought about electric tariffs that do not interrupt the electric service. Instead, these meters allow electric companies to apply maximum-power-dependent prices. For example, electric companies apply different prices depending on whether the demanded power of the customer exceeds the contracted power, or whether it is lower than a particular percentage of this contracted power.

Power cost is related to the infrastructure costs of electricity distribution companies. Trading companies use (and pay for) the infrastructure and in turn charge their customers for provid-

[3]Coalitions in general are goal-directed and short-lived; they are formed with a purpose in mind and dissolve when that purpose no longer exist, or when they cease to suit their designed purpose, or when the profitability is lost as agents depart [Horling and Lesser, 2005].

ing the required service (providing energy). As a consequence, trading companies have no margin to decrease the power cost (it is set by distribution companies), but they are interested in advising their customers on how they could reduce this part of their electricity bill. Furthermore, several companies, such as Arista Power (US), MeasurLogic (US), EnerNoc (US) or Circuitor (Spain), offer technological solutions (storage systems and load control devices) for reducing power costs, evidencing consumers' interest on it.

For this reason this dissertation proposes a new method called Power Re-Allocation (PRA) whereby customers consent to be assigned demanded power from others in order to keep all of them below the contracted power. Then customers who do not use all of their contracted power transfer their surplus to neighbours who exceed it. Therefore, power costs are reduced without reducing the sum of demanded power by all customers; it just re-allocates the demand among them. Additionally, this section presents some strategies to complement PRA and establish which customers have priority when not all can be put below the contracted power.

The resulting benefits of using the PRA method compensate for the large investment required to implement the approach; mainly, individual customers converted to a single one, close in distance.

3.3.1 Problem Statement

In recent years the problem of determining the power cost of a customer has changed due to the smart grid. The use of maximeters allows electricity companies to charge consumers for their maximum demanded power m, throughout a time window W. However, electricity companies penalise customers when m exceeds the contracted power c. For example, in Spain, when $m < 0.85c$ the electric company charges for 85% of c; when $0.85c \leq m \leq 1.05c$ the company charges for m; and when $m > 1.05c$ the company charges for $m + 2(m - 1.05c)$. Moreover, electric companies apply different billing periods that consist of classifying the demanded power according to the time-slot (time of the day) it is required. In this way, each period represents a particular part of every day, i.e. from 00:00 to 08:00. Continuing with the Spanish example, Spanish law dictates that each day must be divided into three periods, and therefore, there must be a maximum demanded power for each one.

In the general case, the payment or power costs of a customer can be formalised according to the following notation.

Customer: i is the customer index ($i \in [1, N_c]$);

Time window: W, time duration between two bills of a set of customers (usually a month).

Period: k, fraction of a day corresponding to a power tariff; $k \in [1, N_p]$; N_p is the number of periods which divide each day.

Slot: t is the time index in a period; $t \in \left[1, \frac{W}{N_p}\right]$.

Contracted power: $c_{i,k}$, the contracted power that gives the customer i the rights of demanding up to $\beta_{i,k} c_{i,k}$ (kW) in period k without paying extra charges. $\alpha_{i,k} c_{i,k}$ is the minimum power to pay for.

Under-power demand parameter: $\alpha_{i,k}$.

Over-power demand parameter: $\beta_{i,k}$.

Demanded power: $\rho_{i,k,t}$, the demanded power of customer i in period k at time t.

Power profile: $\rho_i = \{\rho_{i,k,t}\ \forall k, t\}$, is the power of any customer i in a given time window (see for example p1 in Figure 3.5).

Maximum demanded power: $m_{i,k}$, the maximum demanded power (in kW) of customer i throughout all k periods of the time window W. It is calculated as

$$m_{i,k} = \max_t \left(\rho_{i,k,t}\right) \tag{3.43}$$

It is important to point out that a unique high value of a slot t determines the maximum power, compromising the power costs of the whole period.

Penalty factor: K is the penalty factor that determines the price increment ($K > 1$) when $m_{i,k} > \beta_{i,k} c_{i,k}$.

Power price: $\pi_{i,k}$, the power price (€ /kW) for the period k.

In such a way, the power cost of consumer i for period k can be computed as follows:

$$cost(m_{i,k}) = \begin{cases} \alpha_{i,k} c_{i,k} \cdot \pi_{i,k} & m_{i,k} < \alpha_{i,k} c_{i,k} \\ m_{i,k} \cdot \pi_{i,k} & \alpha_{i,k} c_i \le m_{i,k} \le \beta_{i,k} c_{i,k} \\ \left(m_{i,k} + K\left(m_{i,k} - \beta_{i,k} \cdot c_{i,k}\right)\right) \cdot \pi_{i,k} & \beta_{i,k} c_{i,k} < m_{i,k} \end{cases} \tag{3.44}$$

In this scenario, consumers with $m_{i,k} < \alpha_{i,k} \cdot c_{i,k}$ are paying more than the power they demand and those with $\beta_{i,k} \cdot c_{i,k} < m_{i,k}$ are highly penalised for exceeding their contracted power. Thus, in a given group of customers, those that do not exceed $\alpha_{i,k} \cdot c_{i,k}$ could be

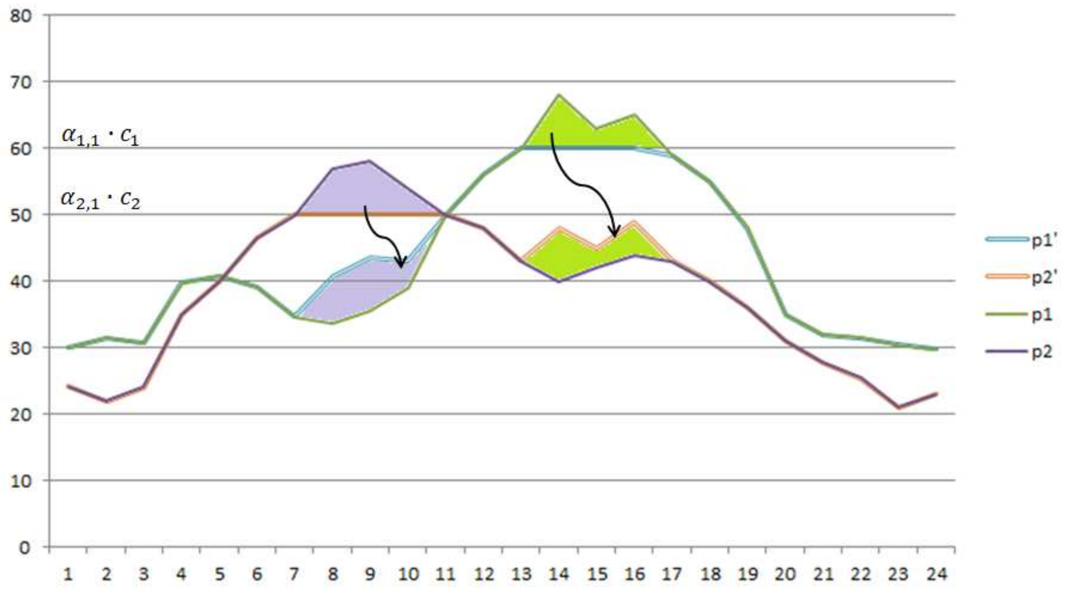

Figure 3.5: Illustration of how PRA re-allocate the excess of power of some consumers to others. Here, $\rho 1$ and $\rho 2$ represent the original power profiles and $\rho 1'$ and $\rho 2'$ represent the respective power profiles after power re-allocation.

interested in sharing their power rights with those that do exceed $\alpha_{i,k} \cdot c_{i,k}$ (especially those that exceed $\beta_{i,k} \cdot c_{i,k}$). One day a customer could be on the *giving* side, when in another it could be on the *receiving* side, obtaining mutual benefits over the long term.

Despite the starting point being Spanish electricity billing, it can be generalised to other electricity billing based on charging consumers according to their demand peaks. For example, the power re-allocation problem stated in this dissertation is extensible to other countries such as Germany, the United Kingdom, Austria, Czech Republic, etc. In general, it can be said that most countries use a billing methodology based on the demand of the consumers, but they differ in the types of consumers (big consumers, special consumers, small consumers, etc.) they apply these tariffs to, the weight of demand charges on the whole price of the electricity services, the use of time dependent prices, the division of the billing in periods, etc.

The power re-allocation problem consists of finding the $m_{i,k}$ that minimises consumers' costs, that is,

$$\min_{i,k} \left\{ \sum_i cost(m_{i,k}) \right\} \tag{3.45}$$

The minimisation problem is constrained to the fact that no consumer can see increased their corresponding payment increased due to power re-allocation.

Assumptions and limitations

The presented problem formulation is a generalisation of electricity bills based on peaks of power demand. Therefore, the applicability of the following solution approach is limited to situations where consumers are charged for their peaks of power demand and not only for the volume of energy consumed. In addition, the following solution approach is useful in a context where consumers cannot *sell* their rights to demand power to other consumers, due to law restrictions, for example.

3.3.2 Solution approach

The method PRA re-allocates demanded power among customers close to each other, so that they can reduce their power costs. In this way, the method consists of re-allocating demanded power from those customers that exceed $\alpha_{i,k} \cdot c_{i,k}$, and preferably those that exceed $\beta_{i,k} \cdot c_{i,k}$, to those customers that do not exceed the minimum power, $\alpha_{i,k} \cdot c_{i,k}$. Figure 3.5 illustrates power re-allocation between two customers.

In doing so, an umbrella entity is proposed, which aggregates the demanded power of all of its customers and agrees a single contract with the power company (see Figure 3.6). It is proposed that electricity trade companies offer to manage the umbrella entity for their customers without an extra cost for the consumers. Thus, they might offer this service to catch customers thanks to its economic benefits, and they might offer it free because the cost of running this service is negligible compared to current costs of electricity services: collecting consumers' power data is carried out by already (or being) implanted smart meters and an extra smart meter (300€) for the umbrella entity. Furthermore, electricity companies might offer this service free as they are currently offering services to optimise the contracted power (adjusting it to the consumption).

Regarding the umbrella entity, this internally re-allocates the demanded power and computes the costs of such demands, which are finally paid to the distribution company. If the demand peaks do not occur simultaneously, the total cost would be less than the sum of costs separately. In this regard, consumers would be able to reduce their aggregated demanded power while flattening the load of the grid with respect to the contracted power. This benefits distribution companies because they must provide an infrastructure able to support these contracted powers and this would avoid having to increase the infrastructure by using it more efficiently. In this regard, PRA can be used as a tool for increasing network usage, which is one of the main drawbacks (poor network usage) of using an electricity billing method based on

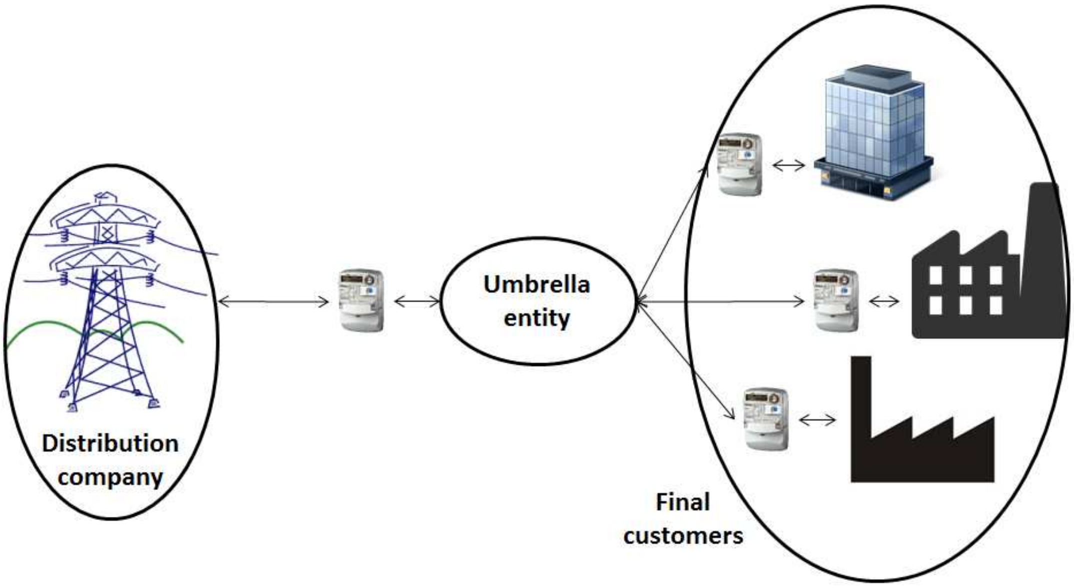

Figure 3.6: Illustration of the structure of the relationship between the different entities

demand charge. Figure 3.6 illustrates the relationship between the different agents involved. Note that it is not the same as a microgrid or a VPP [Bakari and Kling, 2010, Pudjianto et al., 2007].

PRA can also be seen as an incentive for locally smooth electricity demand, one of the main objectives for the future smart grid. Smoothing of the demand conveys a reduction of reserve generators which are usually active, but disconnected, waiting to cover a peak of demand. Then, a reduction of the active generators, and even a reduction of the installed generators may help to decrease the global need of energy and the over-exploitation of the Earth with its climatic consequences. Thus, PRA can be added to other activities aimed to smooth and reduce power demand such as energy efficiency measures. See [Meir and Pearlmutter, 2010, Meir et al., 2012] for architectural energy efficiency measures and consequences of the climatic change.

Umbrella entity

The umbrella entity demands power equal to the sum of the power demands of the consumers behind it. This umbrella entity then pays the distribution company according to this aggregated demanded power, taking into account the maximum demanded power behaviour. On the one hand, it agrees a power contract for period k, c_k^u, equal to the sum of the contracted powers,

$$c_k^u = \sum_i c_{i,k} \tag{3.46}$$

On the other hand, the maximum demanded power by the umbrella entity, m_k^u at a given period k is

$$m_k^u = \max_t \{\sum_i \rho_{i,k,t}\} \tag{3.47}$$

Given the under and over power demand parameters for the umbrella entity, α_k and β_k, the payment for the umbrella entity is,

$$cost(m_k^u) = \begin{cases} \alpha_k c_k^u \cdot \pi_k & m_k^u < \alpha_{i,k} c_k^u \\ m_k^u \cdot \pi_{i,k} & \alpha_k c_k^u \leq m_k^u \leq \beta_k c_k^u \\ \left(m_k^u + K\left(m_k^u - \beta_k \cdot c_k^u\right)\right) \cdot \pi_{i,k} & \beta_k c_k^u < m_k^u \end{cases} \tag{3.48}$$

For example, consider an umbrella entity that aggregates the consumption of two consumers like Figure 3.7. Both consumers have the same contracted profile which is registered in three periods ($k = 1, \ldots, 3$), of equal length, all of them are: $c_{i,1} = 40kW$ (time slots 1 to 3), $c_{i,2} = 50kW$ (time slots 4 to 6), and $c_{i,3} = 30kW$. The resulting aggregated contracted power for the umbrella entity is then, $c_1^u = 80kW, c_2^u = 100kW, c_3^u = 60kW$. For $t = 2$, consumer one demands $45kW$ going above its contracted power ($c_{1,1} = 40kW$); when managing power under the umbrella entity, no consumer exceeds the contracted power ($c_1^u = 80kW$). A similar situation happens for $t = 7$ and $t = 8$. However, for $t = 5$, the maximum demanded power of consumer three (60) cannot be flattened to c_2^u, although it is somehow diminished. The difference between $m_2^u - c_2^u$ (105-100) is shorter than $m_{2,k} - c_{2,k}$ (60-50), and so, depending on the β_k value, the umbrella entity would be penalised or not, affecting the payment of consumer two. In case two consumers have exceeded their allowed peak power at the same time, no re-allocation would have been carried out.

Regarding the payment, and assuming a power price $\pi_{i,k} = 1$ for all i, k, $\alpha_{i,k} = 0.85$, and $\beta_{i,k} = 1.05$, consumer 1 out of the umbrella entity would pay, according to Equation 3.45,

- Period 1: 51€, since $1.05 \times 40 = 42.00 \leq m_{i,k} = 45$
- Period 2: 45€, since $0.85 \times 50 = 42.50 \leq m_{i,k} = 45 \leq 1.05 \times 50 = 52.50$
- Period 3: 42€, since $1.05 \times 30 = 31.50 \leq m_{i,k} = 35$

equalling a total of 138.00 €. On behalf of consumer two, the payment would be,

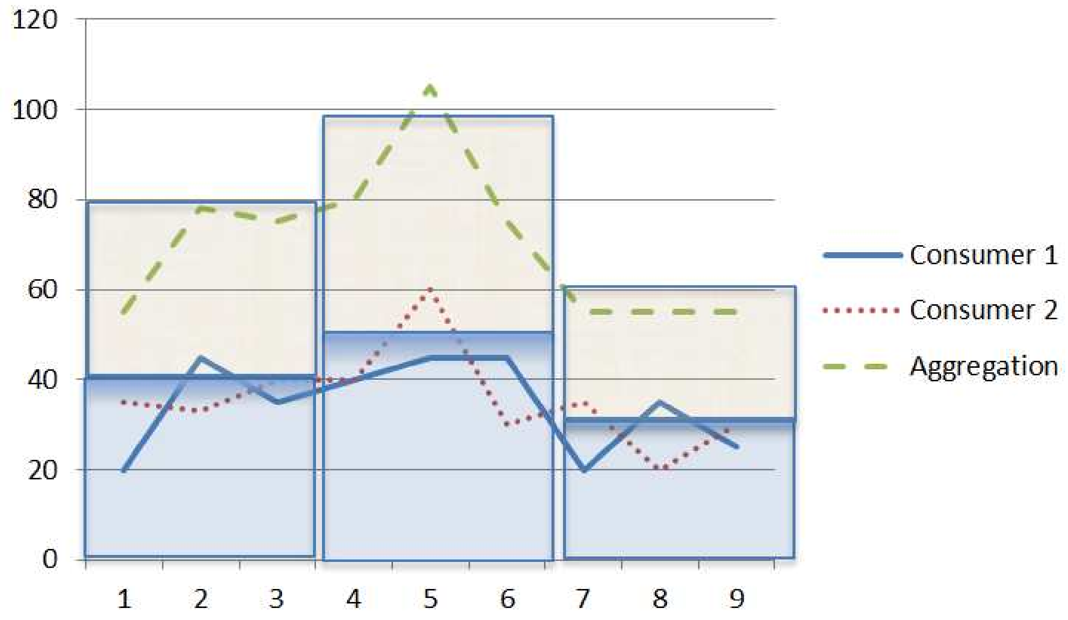

Figure 3.7: Example of energy consumption aggregation.

- Period 1: 40€, since $0.85 \times 40 = 34.00 \leq m_{i,k} = 40 \leq 42.00$
- Period 2: 75€, since $52.50 \leq m_{i,k} = 60$
- Period 3: 42€, since $31.50 \leq m_{i,k} = 35$

equalling a total amount of 157.00€. The sum of costs incurred without the umbrella entity is then 295.00€. On the other hand, according to Equation 3.48 and assuming $\alpha_{i,k} = \alpha_k = 0.85$ and $\beta_{i,k} = \beta_k = 1.05$, the umbrella entity would pay the following amounts for each period:

- Period 1: 78€, since $0.85 \times 80 = 68.00 \leq m_{i,k} = 78 \leq 1.05 \times 80 = 84.00$
- Period 2: 105€, since $0.85 \times 100 = 85.00 \leq m_{i,k} = 105 \leq 1.05 \times 100 = 105.00$
- Period 3: 55€, since $0.85 \times 60 = 51.00 \leq m_{i,k} = 55 \leq 1.05 \times 60 = 63.00$

Totalling the amount of 238.00€. The benefits are then considerable. The issue is how these benefits are shared among all the members of the coalition.

Current law forbids the resale of energy or power, thus the re-allocation of power needs to be done without an exchange of money. This fact limits the global saving that the community could achieve, i.e. a customer in the situation $\alpha_{i,k}c_{i,k} \leq \rho_{i,k,t} < \beta_{i,k}c_{i,k}$ could receive power from another one where $p_{i,k,t} > \beta_{i,k}c_{i,k}$ in exchange of a payment. The second customer will be penalised for its high power demand and thus it will be predisposed to pay the first consumer, to avoid these extra charges. However, due to law issues, it is forbidden to follow this unconstrained coalition approach, and the solution approach must avoid money exchange.

PRA assumes agents collaboration, so that in some occasions one agent would receive power, while on other ones will give, with a common goal to reduce all of their costs. Each agent follows Equation (3.45) to compute their payment. The umbrella entity reallocates power among agents, so that the maximum demanded power by each agent $m_{i,k}$, for all k, is diminished due to the power exchange, so at the end, all agents have their costs reduced. Therefore, this guarantees that any consumer will pay less than running alone. Furthermore, the amount of money the umbrella entity will have to pay will be equal to or lower than the sum of payments each customer would have to pay if they were running alone.

PRA basics

PRA analyses the demanded power in repetitive slot series of the time window W, and seeks the power profiles that minimise power costs guaranteeing that no consumer will pay more than without PRA.

The ideal situation happens when all consumers' demand is exactly $m_{i,k} = \alpha_{i,k} c_{i,k}$ according to the power costs expressed by Equation 3.28. If they demand a lower amount, they will pay the same; if they demand more, they will pay more and they will even be penalised with extra charges.

Given the profiles of a set of customers, $\rho_{i,k,t} \forall i, k, t$, and their contracted power $c_{i,k}, \forall i, k$, PRA computes the new power profiles to minimise their maximum demanded power (Equation 3.45), meaning, they are all below $\alpha_{i,k} c_{i,k}$. To this end, power is shifted from one customer to another in order to keep each customer below the contracted power.

However, it is sometimes impossible to keep all demanded power at each slot t below $\alpha_{i,k} c_{i,k}$. In such a situation, when at some slot t a particular consumer has its maximum demanded power $m_{i,k} > \alpha_{i,k} c_{i,k}$ and it is impossible to reduce it, the consumer will have to pay, at least, for this $m_{i,k}$ throughout all the period k of the time window W. That means that the consumer is only consuming the power it demands in a single slot, while in the remaining time window it is paying for power that is not used. To avoid such a situation, PRA increases the capacity of the consumer to receive power from others without increasing the amount of money it will pay.

To model this customer capacity, the target power of each consumer i for each period k is

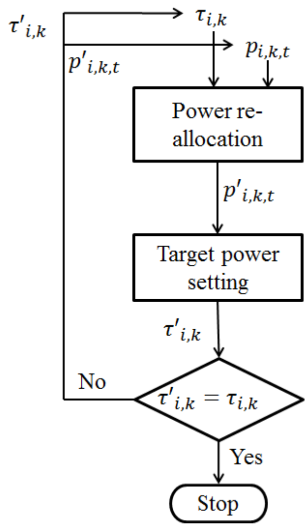

Figure 3.8: PRA iteration process

defined as $\tau_{i,k}$, which is initialised to $\alpha_{i,k}c_{i,k}$.

When at some point a particular consumer has their maximum demanded power $m_{i,k} > \tau_{i,k}$ and it is impossible to reduce it, PRA sets the target power to this new value $\tau'_{i,k} = m_{i,k}$. The consumer will have to pay, at least, for this $m_{i,k}$ but will have more capacity to accept demanded power from others.

Summarising, PRA is an iterative process, in which power re-allocation and target power setting is repetitively applied until target powers become steady (see Figure 3.8). In the experimentation, a mean of 4.15 times with a standard deviation of 7.47 were sufficient in order to find the optimal re-allocation.

On the other hand, re-allocation of power can be conducted according to different strategies, responding to a strategic decision of the trading company. This section presents a proportional strategy and two approaches based on priorities (received frequency and received amount strategies). The remainder of this section details the steps of the algorithm, including the strategies.

Power re-allocation step

PRA tries to re-allocate power so that all consumers reach their target power. In doing so it determines that there are two kinds of roles among consumers:

- Receiver: if $m_{i,k} < \tau_{i,k}$. They *receive* power from other consumers.

- Giver: if $m_{i,k} > \tau_{i,k}$. They need to give power to other customers; otherwise they will pay extra charges due to extra demand.

First of all, it is important to know whether the addition of all the contracted powers is enough to keep every customer below their target power, in a given time slot k, considering the sum of all the power demanded by them. In doing this, it is assume that the length of the slots reported by all the customers is the same. Note, however, that considering different time slots is an easy extension of the presented method by recursively applying the method with another scale. Then, the following variables are defined:

Accumulated Power Rights (APR): $APR_{k,t}$ is the addition of all the contracted powers,

$$APR_{k,t} = \sum_{i=1}^{N_c} \tau_{i,k} \tag{3.49}$$

Note that $APR_{k,t}$ is calculated according to $\tau_{i,k}$ since it tells us the maximum power that a customer can demand without increasing the amount of money it has to pay.

Accumulated Demanded Power: $ADP_{k,t}$ is the addition of all the power demanded by consumers,

$$ADP_{k,t} = \sum_{i=1}^{N_c} \rho_{i,k,t} \tag{3.50}$$

Power Sharing: $PS_{k,t}$ as the capacity of all customers to receive power from others without increasing their individual cost,

$$PS_{k,t} = \sum_{i=1}^{N_c} \max\left(\tau_{i,k} - \rho_{i,k,t}, 0\right) \tag{3.51}$$

If there is enough $APR_{k,t}$, that is, $ADP_{k,t} \leq APR_{k,t}$, then, there would be some power sharing to negotiate. The $PS_{k,t}$ is distributed by all the receivers according to some strategy.

Otherwise, if there is not enough $APR_{k,t}$, that is, $ADP_{k,t} > APR_{k,t}$ there would be some givers that cannot fulfil their target power. In spite of this, there could be givers and receivers, the latter offering power sharing (if $PS_{k,t} > 0$), although not enough to cover all the demand. In this case, the givers can be classified into two categories:

- Non penalised customers: those who keep their demanded power between the target power and $\beta_{i,k} c_{i,k}$ (over-power demand).
- Penalised customers: those who exceed $\beta_{i,k} c_{i,k}$.

PRA first tries to reduce the demanded power of the penalised customers to lower them to either reach a value under $\beta_{i,k}$ otherwise the $PS_{k,t}$ is saturated (reaches 0). After attending penalised receivers, if there is still power sharing available ($PS_{k,t} > 0$), then all the givers are treated according to the re-allocation strategy to lower their demanded power as much as possible. The power re-allocation algorithm is summarised in Algorithm 3.4.

Algorithm 3.4 Power Re-Allocation

Require: power profiles $\rho_{i,k,t}$ and contracted powers $c_{i,k}$
for $k \leftarrow 1$ **to** N_P **do**
    for $t \leftarrow 1$ **to** $\frac{W}{N_P}$ **do**
        if any customer $p_{i,k,t}$ exceeds its target power $\tau_{i,k}$ **then**
            if $ADP_{k,t} < APR_{k,t}$ **then**
                Re-allocate power from those that exceed $\tau_{i,k}$ to those that do not
            else if $PS_{k,t} > 0$ **then**
                Re-allocate power from those customers that $\rho_{i,k,t} > \beta_{i,k}c_{i,k}$ until $PS_{k,t} = 0$ or $\rho_{i,k,t} = \beta_{i,k}c_{i,k}$ to those that $\rho_{i,k,t} < \tau_{i,k}$
                Re-allocate power from those customers that exceed the target power $\tau_{i,k}$ to those that do not until $PS_{k,t} = 0$
            end if
        end if
    end for
end for

Considering that two profiles are complementary when one exceeds its contracted power, the other is below $\alpha_{i,k}c_{i,k}$, then it can be said that the more complementary the demand profiles of the consumers are, the greater savings that PRA could achieve. Some examples of complementary profiles could be residential buildings with commercial or office buildings. However, even when demand profiles are very similar, PRA can achieve important benefits because it is scarcely possible that $m_{i,k}$ of each customer throughout the time window (i.e. a month) will correspond to the same time t. Besides, this method is not constrained to a maximum number of consumers. However, the addition of non-complementary consumers to a given coalition using PRA may reduce the individual savings but never the absolute global savings. Furthermore, this methodology is applicable to any kind of consumer who has an electricity billing depending on its maximum demanded power by using maximeters. Nevertheless, this kind of electricity bill is usually reserved to consumers with a contracted power greater than 15kW (when maximeters are mandatory) while domestic contracted power is usually smaller than 5kW. Therefore, this excludes, for the time being, multi-family buildings with no centralised consumption accounting. However, the generalisation of smart meters, capable of measuring the maximum demanded power, may change this fact.

Target power setting step

Target power $\tau_{i,k}$ is initially set to $\alpha_{i,k}c_{i,k}$, and is adjusted iteration after iteration. That is, after a PRA iteration, it calculates the new maximum demanded power $m'_{i,k}$ for each consumer. If PRA does not achieve the ideal situation, in which all customers $m'_{i,k} \leq \tau_{i,k}$, those which $m'_{i,k} > \tau_{i,k}$ will be charged for the $m'_{i,k}$ for all of period k. Therefore, $\tau_{i,k}$ is shifted closer to the new maximum, in order to increase the power sharing for the whole community. Notice that this does not increase $m_{i,k}$ and thus not the payment either.

In order to modify $\tau_{i,k}$, it must be taken into account that some other customers could be in a similar situation. If they are requiring power in the same t, one can think of modifying $\tau_{i,k}$ according to the new $m'_{i,k}$ value; but if their needs correspond to different t, a small increase in several customers could be enough to cover most of their needs. Therefore, $\tau_{i,k}$ is adjusted according to the second maximum as follows:

$$\tau^n_{i,k} = \max\left(\alpha_{i,k}c_{i,k}, \max_{\forall t|\rho_{i,k,t}<\max_t(\rho_{i,k,t})}\left(\rho_{i,k,t}\right)\right) \tag{3.52}$$

Observe, that the first iteration is equivalent to $\tau^1_{i,k} = \max\left(\alpha_{i,k}c_{i,k}, 0\right)$.

Going back to the example of Figure 3.7 and Subsection 3.3.2, the payment corresponding to each consumer using PRA would be:

- Consumer 1: 112.5€
  - Period 1: 40€, since its final power profile at $k = 3$ would be $p_{1,1,t} = [20, 40, 36]$ with $0.85 \times 40 = 34.00 < m_{1,1} = 40 < 1.05 \times 40 = 42.00$.
  - Period 2: 45€, since there is no power re-allocation because both peak power are at the same time and both exceed $0.85 \times 50 = 42.50$.
  - Period 3: 27.5€, since its final power profile would be $p_{1,3,t} = [27.5, 27.5, 27.5]$ at $k = 3$ with $0.85 \times 30 = 25.50 < m_{1,3} = 27.5 < 1.05 \times 30 = 31.50$.
- Consumer 2: 141.5€
  - Period 1: 39€, since its final power profile at $k = 1$ would be $p_{2,1,t} = [35, 39, 39]$ with $0.85 \times 40 = 34.00 < m_{2,1} = 39 < 1.05 \times 40 = 42.00$.
  - Period 2: 75€, since there is no power re-allocation because both peak power are at the same time and both exceed $0.85 \times 50 = 42.50$.

– Period 3: 27.5€, since its final power profile would be $p_{2,3,t} = [27.5, 27.5, 27.5]$ at $k = 3$ with $0.85 \times 30 = 25.50 < m_{2,3} = 27.5 < 1.05 \times 30 = 31.50$.

It is worth pointing out that power re-allocation at periods 1 and 3 is possible thanks to re-setting the target power of each consumer. Furthermore, the total amount to pay by the two consumers rises to 254€ which is more than the 238€ of the umbrella entity. This fact is caused because no consumer has to pay more than running alone and so power re-allocation is limited. Then, in some situations there would be a surplus of money between the amount paid by the consumers respecting the money paid by the umbrella entity which will have an extra income.

Re-allocation strategies

The distribution of power among givers and receivers can be performed following different strategies. The simplest one is a proportional strategy; other strategies could take advantage of the exchange history. But other strategies could also be used throughout the PRA application. Customers change their role from givers to receivers and vice versa according to their profiles and the APR. Therefore, it is possible to keep the history of each customer, and register how many times customers have received power from others. From the historical data it is possible to apply different strategies. In particular, we are interested in fair strategies as they have been proved to be more beneficial than utilitarian strategies in the long term [Murillo Espinar, 2010]. To that end, the Received Frequency Priority (RFP) and Received Amount Priority (RAP) are proposed.

Proportional re-allocation: The power each receiver gets is proportional to the difference between its target power and its maximum demanded power. For example, consider that there are three customers with the same target power of 50kW whose demanded powers at time t are 41kW, 44kW and 60kW. So, the third customer *gives* 6kW to the first customer (and then, its demanded power would be 47kW) and 4kW to the second customer (and then, its demanded power would be 48kW).

Consider a second example in which there is not enough power sharing, where the three customers have the same target power equal to 50kW and the same $\beta_{i,k} c_{i,k} = 60$. Their respective demanded powers at time t are 40kW, 55kW and 65kW. The latter customer is greater than $\beta_{i,k} c_{i,k}$ and so would be penalised. Thus, PRA re-allocates the power of this customer to the receiver converting their consumptions to 60kW and 45kW respectively. Since, there is still power sharing available it re-allocates again the power of all customers exceeding their target power to receivers, until $PS_{i,k}$ is saturated. Then the three corresponding demanded powers would be 50kW (receiver), 53.33kW and 56.67kW. Givers give an amount of power proportional to the difference between their demanded power and their target power.

RFP: This strategy prioritises customers who have often received power from other customers, when they are required to give power.

Priority is defined in $[0, 1]$, where 0 represents the lowest priority and 1 the greatest.

Moreover, since power has different prices in different slots, it could be convenient to distinguish a priority per customer and period, $priority_{i,k}$. Given the time window W in which PRA is applied, there are up to W/N_p times that the same slot has been considered. On the other hand, $x_{i,k}$ is defined as the number of times it has received power from others in slot k. Then, the priority of each customer is calculated according to Equation (3.53).

$$priority_{i,k} = \frac{x_{i,k}}{W/N_P} \tag{3.53}$$

RAP: The aim of this strategy is to focus on the amount of energy received in the past, instead of the frequency. To this end, it needs to be aware of the maximum capacity that any customer can receive, i.e., $\alpha_{i,k}c_{i,k}$.

The amount of power that customer i has received from others, at instance t in period k is defined as $z_{i,k,t}$. Consistently, priorities are calculated according to Equation (3.54).

$$priority_{i,k} = \frac{\sum_{t=1}^{W/N_P} z_{i,k,t} / \left(\alpha_{i,k}c_i\right)}{W/N_P} \tag{3.54}$$

Priorities can also be set according to customer types or according to other strategies that can be studied in further work.

3.4 Summary

This chapter has presented different methodologies to provide the user with a certain capacity of response in front of DSM strategies. In particular, the first part of the chapter is focused on defining and tackling the e-MPSP which consists of allocating tasks to resources and scheduling them taking into account the energy consumption and variable energy prices besides other objectives such as the makespan. For solving the problem, the chapter considers two possible scenarios: (i) the first where all resources are managed by the same agent or organisation; (ii) and the second where some or all the resources are managed by external agents and, therefore, tasks are outsourced to those external agents.

For the first scenario, it is proposed to solve the e-MPSP using B&B or GA, the latter especially for large instances of the problem. For the second scenario the chapter proposes the use of multi-attribute combinatorial auctions to solve the allocation problem. In this regard, the auctioneer (the agent that needs some tasks to be carried out) summons auctions and the bidders (external agents) offer their work capacity to perform the tasks in exchange for a payment. The chapter proposes a new formulation for combinatorial auctions based on set up vectors that indicate attributes modifications when other bids from the same bidder are selected as winner bids for other tasks. After the auctioneer has received all the bids, it determines the winner bids to carry out the bundle of tasks and finally it pays the bidders for the work performed. In order to incentivise bidders to behave honestly and deliver tasks according to the bid attributes, a two case method payment rule is proposed. In case of a good delivery, an extended Vickrey payment rule for combinatorial auctions is proposed. Then, the bidder receives a payment equal to the price value it should have offered to achieve a valuation of the bid equal to the second best bid. On the other hand, if the task is not delivered in the agreed conditions, the bidder receives a payment such that the value of the delivered task with the payment is equal to the value of the initial bid. This, mechanism is thought to avoid cheating behaviours, but it is ineffective to protect the auctioneer from bidders that involuntarily misestimate their abilities or the workload, and involuntarily misdeliver tasks. Then the chapter extends the proposed auction system to include trust to protect the auctioneer against those inaccurate bidders.

The second part of the chapter focuses on the creation of coalitions of consumers to reduce the power peak demand related costs. The chapter first formulates the problem and the costs derived from the power peak demand. Then, it describes a power re-allocation algorithm to reduce power demand peaks and, therefore, reduce the contracted power and the power costs. Finally, it complements the power re-allocation algorithm with some fairness strategies in order to prioritise the most generous consumers (those that accept more power from others).

CHAPTER 4

ENERGY DEMAND ALLOCATION

This chapter deals with the problem of managing DERs seeking a fair participation among all the generators involved. To that end, this chapter proposes a self-organising allocation method based on distributive justice[1] [Rescher, 1966] to determine the amount of energy each DER should produce at each time in a DG context. First it introduces the problem and the proposed approach. Then it explains the necessary background (in addition to Chapter 2) needed to understand the proposed approach. Next it formulates the energy demand allocation problem. Finally it presents an innovative approach to tackle the problem.

4.1 Introduction

The energy sector is being driven to a new era where considerable portions of electrical demand will be met through embedded generators or DERs. However, DERs have been connected to the electric network following a *connect and forget* procedure, meaning that they are not visible to the network operator and, therefore, it has no control over them. This procedure, where DERs inject all the power they can produce to the network, is no longer feasible if their contribution is meant to be significant. However, the complexity associated with integrating embedded generation into an already labyrinthine distribution system and the unpredictability of RES have slowed the timing.

The key to addressing this issue is to minimise the changes felt at the distribution level by simplifying the interface to the embedded resources. VPPs and micro-grids aggregate and locally control a collection of DERs, which at the same time are considered as a single unified load or generator by the operator of the main network. Then, they represent a way to facilitate

[1] See Section 4.2

a high penetration of distributed generators.

In power systems with DERs (see Figure 4.1), energy demand allocation consists of working out the energy production of each DER, or in other words, which portion of the energy demand should cover each DER. In this regard, the energy demand allocation problem becomes a problem where different agents (DERs) are competing to appropriate a particular amount of a common pool resource (energy demand). When the number and kind of DERs increase, so does the complexity of the allocation problem, which is also increased due to the unpredictability of the renewable energy resources.

DERs can be managed in a centralised way (as proposed in [Oyarzabal et al., 2009]) or in a decentralised way. Distributed Artificial Intelligence has studied decentralised mechanisms for a long period, showing interesting results regarding scalability while keeping agents benefits [Shoham and Leyton-Brown, 2009, Weiss, 1999].

However, without a centralised authority, it may seem ineffective to rule situations where a resource has to be allocated among a group of agents that are willing to appropriate a particular amount, because agents could tend to appropriate as much as they can, draining the resource and damaging the community or even destroying it. Nevertheless, Ostrom [Ostrom, 1990] observed that some communities without a centralised intervention formed institutions defining a set of rules which regulate the resource allocation in order to preserve throughout time either the institution or the resource. On the other hand, [Rescher, 1966] observed that an adequate allocation needs to treat people wholly or primarily according to seven *canons* (established principles expressed in English). However, Rescher did not say anything about how to represent the canons. Thus, [Pitt et al., 2012] proposes an implementation of these canons to allocate a common pool resource among self-organised agents, in regard to a linear public good game. This chapter proposes a methodology to determine the energy production of each DER in the context of a VPP, where a set of DERs makes joint decisions regarding the energy demand allocation problem.

In this thesis, as stated in the previous chapter, fairness strategies are proposed to seek a satisfactory cooperation among agents [Kash et al., 2014, Murillo Espinar, 2010]. To that end, the steps of the methodology of [Pitt et al., 2012] are grounded to the energy demand allocation problem. Thus, the presented approach allows heterogeneous DERs to have fair outcomes, including situations in which external interferences could arise, as when a minimum renewable energy production share is imposed.

4.2 Preliminary concepts

Institutions define a set of rules that determine several aspects of a system: who can perform what actions and under what circumstances; what are the consequences of performing such actions; how are agents sanctioned when not complying with the rules; etc. Ostrom [Ostrom, 1990] observed that an efficient management of the resources need not resort to centralised approaches, but instead could be done by the members of the institution themselves (i.e. self-governance). From her fieldwork and subsequent analysis, she derived a set of principles that are necessary and sufficient conditions for a self-governed institution to endure (i.e. not ending up in a depletion of its resources or all members abandoning the institution). These principles are the following [Ostrom, 1990]:

1. Clearly defined boundaries. The members of the institution have to be clearly defined as well as those not belonging to it.

2. Congruence between appropriation and provision rules. Rules regarding the appropriation and provision of common resources need to be adapted to local conditions and have to prevail the local environment.

3. Effective monitoring by monitors who are part of or accountable to the appropriators.

4. A scale of graduated sanctions for resource appropriators who violate community rules

5. Access to fast, cheap conflict-resolution mechanisms.

6. Existence of and control over their own institutions is not challenged by external authorities.

7. In case of larger common-pool resources, organisation in the form of multiple layers of nested enterprises, with small common pool resource at the base level.

The contribution of this chapter is concerned with the second and third principles, since they are the ones related to the allocation methodology. Despite this, Chapter 6 tests the proposed method but also analyses the robustness of the method against external interferences, and therefore how it minimises the non-compliance of the seventh principle.

On the other hand, the allocation of resources was studied by Rescher in [Rescher, 1966], who introduces the concept of distributive justice in which people are treated according to different concepts (or canons) of justice:

1. **Canon of equity:** treatment as equals.
2. **Canon of needs:** treatment according to their needs.
3. **Canon of productivity:** treatment according to their actual productive contribution.
4. **Canon of effort:** treatment according to their efforts and sacrifices.
5. **Canon of social utility:** treatment according to a valuation of their social-useful services.
6. **Canon of supply and demand:** treatment according to supply and demand regarding which are the most desired agents and which the less common.
7. **Canon of ability:** treatment according to their ability, merits or achievements.

Rescher argued that each canon alone was inadequate as a sole dispensary of distributive justice. Instead, he held that distributive justice was found in the *canon of claims*, which consists of treating people according to their legitimate claims, leaving open questions of what the legitimate claims are, how they are accommodated in case of plurality, and how they are reconciled in case of conflict.

4.3 Problem formulation

VPPs are constituted by a collection of different DERs, which are usually independent and have their own interests. Each DER wants to produce a particular amount of energy to increase its benefits and satisfaction. The mission of a VPP is to manage DERs or to provide tools for coordination and/or cooperation in order that they can cover a load, so that there is balance between energy production (fulfilling DERs' requirements and/or constraints) and consumption (load). Thus, this scenario presents a resource allocation problem where an infinitesimal divisible good (load) has to be allocated among a set of agents (DERs), $\{1, \ldots, N_{DER}\}$, in such a way that DERs' constraints are satisfied.

DERs constraints are determined by design (minimum and maximum DER generation bounds) and by their present running state and context (minimum and maximum available production). First, design constraints mean that the DER would not be able to produce in any situation an energy amount out of the design limits, p_i^{min} and p_i^{max}. And second, when a DER is actually producing $p_i(t)$, the generation bounds for $t+1$, $p_i^{min}(t+1)$ and $p_i^{max}(t+1)$, depend on the

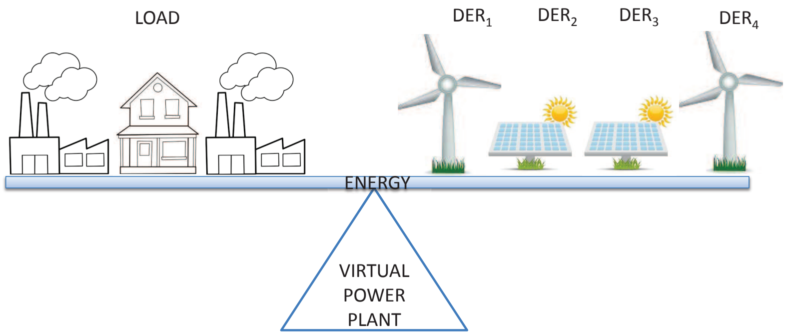

Figure 4.1: Problem scenario.

technical specifications of the DER as well as the weather forecast (i.e. wind or solar radiation) as follows:

$$\begin{aligned} p_i^{min}(t+1) &= \max\left\{p_i^{min}, p_i(t) - s_i^d\right\} \\ p_i^{max}(t+1) &= \min\left\{p_i^{max}, p_i^{forecast}(t+1), p_i(t) + s_i^u\right\} \end{aligned} \tag{4.1}$$

where $p_i^{forecast}(t+1)$ is the expected production conditioned to the weather forecast; and s_i^u and s_i^d are the up and down ramp limits respectively, as determined by the technical specifications of the DER. Summarising, constraints regarding the production $p_i(t)$ of a DER can then be expressed as follows:

$$p_i^{min} \leq p_i^{min}(t) \leq p_i(t) \leq p_i^{max}(t) \leq p_i^{max}, \forall i \tag{4.2}$$

Consistently, the total minimum and maximum energy production limits of the VPP at time t can be defined as follows:

$$\begin{aligned} P^{min}(t) &= \sum_{i=1}^{N_{DER}} p_i^{min}(t) \\ P^{max}(t) &= \sum_{i=1}^{N_{DER}} p_i^{max}(t) \end{aligned} \tag{4.3}$$

According to their strategic goals, each DER is interested in producing a given amount of energy $d_i(t)$, subject to the constraints shown in Equation 4.2. Whenever $d_i(t) \leq p_i(t)$ or $d_i(t) \geq p_i(t)$ that would depend on the DERs' business, but $d_i(t)$ never can surpass DERs' energy bounds.

Consistently, the total demanded energy production (henceforth total demand) inside the VPP is defined as follows:

$$D(t) = \sum_{i=1}^{N_{DER}} d_i(t) \tag{4.4}$$

subject to $P^{min}(t) \leq D(t) \leq P^{max}(t)$.

The inputs of the problem are the load $L(t)$, and the DERs demand $d_i(t) \forall i$, which vary throughout time. Load and total demand do not necessarily match, and the VPP should decide which is the amount of energy $a_i(t)$ each DER should produce, subject to DERs constraints. Thus, the energy demand allocation problem consists on determining the amount of energy each DER should produce $a_i(t)$ optimising a set of criteria. These criteria are agreed by all DERs according to the methodology explained in the next section.

Assumptions and limitations

The presented methodology is limited to situations where the load is within the minimum and maximum energy production of the set of DERs. Moreover, despite the fact that the following methodology aims to maximise the reliability of the allocation (the allocated power production is then delivered by the corresponding DERs), it also seeks other objectives (i.e. equity). Then there is a trade-off that may reduce the level of reliability. This may be a sufficient reason to discard the applicability of this methodology to the final step of balancing the energy generation and load, leaving the applicability of this methodology to longer-term steps, i.e. day-ahead.

4.4 Self-organising energy demand allocation based on distributive justice

The allocation methodology proposed consists of a self-organised approach based on distributive justice. Self-organised means that DERs participate in the decision-making of the allocation process. Then the allocation is carried out by the VPP coordinator which role can be assumed for any agent; i.e. they can take turns in that role. Distributive justice means that the allocation is performed according to a set of canons (see Section 4.2).

To this end, to agree the allocation of the load at a given time t (hour), the following procedure is proposed:

1. The VPP coordinator has information about the load $L(t)$
2. Each DER_i sends a demand message to the VPP coordinator for covering $d_i(t)$ of this load
3. The VPP coordinator computes the total demand $D(t)$. There may be different situations:
   (a) $L(t) \leq P^{min}(t)$. If the equality fits, all DERs produce at their minimum capacity, $a_i(t) = p_i^{min}$. Otherwise, there is a surplus of energy and mechanisms such as the disconnection of DERs or energy export to the main grid should be activated to balance the energy generation and the load.
   (b) $\boldsymbol{P^{min}(t) < L(t) < P^{max}(t)}$: DERs get individual allocations within their feasible production range. The VPP coordinator calculates the energy production of each DER according to a ranking based on a set of weights. Weights are set up among all of the DERs according to an achieved consensus among the relevance of a set of canons.
   (c) $L(t) \geq P^{max}(t)$: all DERs produce at their maximum capacity, $a_i(t) = p_i^{max}$, but, if the equality is not fulfilled, the load cannot be covered with DERs' production. Thus, other mechanisms should be activated to meet the load, i.e. disconnecting loads or importing energy from the main grid.
4. The VPP coordinator sends to each DER the computed allocation $a_i(t)$
5. Each DER delivers an energy amount $r_i(t) \sim a_i(t)$. The ideal situation is $r_i(t) = a_i(t)$ but uncertainty on generation cannot guarantee that the equality is fulfilled.
6. Each DER receives a payment $\tau_i(t)$ according to the delivered energy $r_i(t)$

The key step of the protocol is 3(b) where the agents, according to the distributive justice fundamentals, should agree on how the load is shared. For carrying out the allocation, the legitimate claims of Rescher's canons are implemented as voting functions f_* and the importance of each function is determined by its corresponding weight w_*. Basically, the determination of how the load is shared is an allocation process which is repeated over time. The initial value of the weights is set to $w_* = \frac{1}{m}$ (where m is the number of functions) and the process follows the next protocol:

1. **Sorting**. Each function f_* sorts all DERs and the VPP coordinator takes all partial orders and computes a new ranking of DERs taking into account the weight w_* assigned to each function.

2. **Allocation**. The VPP coordinator computes the allocation $a_i(t)$ of each DER_i according to the resulting ranking

3. **Voting**. Each DER_i votes about the relevance of each function f_*, $v_{i,*}$ and the VPP computes a ranking of functions based on a consensus method that updates the weight w_* for each function to be used in the next allocation round.

In the remainder of the chapter, the implementations of the claims and the different steps of this protocol are explained.

Before continuing, it is worth noting, that the application of this methodology assumes that no monitoring costs are incurred and there is no cheating on the reporting of $p_i^{min}(t)$ and $p_i^{max}(t)$.

4.4.1 Legitimate claims

Canons are used to determine rank lists, reflecting DERs' relative merits in the VPP. They are based on statistical data during the time-range T_i in which the DER has been an active member of the VPP. T_i varies throughout time ($T_i(t)$), but for the sake of clarity it is denoted T_i.

A total of six canons have been used, out of the seven available in the methodology proposed in [Pitt et al., 2012]: equality, need, productivity, effort, social utility, and supply and demand. The last canon, ability has been embedded in the other canons. They have been instantiated to the faced energy demand allocation problem, while pursuing a fair strategy.

Canon of equality: this has been represented in three ways: by their average allocations (f_{1a}), by the number of rounds they have received allocation (f_{1b}), and by the average payment received (f_{1c}).

$$
\begin{aligned}
f_{1a}(DER_i, T_i) &= \frac{\sum_{k=1}^{T_i} a_i(k)}{T_i} \\
f_{1b}(DER_i, T_i) &= \frac{\sum_{k=1}^{T_i} (a_i(k) > 0)}{T_i} \\
f_{1c}(DER_i, T_i) &= \frac{\sum_{k=1}^{T_i} \tau_i(k)}{T_i}
\end{aligned} \tag{4.5}
$$

where τ_i is the payment received. Note that f_{1a} and f_{1b} represent equality according to the workload and f_{1c} represents equality according to the awards for producing energy.

Canon of needs: this second canon, f_2, ranks the agents in increasing order of their satisfaction $\sigma_i(t)$ (therefore $f_2(DER_i, t) = \sigma_i(t)$). Note that satisfaction is not a verifiable attribute, so it has to be based on an estimation of it like equation (4.6). Then DERs increase or decrease their satisfaction depending on whether the allocation received is (or not) close to their demand. To represent the concept of closeness to the demand, it is defined the interval $I_i = \left[\underline{d}_i(t), \overline{d}_i(t)\right]$ as the interval which determines whether the DER i increases (or not) its satisfaction if the allocation received is inside (or not) such interval. In this regard, satisfaction is modelled as follows:

$$\sigma_i(t+1) = \begin{cases} \sigma_i(t) + \alpha \cdot (1 - \sigma_i(t)) & a_i(t) \in I_i \\ \sigma_i - \beta \cdot \sigma_i(t) & a_i(t) \notin I_i \end{cases} \tag{4.6}$$

where α and β are coefficients in [0, 1] which determine the rate of reinforcement of satisfaction and dissatisfaction respectively. α and β are the same for all DERs but eventually a different value could be defined by each DER_i, representing their tolerance.

Canon of productivity: this canon f_3 ranks the agents in decreasing order of their average production success rate defined as the relationship between the allocated load $a_i(t)$ and the delivered energy $r_i(t)$, as follows:

$$f_3(DER_i, T_i) = \frac{\sum_{k=1}^{T_i} \frac{r_i(k)}{a_i(k)}}{T_i} \tag{4.7}$$

Therefore, f_3 is measuring the DER reliability.

Canon of effort: this canon f_4 ranks the agents in decreasing order of the time spent as an active member of the VPP, i.e. T_i, thus the time the DER has been a member of the VPP except the time where the DER has been stopped due to maintenance or reparation tasks.

Canon of social utility: there are two representations of social utility: first f_{5a} rank the agents in decreasing order of the amount of time spent in a distinguished role, i.e. being the VPP coordinator. Second, f_{5b} rank the agents in increasing order of their CO_2 emissions.

Canon of supply and demand: The sixth canon, f_6 ranks agents in decreasing order according to

$$f_6(DER_i, T_i) = \frac{1}{T_i} \sum_{k=1}^{T_i} \left(\varpi_i(k) \cdot L(k) \sum_{j=1, j \neq i}^{N_{DER}} \left(1 - \varpi_j(k)\right) \right) \tag{4.8}$$

where $\varpi_i(k) = \frac{p_i^{max}(k)}{p_i^{max}}$ indicates the relative generation capacity of DER i at time k. This canon is used to pamper those DERs that can produce energy when it is needed and when the others cannot, fostering complementary DERs.

Summing up, there are a total of $m = 9$ criteria derived from the six canons.

4.4.2 Sorting

Each function f_* makes a sorted list of all DERs. Then a consensus should be agreed on a single ranked list of the DERs to proceed to the allocation accordingly. To that end, [Pitt et al., 2012] proposes a Borda count protocol [Emerson, 2007], which is considered a consensus-based voting method. Then, for each partial rank list provided by each function f_*, Borda points $\rho_{i,*}^{DER}$ are assigned to each DER_i, so rank k scores $N_{DER} - k + 1$ points.

The points from each DER regarding f_* are multiplied by the corresponding weight w_* and summed for all the functions to give a total Borda score to each DER to finally make the sorted list of DERs used to allocate the load. Therefore it can be said that canons *agree* a ranked list of the DERs.

4.4.3 Allocation

Once agents are sorted according to the canons, the allocation method proceeds to decide the amount of energy each DER has to generate according to the DER's demand and system constraints.

It is worth pointing out that first, the allocation required meets the minimum and maximum DERs' generation limits ($P^{min}(t) < L(t) < P^{max}(t)$, see Step 3b). However, the allocation depends on whether there is scarcity of load or not regarding the available demand; that is:

1. $L(t) < D(t)$: there is scarcity of load and some DERs have to produce below their demanded amount d_i.
2. $L(t) = D(t)$: all DERs produce the demanded amount d_i.
3. $L(t) > D(t)$: there is a surplus of load and some DERs have to produce over their demanded amount d_i.

Then, for cases 1 and 3, the VPP adjusts the allocation each DER receives according to the list sorted by the canons. Note that since there are opposite cases (scarcity of load versus excess of load) the methodologies to follow are also opposite. On the one hand, when there is scarcity the most meritorious DER is the first to receive allocation. On the other hand, when there is an excess of load, the least meritorious DER is the first to receive an allocation greater than its demand.

Scarcity of load: each agent receives an allocation equivalent to $p_i^{min}(t)$. Then each agent (from the first to the last on the list) receives another allocation equivalent to:

$$a_i(t) = \min\left\{LR(t), d_i(t) - p_i^{min}(t)\right\} \tag{4.9}$$

where $LR(t)$ is the (yet) non-allocated load. When an allocation $a_i(t)$ is assigned, its value is subtracted from $LR(t)$.

Excess of load: each agent receives an allocation equivalent to $d_i(t)$. Then each agent (from the last to the first on the list) receives another allocation equivalent to

$$a_i(t) = \min\left\{LR(t), p_i^{max}(t) - d_i(t)\right\} \tag{4.10}$$

All the allocation procedures can be constrained by external authorities, as for example, imposing some quotas of green energy. When that is the case the allocation method first fulfils operational constraints, second allocates energy demand to green DERs following the rank list until the green quota is completed or there is no more energy demand. Finally, if there is still energy demand to allocate, it is shared among all DERs according to the list. In doing so, the community is expected to be more robust to external interferences.

4.4.4 Voting

To enable the participation of the DERs in the allocation method, each DER i votes each function f_*, giving it Borda [Emerson, 2007] points $p_{i,*}^c$ according to the rank index f_* has given to DER i at time t. Therefore the canon that has given the best rank to i, receives the best Borda punctuation m (being m the number of functions) from DER_i. In case of a draw, each canon receives a punctuation equal to the sum of points reserved for the positions they occupy divided by the number of canons in the draw. For example, suppose there are four functions which ranked DER_i second, third, third and fourth. Then DER_i's vote would give 4 points to the first function, 2.5 points to the second and third functions (they share the punctuations of $3+2$), and 1 point to the fourth function.

Once DERs have voted canons, all Borda points of each function are summed and the resulting scores are used to update the weight w_* of each function f_* as follows:

$$w_*(t) = w_*(t) + w_*(t)\,\frac{Borda(f_*, VPP) - AvgBorda}{TotalBorda} \tag{4.11}$$

where $Borda(f_*, VPP)$ is the total Borda points that function f_* receives from DERs

$$Borda(f_*, VPP) = \sum_{i=1}^{N_{DER}} \rho_{i,*}^{c} \tag{4.12}$$

$AvgBorda$ and $TotalBorda$ are the average and total Borda points of all functions in the current round t

$$AvgBorda = \frac{1}{m} \sum_{\forall f_*} Borda(f_*, VPP) \tag{4.13}$$

$$TotalBorda = \sum_{\forall f_*} Borda(f_*, VPP) \tag{4.14}$$

It is worth pointing out that those canons that perform better than the average increase their weight in the next round. Thus, DERs affected by the allocation method *agree* the weight of each canon representation and so its relative importance in the allocation process.

4.5 Summary

This chapter tackles the resource allocation problem known as *energy demand allocation*. This consists of a given collection of distributed generators which constitute a VPP, determining the energy generation of each one in order to meet the demand. The chapter first formulates the problem and then proposes a method to solve it, considering that each generator is operated by an independent agent. Despite the multi-agent nature of the problem, this chapter does not propose an auction-based method to perform the allocation as does Chapter 3. The proposed method aims to be dynamic and self-adaptable to new contexts or situations, and fair and robust against external interferences in order to endure the institution throughout time.

The proposed allocation method is based on self-organisation, and therefore aims to fulfil Ostrom's principles regarding resource allocation methods for enduring self-organised institutions. These are: (i) congruence between provision and allocation (generators cannot produce more energy than the demand), and (ii) that those affected by the allocation method (distributed generators) must participate in its definition or decision process. In addition, fairness is sought due to its importance in multi-agent systems to incentivise beneficial behaviours for the community. Fairness is achieved through the concept of distributive justice, which relies on a set of different canons (principles) of justice. These concepts of justice are implemented through voting functions that rank agents according their merits or features regarding the corresponding canon (i.e. equality, reliability, etc.).

In the proposed method, agents publish their desired energy production and then canons implementations rank agents following a Borda protocol. In this regard, all canons agree a consensus of justice to rank agents. Following this rank, agents receive an allocation (a portion of the energy demand to cover) that depends on the constraints to satisfy, the published desired production and the corresponding load to cover. Next, agents participate in the allocation process, voting for the importance (weight) of each canon implementation. These weights are used to achieve the consensual rank of agents in the next round. The fact that in each round the weights of the canons are updated and that these canons cover a wide range of concepts, makes the method dynamic and provides it with a capacity to self-adapt to new situations. Therefore, the method presents some robustness against external interferences by the promotion of those canons that are opposite to these interferences. This latter property is directly related to the capacity of the institution to endure throughout time, because Ostrom's sixth principle regarding enduring self-organised institutions requires that the control of the institution is not challenged by external authorities. Therefore, in case of the presence of external interferences, the presented method minimises their harmful effects and help the institution to endure throughout time.

CHAPTER 5

PLANNING OF NEW GENERATORS BASED ON RENEWABLE ENERGY SOURCES

This chapter deals with the problem of integrating renewable energy resources to cover an energy demand in the smart grid. To that end, it introduces and formalises the problem of determining the optimal locations to place new DERs, as well as working out the most appropriate type of generator and its size. Next, it explores the use of meta-heuristic algorithms to solve the posed problem.

5.1 Introduction

The Intergovernmental Panel on Climate Change stated that even if greenhouse gas concentrations are established, the *anthropogenic warming and sea level rise would continue for centuries* [Working Groups I, II and III, 2007]. The response to such statements should be to pursue techniques, technologies and policies that will fundamentally reduce emissions without foregoing economic pragmatism. Given that the energy sector represents one of the three largest recent contributors to the growth of greenhouse gas concentrations (together with industry and transport) [Working Groups I, II and III, 2007], and that electricity accounts for more than one third of all greenhouse emissions [US Environmental Protection Agency, 2012] there is an unequivocal need to forge new paths in power generation and distribution.

One such path endeavours to address the efficiency problems inherent in traditional power generation and distribution systems by provoking a reconsideration of a core conceit: power stations need to be big. The rationale for this de facto norm is reasonable enough and is related to economies of scale, but the size and nature of standard plants means that they are typically removed from most end-users (for a variety of reasons related to pollution, aesthetics, land costs and the practicality of distribution), which means that the power network is composed of several very big power plants (usually thermal power plants in which up to two thirds of the primary energy used to generate electricity is lost in form of heat) far from the consumers. This conveys additional energy losses due to long-distance transportation and distribution and a very reduced control of the consumer side of the network.

In this regard, an interesting avenue for tangible beneficial change is begining to take shape, abandoning the belief that big is always best. Recent technological advances have made available small power plants from 10kW to several MW, leading a growth of the prevalence of distributed generators. The use of small (distributed or embedded) generators provides an important level of flexibility that is absent in large centralised stations. The reduction in physical size allows distributed generators to be co-located with loads, enabling better matching of resources, curtailment of transmission and distribution losses [Celli et al., 2005], greater robustness in the face of extreme weather events or attack [Office of Electric Transmission and Distribution, 2003], improved reactive power support and voltage control [Celli et al., 2005, Piagi and Lasseter, 2006] and decreased deployment time [Working Group III, 2007].

Despite the potential advantages, the placement of new DERs in the power network may be detrimental if it is not done according to a proper planning. In this regard, the key questions about DERs are where they should be located, which types (PV, wind, gas turbine, fuel cell, etc.) they should be, their dimensions and, lastly, the number of new generators to locate. These questions set up the complex problem called Distributed Generation Location and Sizing (DGLS) and a decision support tool could help electrical engineers to solve it. This thesis aims to contribute to the development of such tool as explained in this chapter.

As reviewed in Chapter 2, most works tackle the problem for a given number of generators and only a few solve it for an unfixed number of units. Also few works answer the question of which types of DER, for a given number of generators, are the most appropriate, in addition to their location and size. Nevertheless, there is a lack of research tackling the problem of jointly determining the location, size and type of an unfixed number of DERs (represented in green and dashed boxes in Figure 5.1). Thus, this chapter contributes to minimising this gap of the DGLS problem literature, extending and generalising the DGLS problem to determine not only the location and size of DERs, but also their most appropriate type and number for a given set of types of generators, a grid, a time-dependent load and certain meteorological conditions.

In addition, the DGLS literature aims to optimise some parameters of the power grid or power systems, which are usually power losses, voltage profiles and economic costs of in-

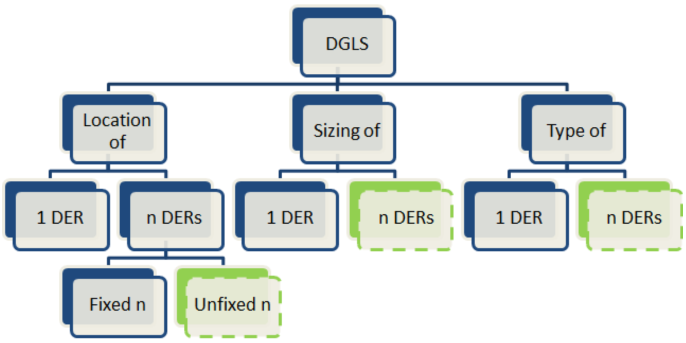

Figure 5.1: Classification of the questions tackled by the DGLS problem. In green, the questions tackled in this dissertation. Same as Figure 2.4 and repeated here for convenience.

stalling new generators, or alternatively their profit. In this regard, the formulation presented in this chapter aims to jointly optimise power losses, voltage profiles and DERs' profit.

Due to the complexity of the problem posed, meta-heuristic based approaches such as SA, GA or PSO have been chosen to solve the problem. Thus, this chapter presents these algorithms and explains how they have been adjusted to solve the DGLS problem. Chapter 6 provides a comparison of them.

5.2 Problem statement

The problem this chapter deals with aims to find the values of a set of variables (location, type and size of DERs in a grid) that achieve the best results for the criteria of the problem (profit, energy losses, voltage profile) while fulfilling the constraints of a given power system. Below, such variables, criteria, constraints and input data regarding the power system of the problem are described. Appendix A.3 summarises, for the sake of readability, the notation used.

5.2.1 Input data

The DGLS problem posed in this Chapter consists of determining the location, type and size of DERs given the following data (where i and k are the bus and DER indexes respectively):

- The available types of DERs with their associate amortisation $C_{i,k,amortisation}$, maintenance $C_{i,k,maintenance}$, production $C_{i,k}$, start up $SUC_{i,k}$ and shut down $SDC_{i,k}$ costs which may depend on the bus they are connected to.

- The energy selling price π^t for each time t.
- The resource availability forecast $r^t_{i,k,forecast}$. It is used to compute the generation capacity, at each time t, of DERs such as photovoltaic generators that use a stochastic energy source.
- The time-dependent active and reactive load profiles at each bus for each time t, $L^t_{P,i}$ and $L^t_{Q,i}$.
- The network features such as number of buses N_{bus}, conductivity parameters (i.e. maximum power flow $S^{max}_{i,j}$, resistance $R_{i,j}$, admittance $Y_{i,j}$), voltages limits (V^{min}_i and V^{max}_i), etc.

5.2.2 Decision variables

The decision variables of the posed problem are the location, type and size of the DERs. Considering that there is one DG unit per bus i and type k, the decision variables can be represented as the production capacity at each bus and for each type of DG, $P^{max}_{i,k}$. Note that considering a single DG unit per bus and type is equivalent to the aggregation of a collection of DERs of the same type connected to the same bus.

5.2.3 Constraints

Benefits of DG are calculated based on a generation and load schedule that has to fulfil a set of constraints:

- Bus voltages V^t_i must be within their limits

$$V^{min}_i \leq V^t_i \leq V^{max}_i, \quad \forall i \in [1, N_{bus}] \tag{5.1}$$

- Apparent power flow $\left|S^t_{i,j}\right|$ between buses i and j cannot exceed line thermal limit $\left|S^{max}_{i,j}\right|$ for all t

$$\left|S^t_{i,j}\right| \leq \left|S^{max}_{i,j}\right|, \quad \forall i, j \in [1, N_{bus}]\ \forall t \tag{5.2}$$

- Active and reactive power generation, $P_{i,k}^t$ and $Q_{i,k}^t$, must be balanced with active and reactive power demand, $L_{P,i}^t$ and $L_{Q,i}^t$, respectively

$$\sum_{k=1}^{N_{DGtypes}} P_{i,k}^t - L_{P,i}^t = \sum_j V_i^t V_j^t Y_{i,j} \cos\left(\delta_i^t - \delta_j^t - \theta_{i,j}\right), \quad \forall i \in [1, N_{bus}] \ \forall t \tag{5.3}$$

$$\sum_{k=1}^{N_{DGtypes}} Q_{i,k}^t - L_{Q,i}^t = \sum_j V_i^t V_j^t Y_{i,j} \sin\left(\delta_i^t - \delta_j^t - \theta_{i,j}\right), \quad \forall i \in [1, N_{bus}] \ \forall t \tag{5.4}$$

- Generation output cannot exceed the maximum power generation of the DG.

$$P_{i,k}^t \leq P_{i,k}^{max}, \quad \forall i,k \ \forall t \tag{5.5}$$

- Power generation cannot exceed the expected generation due to the resource availability forecast

$$P_{i,k}^t \leq P_{i,k}^{max} r_{forecast,i,k}^t, \quad \forall i,k \ \forall t \tag{5.6}$$

Note that the location and size of the DERs affect the maximum power output of DG, equation (5.5), and where (which bus) they inject power.

5.2.4 Objective function

The DGLS problem presented in this chapter aims to maximise DG units profit f_1, minimise system energy loss f_2 and improve the voltage profile f_3.

First, DERs' profit is the accumulated revenue of each DG unit for selling energy minus the cost of producing this energy, maintaining the DG and the amortisation of the DG unit.

$$\begin{aligned} f_1 = & \frac{1}{T} \sum_t \left(revenue^t - cost^t\right) - \\ & \sum_{i=1}^{N_{bus}} \sum_{k=1}^{N_{DGtypes}} P_{i,k}^{max} \cdot \left(C_{i,k,maintenance} + C_{i,k,amortisation}\right) \end{aligned} \tag{5.7}$$

where

$$revenue^t = \sum_{i=1}^{N_{bus}} \sum_{k=1}^{N_{DGtypes}} P_{k,i}^t \cdot \pi^t \tag{5.8}$$

$$cost^t = \sum_{i=1}^{N_{bus}} \sum_{k=1}^{N_{DGtypes}} \left(C_{i,k} \cdot P_{i,k}^t + \beta_{i,k}^t \cdot SUC_{i,k} + \gamma_{i,k}^t \cdot SDC_{i,k}\right) \tag{5.9}$$

Note that the $revenue^t$ and $cost^t$ do not directly depend on $P_{i,k}^{max}$ but they ($P_{i,k}^{max}\ \forall i,k$) will act as limiters of the power production $P_{i,k}^t$ at each time t.

Second, system energy loss is the amount of energy lost in the system lines and is formulated as follows:

$$f_2 = \sum_t \sum_{i=1}^{N_{bus}} \sum_{j=i+1}^{N_{bus}} K_{i,j}^t \left|S_{i,j}^t\right|^2 \rho^t \tag{5.10}$$

where the apparent power flow $\left|S_{i,j}^t\right|$ and the power loss factor $K_{i,j}^t$ are defined as:

$$\begin{aligned} \left|S_{i,j}^t\right|^2 = &\cos\left(\delta_i - \delta_j\right) \sum_k \left(P_{i,k}^t P_{j,k}^t + Q_{i,k}^t Q_{j,k}^t\right) + \\ &\sin\left(\delta_i - \delta_j\right) \sum_k \left(Q_{i,k}^t P_{j,k}^t + P_{i,k}^t Q_{j,k}^t\right) \end{aligned} \tag{5.11}$$

$$K_{i,j}^t = \frac{R_{i,j}}{\left|V_i^t V_j^t\right|} \tag{5.12}$$

It is important to point out that it is impossible to determine who has produced the energy lost in the system when there are multiple generators and, therefore, its cost. In this regard it is proposed to multiply the energy loss by an estimation of the cost of the energy injected in the system, ρ^t, to estimate the cost of such loss.

And third, to improve the voltage profile (the voltage at each bus at each time t), it is proposed to reduce the mean squared differences between the desired voltage and the obtained voltage.

$$f_3 = \frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{N_{bus}} \left(V_i^t - V_i\right)^2 \tag{5.13}$$

However, any other voltage index could be used. See [Moradi and Abedini, 2012] for other indexes for improving voltage quality.

Similarly to $revenue^t$ and $cost^t$, f_2 and f_3 do not directly depend on $P_{i,k}^{max}$, however the power production is constrained by $P_{i,k}^{max}$ and the voltage at each bus depends on the injection of power in the system.

Once the objective criteria are set, the optimisation problem consists of finding the size, type and location of the DERs that maximises the following objective function:

$$f = w_1 f_1 - w_2 f_2 - w_3 f_3 \tag{5.14}$$

where w_i is the weight of criterion f_i.

f (henceforth fitness) works as an indicator of the quality of a solution.

The decision variables are $P_{i,k}^{max} \forall i, k$ (which values represent the size of the DG, and the indices identify the type k and location i of the DG). However, the computation of the objective function f involves calculating the power output of each DG unit ($P_{i,k}^t$) at each time t (see equations (5.7), (5.10) and (5.13)). The methodology for computing the production schedule (($P_{i,k}^t \forall t$) is out of the scope of this Chapter (see Chapter 4 for a solution approach to this problem). In the experimentation, Section 6.5, a naive methodology is used that proportionally shares the load of the grid among all the available generators considering their generation capacity and the constraints of the grid.

Assumptions and limitations

The formulated problem assumes that the relation between objectives is known and can be expressed with weights w_i. On the other hand, the formulation assumes that the load profile of the grid is known for a long period of time (similar to the amortisation time of DERs to locate), and it does not consider the possibility of other DERs being installed in the grid. However, these issues could be tackled solving the problem for different scenarios of load and future DERs.

5.3 Using meta-heuristics for solving the DGLS problem

For solving the DGLS problem posed in this chapter, the performance of different meta-heuristic algorithms and combinations of them is analysed. The chosen meta-heuristic algorithms are GA, SA and PSO. They have been chosen because their use does not involve many mathematical assumptions about the problem and they are good tools to tackle very complex problems providing good solutions (although not the optimal) in a given amount of time. Furthermore, they represent different paradigms used in meta-heuristics (see Chapter 2) such as single point or population based algorithms, swarm algorithms, evolutionary algorithms, stochastic search, etc. These algorithms are expected to find the size, type, location (the bus they are connected to) and number of DERs that optimises the aggregation function expressed in Equation (5.14).

$$\begin{array}{cc} & \overleftrightarrow{N_{DGtypes}} \\ N_{bus} \updownarrow & \begin{pmatrix} 0.5 & 0.0 \\ 0.2 & 0.0 \\ 0.0 & 0.0 \end{pmatrix} \end{array}$$

(a)

$$\overleftrightarrow{N_{DGtypes} \times N_{bus}}$$
$$\begin{pmatrix} 0.5 & 0.0 & 0.2 & 0.0 & 0.0 & 0.0 \end{pmatrix}$$

(b)

Figure 5.2: (a) Example of a candidate solution of SA or GA with 2 DG units of type 1 of size 0.5MW and 0.2MW located at buses 1 and 2. (b) Example of the same candidate solution of (a) but as a 6-dimensional vector for PSO.

This section explains the particular implementation of these algorithms used to solve the posed problem.

5.3.1 Simulated annealing

SA is a meta-heuristic algorithm that was independently described by Kirkpatrick *et al.* [Kirkpatrick et al., 1983] in 1983 and Cerný [Černý, 1985] in 1985. It is based on a metallurgy technique that consists of heating and cooling a material to increase the size of its crystals and reduce its defects. When the material is heated, the atoms are freed from their initial positions (local energy minimums) and wander randomly across the space. Then, the slow cooling gives them more chances of falling into a lower energy state than the initial one. Hence, at each iteration, SA consists of iteratively improving a candidate by moving it around the problem space. To avoid local optima and flat zones, there are some chances that it will make some *bad movements* and so not move towards the closest optimum.

SA starts with an initial random solution. Then, at each iteration it selects a *neighbour* solution s' and compares it with the current solution s. If s' is better, SA moves towards it and replaces s by s'. Otherwise it also can move towards s' (*bad movement*) with a probability $e^{\frac{fitness(s')-fitness(s)}{T}}$ or stay on s with a probability of $1-e^{\frac{fitness(s')-fitness(s)}{T}}$, where T is the temperature of the environment and controls the probability of bad movements. Algorithm 5.1 shows the procedure of SA.

A candidate solution is given by a matrix whose values indicate the size of the DG connected to the bus indicated by the column index (Figure 5.2 shows an example). The type of the generator is given by the row index. For example, if the value of column i and row k is zero, it indicates that no generator of type k is placed at bus i. However, if the value is 0.5, this indicates that a DG of type k and with $P_{i,k}^{max} = 0.5$MW is placed at bus i.

The fitness of each candidate solution is computed according to equation (5.14).

Algorithm 5.1 SA

Make an initial candidate solution S
while $T_f \leq T$ **do**
  Select a neighbour solution s'
  if $fitness(s) < fitness(s')$ **then**
    $s \leftarrow s'$
  else
    $x \leftarrow U(0,1)$
    if $x < e^{\frac{fitness(s') - fitness(s)}{T}}$ **then**
      $s \leftarrow s'$
    end if
  end if
  $T \leftarrow T \cdot \delta$
end while

A key point of every SA algorithm is selecting the neighbour solution for a given current solution. This dissertation proposes two strategies for selecting neighbour solutions that are then compared and analysed in the next chapter. These strategies are:

- Accumulation: this strategy consists of adding a random value given, by a uniform distribution $U\left(-\frac{SIZE_{i,k}^{max}}{K}, \frac{SIZE_{i,k}^{max}}{K}\right)$ (where $SIZE_{i,k}^{max}$ is the maximum allowed value for $P_{i,k}^{max}$ and K is a real number greater than 1), to each value of the solution matrix for a given probability. The probability of modifying a particular value of the solution matrix is given by the relative generation capacity it represents in respect of the capacity of the whole solution. For example, a particular value a of the solution matrix has a probability of $\frac{a}{A}$ where A is the sum of all the values of the matrix. All values of the matrix must be within its corresponding $\left[0, SIZE_{i,k}^{max}\right]$. This approach is labelled SAacc.

- Random value: as in the previous strategy, each value of the solution matrix has a probability of being modified that depends on the relative generation capacity of the generator it represents. However, this mechanism modifies the values of the matrix by assigning them new random values within $\left[0, SIZE_{i,k}^{max}\right]$. The probability of 0 is 50% and the other values within $\left(0, SIZE_{i,k}^{max}\right]$ are uniformly distributed. This approach is labelled SAran.

Both strategies give the same chances to a generator of being modified and it depends on its relative importance (small generators have more chances of being modified because it is supposed that their modification has less implications).

5.3.2 SA and linear random search

The problem posed in this chapter consists of finding the optimal place, type and size of DERs in a given grid. This can be seen as a two-step problem consisting, first, of finding the places and types of the generators (which DERs should be placed and where) and second, of setting the appropriate size of the DERs given from the first step. In this way, it is proposed to solve the first step through SA because it is a global search technique (bad movements enable it to avoid local optima and flat regions) and because it only needs to compute the fitness of a single solution at each iteration (conversely to GA or PSO which are population-based algorithms). This point is very important because the fitness function is very time consuming (the power flow has to be computed for each time step) and thus, it limits the number of times that it is feasible to compute. For the second step, a Linear Random Search (LRS) algorithm is proposed. This is a local search technique that consists of giving a solution, creating a new one modifying the size of DERs randomly (adding, to each one, a random number, i.e. $U\left(-\frac{SIZE_{i,k}^{max}}{K}, \frac{SIZE_{i,k}^{max}}{K}\right)$) and then moving to the new solution if it is better than the current one. This algorithm does not need the fitness function to be linear and/or differentiable and despite being a local search technique while the solution space is not convex, its convergence is very fast making it able to work out good size values for the DERs given by the SA. Furthermore, despite LRS being a local search technique, its combination with SA can be considered as a global search technique.

Algorithm 5.2 shows the combination of SA and LRS to solve the DGLS problem. First it starts with an initial random solution. A solution consists of a matrix where each value corresponds to a DER. The row determines the bus where the DER is placed and the column the type of the generator. Then, iteration after iteration, it creates a neighbour solution s' (made up of 0s and 1s where 1 indicates the presence of a DG and 0 the absence), and then it determines the size of the generators using LRS. Finally, it compares the quality of the new solution with the current one. As in SA, if the new solution is better, the algorithm replaces the current solution s by s'; otherwise, the algorithm only replaces s by s' with a probability given by $e^{\frac{fitness(s')-fitness(s)}{T}}$.

Note that this approach is very similar to SAacc, but it tends to perform a more exhaustive local search (in terms of size) for a given set of located generators.

5.3.3 Genetic algorithms

GA [Luke, 2013, Haupt and Haupt, 2004, Torrent-Fontbona, 2012] is a popular meta-heuristic already used in Chapter 3. Each chromosome represents a candidate solution. Chromosomes have a set of genes and each one represents a dimension of the problem space. Chromosomes

Algorithm 5.2 SA+LRS

Make an initial and binary candidate solution s
while $T_f \leq T$ **do**
  Select a neighbour solution s' (only made up of 0s and 1s)
  $s' \leftarrow LRS\left(s'\right)$
  if $fitness\left(s\right) < fitness\left(s'\right)$ **then**
    $s \leftarrow s'$
  else
    $x \leftarrow U\left(0,1\right)$
    if $x < e^{\frac{fitness\left(s'\right) - fitness\left(s\right)}{T}}$ **then**
      $s \leftarrow s'$
    end if
  end if
  $T \leftarrow T \cdot \delta$
end while

are represented as $N_{DGtypes} \times N_{bus}$ matrices, where $N_{DGtypes}$ is the number of the available DG types (Figure 5.2 shows an example). Thus, each gene represents a DER whose size is given by the value of the gene. The type and bus of the DER are represented by the row and column indices respectively.

GA starts creating an initial population of chromosomes (a set of new random solutions) and then it calculates the fitness of each one according to equation (5.14). The size of the initial population is POP_{size}. After evaluating the members of the initial population, generation after generation, GA carries out reproduction and elitism to make the population evolve and improve in order to find better chromosomes. Algorithm 5.3 summarises the procedure of the GA proposed in this chapter and used to solve the DGLS problem.

Algorithm 5.3 GA

Make an initial set of chromosomes
Compute the fitness of each chromosome
for $i \leftarrow 1$ **to** $N_{generations}$ **do**
  Select POP_{size} couples of parents
  Create a couple of children from each couple of parents using crossover and mutation
  Compute the fitness of each child chromosome
  Apply elitism to old and new individuals to obtain the new population
end for

Reproduction consists of three main steps (selection of parents, crossover and mutation) as done for the scheduling method in Chapter 3, and elitism is used to keep the size of the population. The particularity is mutation, which consists of changing some genes of each new child chromosome. In particular two mutation operators are used: the first consists of changing the value of a gene (changing the size of a DER) with a particular probability $mut_{size} = 0.1$. The second consists of interchanging the type of two generators of the same bus with a particular probability $mut_{type} = 0.01$.

5.3.4 Particle swarm optimisation

PSO is a swarm computation technique developed by Kennedy and Eberhart in 1995 [Kennedy and Eberhart, 1995]. Similar to GA, PSO is a population-based optimisation tool. It is inspired by the social behaviour of bird flocking or fish schooling. The members of the population explore the solution space by wandering throughout it. Their moves are apparently random but, at the same time, they tend to wander towards their own best position and the best-known position of the swarm.

Regarding the problem posed in this chapter, each individual (particle) in the PSO is composed of three D-dimensional vectors, where $D = N_{bus} \times N_{DGtypes}$ is the dimensionality of the search space (Figure 5.2 shows an example). These are the current position of the particle $\vec{x}_i$, its past best position $\vec{p}_i$ and the velocity $\vec{v}_i$. The position $\vec{x}_i$ (or the past best position $\vec{p}_i$) of each particle represents a possible solution to the problem to optimise and the value of each slot j of the position vector corresponds to the size of the DER of type $k = j \pmod N)_{DGtypes}$ connected to bus $i = \lceil \frac{j}{N_{DGtypes}} \rceil$. Thus, the matrices used in SA and GA are unfolded.

Algorithm 5.4 summarises the procedure of the algorithm. PSO starts with a group of particles, each having a random initial position $\vec{x}_i$ (step 1) and then it calculates the fitness of the positions of all the particles (step 2) in order to work out the best position of the swarm $\vec{p}_g$. Next it starts a loop, which, at each iteration, updates the previous best position of each particle $\vec{p}_i$ and the best position of the swarm (steps 5-10). Then it computes the velocity of each particle $\vec{v}_i$ using $\vec{p}_i$ and $\vec{p}_g$ as attracting points:

$$\vec{v}_i \leftarrow \omega \vec{v}_i + \phi_1 (\vec{p}_i - \vec{x}_i) + \phi_2 \left(\vec{p}_g - \vec{x}_i\right) \tag{5.15}$$

where, $\omega \vec{v}_i$ can be considered as the inertia of the particle and ω is called *inertia weight*. The term $\phi_1 (\vec{p}_i - \vec{x}_i) + \phi_2 \left(\vec{p}_g - \vec{x}_i\right)$ can be seen as an external force $\vec{F}_i$ that changes the velocity of the particle. In this way, the change in a particle's velocity (particle acceleration) can be written as $\Delta \vec{v}_i = \vec{F}_i - (1 - \omega)$ and, therefore, the constant $(1 - \omega)$ acts as a friction coefficient and ω can be interpreted as the fluidity of the search space. Clerc and Kennedy analysed in [Clerc and Kennedy, 2002] the convergence of PSO depending on the parameters ω, ϕ_1 and ϕ_2 and concluded that $\frac{(\phi_1+\phi_2)}{\omega} > 4$ to ensure convergence. When this constriction method is used, the values are usually set to $\omega = 0.7298$, $\phi_1 = \phi_2 = 1.49618$. These values are also used in this dissertation.

The fitness function used to evaluate particles' positions is, as in SA and GA, equation (5.14).

Algorithm 5.4 PSO

Initialise population with random positions
Compute the fitness of each particle
for $i \leftarrow 1$ **to** $N_{iterations}$ **do**
    for all particle **do**
        if $fitness(\vec{x}_i) > fitness(\vec{p}_i)$ **then**
            $\vec{p}_i \leftarrow \vec{x}_i$
            if $fitness(\vec{x}_i) > fitness(\vec{p}_g)$ **then**
                $\vec{p}_g \leftarrow \vec{x}_i$
            end if
        end if
    end for
    for all particle **do**
        $\vec{v}_i \leftarrow \vec{v}_i \cdot \omega + \Phi_1(\vec{p}_i - \vec{x}_i) + \Phi_2(\vec{p}_g - \vec{x}_i)$
        $\vec{x}_i \leftarrow \vec{x}_i + \vec{v}_i$
    end for
    Compute the fitness of each child chromosome
end for
Select the best position as solution

5.3.5 Combinations of algorithms

PSO and GA are population-based optimisation algorithms, and use such populations to perform a global search of the optimum. On the other hand, SA's search is based on improving a single solution instead of a collection. However it can be also considered a global optimisation tool because it has mechanisms to avoid local optima and flat regions, though PSO and GA perform a much more global search.

Since PSO and GA are population-based algorithms and SA only improves a single solution, it makes sense to use a combination of these algorithms in order to perform, first, a global search using PSO or GA and then to polish such a search using SA starting from the best solution found out by PSO or GA.

This dissertation proposes the combination of GA with SAran and SAacc (GA+SAran and GA+SAacc) and PSO with SAran and SAacc (PSO+SAran and PSO+SAacc) for solving the DGLS problem. Their performances are then analysed in Chapter 6. PSO, GA and SA have been chosen because they represent different types of meta-heuristic algorithms. At the same time, it has been decided to combine GA or PSO with SA to start with a global search (usually population based methods do it better than single point methods) but finishing with a bounded search. Then SA *polishes* the best solution found by GA or PSO.

5.4 Summary

This chapter has highlighted the possible benefits of placing renewable DERs in a power grid, i.e. reduction of the power losses, voltage control, etc. However, these possible benefits can become disadvantages if the planning is not appropriate. Therefore, this chapter has posed the problem of determining the number of new DERs to connect to a given grid, their most appropriate type and the best locations where they should be placed in order to optimise the performance of the grid in addition to the economic benefits. Due to the complexity of the problem, the chapter proposes and explains different meta-heuristic algorithms to tackle and solve the problem, yet not to the optimality.

The selection of algorithms has been done to cover different paradigms used in the development of meta-heuristics (see Chapter 2). In this regard, the chapter fist proposes single point search and memory-less algorithms, i.e. SA and LRS. Then the chapter explores population-based and memory-usage algorithms such as GA, which is also an evolutionary algorithm, and PSO, which is a swarm algorithm. Finally, different combinations of single point search method and population-based methods are proposed. Furthermore, all the proposed algorithms represent stochastic search algorithms, with a static objective function. Deterministic search is not appropriate for the posed problem due to its non-linearity, and other algorithms such as various neighbourhood search and guided search, which represent other paradigms, could be explored in a future work.

CHAPTER 6

EXPERIMENTATION AND RESULTS

This dissertation has presented optimisation methodologies to assist the decision-making in different contexts of the future smart grid, such as demand-response, allocating the energy production in a DG context and planning the installation of new DERs. This chapter aims to present the experimentation conducted regarding these methods and analyses and discusses the obtained results. Finally it provides a general discussion of these methods.

6.1 Introduction

Smart grid involves the building and operation of a more diverse, efficient and sustainable electric system. It covers smart consumption to smart generation of electricity including the smart planning of the grid. Therefore, the involved agents are consumers, producers, distributors, etc. This dissertation aims to present solutions to optimisation problems within the scope of demand-response, energy generation and network planning. This scope is illustrated in Figure 6.1 with the proposed solution approaches. Smart grid needs and fosters smart consumers and producers capable of adjusting themselves to the needs of the other side. In other words, it needs smart consumers capable of adapting their consumption profiles to the energy production requirements, and at the same time, it needs smart producers (or a smart production system) capable of integrating and coordinating different energy resources to meet the demands of consumers. Accordingly, Chapter 3 presents approaches to provide the capacity to schedule the activities of consumers in order to adjust their consumption profile, and then, an approach to incentivise the formation of coalition of consumers. Next, Chapter 4 presents a decentralised approach to coordinate a collection of heterogeneous DERs that belong to a VPP. In this mix of producers and consumers, their aggregation in coalitions or bigger entities, i.e. VPP, will play a key role to achieve an efficient coordination. Despite the needs of smart

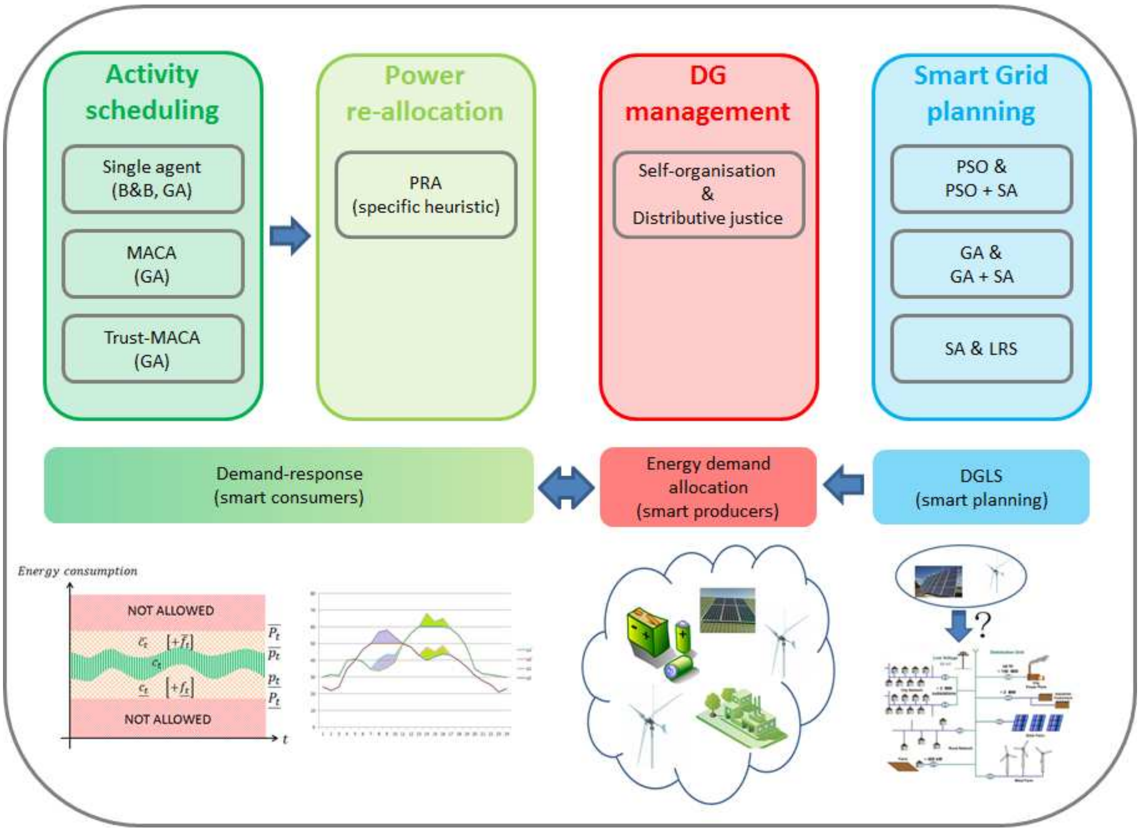

Figure 6.1: Illustration of the scope tackled throughout the dissertation and the solution approaches.

producers and consumers, a key aspect is the planning of the grid to avoid problems from the foundations and to enable the potential of the whole system. Chapter 5 presents meta-heuristic methods to seek optimal solutions to the planning of the grid working out optimal locations and generators to integrate in a given grid.

Since the scope of the thesis covers different problems and presents different approaches to them, the experimentation has been conducted over different datasets. The experimentation is described throughout the following sections of this chapter.

6.2 Energy aware project scheduling problem

This section describes the experimentation related to the demand response methods presented in Section 3.2 to solve the e-MPSP, and analyses the results.

The section aims to expose the importance of considering energy issues in business processes, the complexity associated to the e-MPSP and the benefits of meta-heuristics and the auction-based methods presented in Chapter 3 for solving the problem.

6.2.1 Experimental data

The experimentation was conducted over simulations based on real projects[1] that a company has to schedule and perform using their own resources (7 different resources). Each resource masters a set of skills that allow it to perform activities and has an execution time, cost and energy consumption that depend on the activity to execute.

The experiments have been carried out on a PC with an Intel®Core™i5 @ 2.80GHz CPU, 8.00GB of RAM and Windows 7 64 bits.

6.2.2 Single-agent approach

The experimentation conducted to analyse the e-MPSP is presented below, with the results obtained with the single-agent approaches proposed to solve the problem.

Experimental set up

Three different scenarios are considered:

Scenario 0: Comparison of e-MPSP with MPSP. A set of 80 different projects (of sizes from 4 to 9 activities) has been solved taking into account energy consumption and variable energy prices (e-MPSP) and considering only the makespan as in a typical MPSP. Results are provided in terms of makespan, energy consumption, and economic cost (according to Equations (3.9) to (3.11)), in order to be able to compare the outcomes. The computational time is also provided.

Scenario 1: Analysis and comparison of the performance of B&B and GA. The MPSP has been solved for different projects using B&B and GA. The sizes of the projects vary from 4 to 9 activities and 20 projects for each size were scheduled. The results are provided according to the objective function (Equation (3.14)) and the computational time.

Scenario 2: Analysis of the performance of GA with larger projects (with more activities). This was used to schedule different projects with sizes of 15, 20, 25, 30, 35 and 40

[1] Experimentation data available at `http://eia.udg.es/~apla/fac_data/`

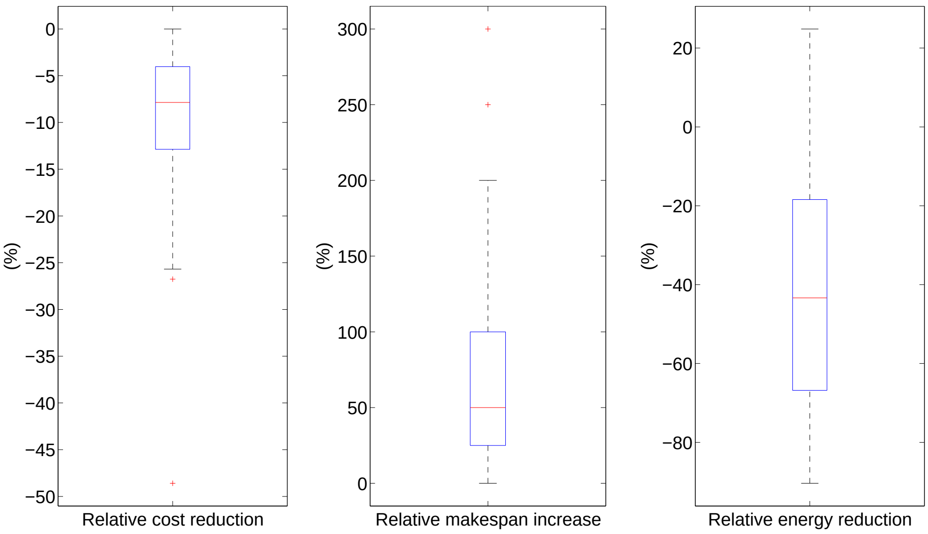

Figure 6.2: Relative difference in cost, makespan and energy consumption of the optimal schedules of different projects of different sizes when energy consumptions and energy prices are considered (e-MPSP) respect when only the makespan is considered as in a typical MPSP.

activities. There are up to 10 projects of size 15 to 25, and up to 5 projects of size 30 to 40. The results are measured in terms of the objective function (Equation (3.14)).

Results: MPSP versus e-MPSP

Figure 6.2 shows the statistical information (minima, maxima and percentiles 25, 50 and 75) of the relative differences of the cost, makespan and energy consumption between MPSP and e-MPSP (scenario 0). It clearly shows that, when the problem solving process considers energy consumption and the price of the energy, the cost and the needed energy of the final schedule is reduced (40% in average) in exchange for increasing the makespan. On the other hand, cost is also reduced (10%). That is expected to happen in any multi-objective optimisation problem. However it is worth highlighting the importance of taking into account energy consumptions and energy prices in project scheduling problems with energy consuming activities such as the projects solved in this dissertation.

Another implication of taking into account variable energy prices, energy consumptions and compromised load shapes is the complexity of the problem to solve. Obviously, variable prices increase the complexity of the e-MPSP in respect of a typical MPSP. Figure 6.3 shows the average time elapsed by the B&B algorithm presented in Chapter 3 to solve 120 projects of

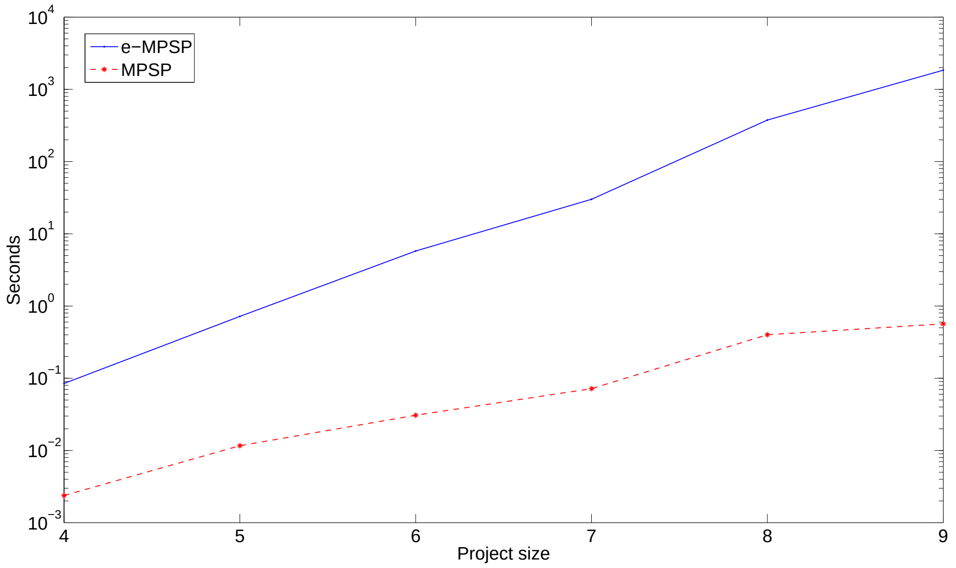

Figure 6.3: Mean elapsed time by B&B algorithm presented in Chapter 3 to solve e-MPSP and MPSP of different sizes.

sizes from 4 to 9 activities (20 projects per size). For scheduling the projects, as in a typical MPSP, the B&B algorithm minimised the makespan without considering energy prices and only considering energy consumption to keep the energy profile $\rho_t \in \left[\underline{P_t}, \overline{P_t}\right]$. Results show that the algorithm needs about 2 to 3 more orders of magnitude of time to solve the problem.

Results: B&B versus GA

Due to the complexity of the e-MPSP, an optimal solution cannot be found within reasonable time using complete methods like B&B when the size of the project increases. A proof of this is the mean elapsed time by B&B shown in Figure 6.4, which rises exponentially with the number of activities and which, for a project with 9 activities, B&B needs an average of 10^3 seconds to schedule. In this regard, the use of meta-heuristic algorithms like GA is amply justified. Nevertheless, GA does not guarantee the optimal solution. Figure 6.4 shows the relative error of the solutions found by GA. It shows that the more activities the project has, the greater the error of the solution.

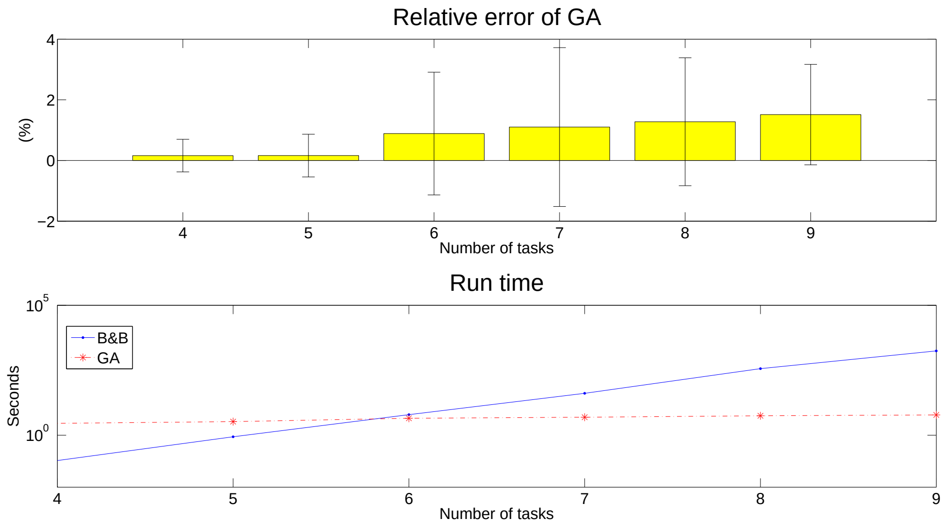

Figure 6.4: Scheduling results from different projects grouped by the number of activities. On the top: relative error (mean and standard deviation) of the solutions found by GA respect the optimums (found by B&B). On the bottom: elapsed time by B&B and GA.

Project ID	Mean	St. dev.	Min	Max	Percentage of minima found (%)
#01	64.28	0.00	64.28	64.28	100.00
#02	58.46	0.55	58.21	60.04	80.00
#03	63.10	0.67	62.81	65.61	80.00
#04	59.74	0.21	59.53	60.12	40.00
#05	58.08	2.72	57.35	69.74	90.00
#06	41.20	0.21	41.08	41.67	75.00
#07	63.83	0.10	63.76	63.99	65.00
#08	66.99	0.00	66.99	66.99	100.00
#09	75.83	0.49	75.67	77.84	85.00
#10	54.12	0.21	54.01	54.65	75.00

Table 6.1: Scheduling results using GA with projects with 15 activities. GA has been run 20 times per project.

Project ID	Mean	St. dev.	Min	Max	Percentage of minima found (%)
#11	80.61	2.03	79.25	87.29	35.00
#12	89.62	0.75	89.26	92.67	35.00
#13	74.83	0.80	74.22	77.41	30.00
#14	40.21	0.00	40.21	40.21	100.00
#15	92.20	0.28	91.89	93.37	5.00
#16	74.15	0.47	73.59	74.59	40.00
#17	81.44	0.31	81.34	82.37	90.00
#18	75.12	0.00	75.12	75.12	100.00
#19	86.80	0.00	86.80	86.80	50.00
#20	89.08	1.32	88.39	93.59	65.00

Table 6.2: Scheduling results using GA with projects with 20 activities. GA has been run 20 times per project.

Project ID	Mean	St. dev.	Min	Max	Percentage of minima found (%)
#21	53.13	0.20	53.02	53.55	80.00
#22	105.03	2.12	103.16	108.88	40.00
#23	87.68	0.00	87.68	87.68	100.00
#24	111.05	0.00	111.05	111.05	100.00
#25	104.57	0.00	104.57	104.57	100.00
#26	86.06	0.29	85.93	86.74	60.00
#27	95.87	0.46	95.37	96.28	45.00
#28	107.10	0.00	107.10	107.10	100.00
#29	90.34	0.00	90.34	90.34	100.00

Table 6.3: Scheduling results using GA with projects with 25 activities. GA has been run 20 times per project.

Project ID	Mean	St. dev.	Min	Max	Percentage of minima found (%)
#30	127.20	0.19	126.94	127.35	35.00
#31	122.11	2.09	120.88	130.20	50.00
#32	120.94	0.82	119.99	123.29	35.00
#33	113.30	0.35	113.10	114.54	40.00
#34	122.65	1.97	121.77	131.01	45.00

Table 6.4: Scheduling results using GA with projects with 30 activities. GA has been run 20 times per project.

Project ID	Mean	St. dev.	Min	Max	Percentage of minima found (%)
#35	150.23	2.10	147.83	156.69	30.00
#36	150.11	4.42	147.49	159.69	65.00
#37	133.87	0.92	133.66	137.86	95.00
#38	149.12	2.23	147.78	154.38	30.00
#39	169.24	6.74	164.52	191.87	30.00

Table 6.5: Scheduling results using GA with projects with 35 activities. GA has been run 20 times per project.

Project ID	Mean	St. dev.	Min	Max	Percentage of minima found (%)
#40	175.58	0.92	175.06	178.30	25.00
#41	197.95	4.29	196.25	215.51	75.00
#42	171.48	0.79	169.60	171.92	15.00
#43	155.25	2.63	154.20	166.41	20.00
#44	172.25	7.72	167.30	204.20	30.00

Table 6.6: Scheduling results using GA with projects with 40 activities. GA has been run 20 times per project.

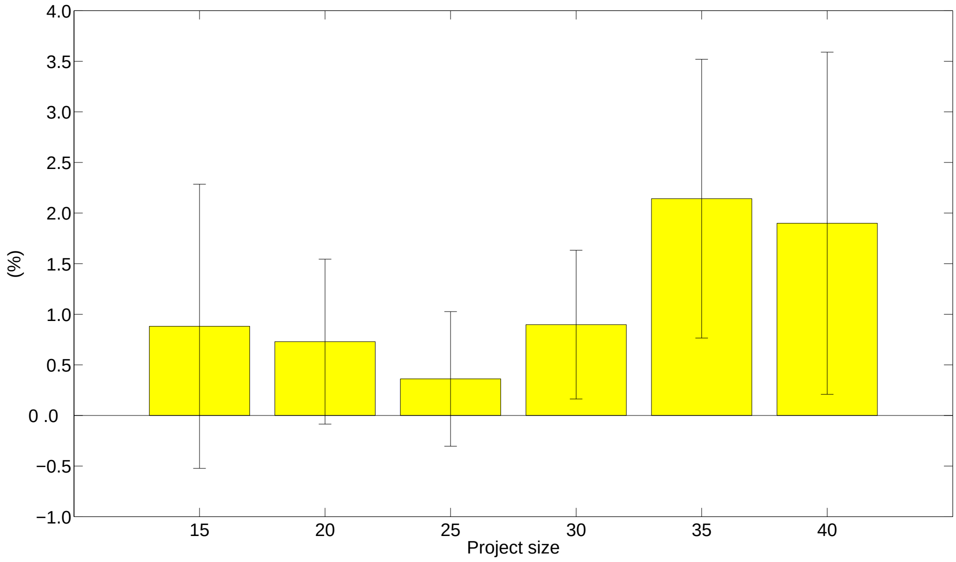

Figure 6.5: Relative distance to the minima of the solutions of the projects shown in Tables 6.1-6.6.

Results: GA performance

Since the optimal schedules of the projects are unknown, each project has been solved 20 times with GA and the statistics of the solutions found for each project (average cost, standard deviation of the cost, minimum cost, maximum cost and percentage of times that GA achieved the minimum cost) are presented on Tables 6.1 to 6.6. When dealing with projects with a particular complexity (Tables 6.1 to 6.3), GA converges on some occasions to the same minimum (see for example, projects #01 and #08 of Table 6.1, projects #14 and #18 of Table 6.1, and projects #23, #24, #25, #28, and #29 of Table 6.3). Therefore, it can be considered that in such situations, it is very likely that the minimum found is the optimal one. In general, the standard deviation obtained in all the solutions found by the GA is around a 2%. However, when the complexity of the projects increases (Tables 6.5 to 6.6), the solutions in each GA run diverge, and then the solution obtained is probably an approximate solution somewhat far from the optimal.

In summary, results on these tables show that although GA is not able to guarantee the optimal schedule, it converges around a particular value at each project. Furthermore, a relative error is defined dividing the distance between the solutions found and the minima by the $\Psi(\mathscr{S},\mathscr{X})$ value of the minima. Figure 6.5 shows this relative error (in percentage) according to the different project sizes. It can be stated that the relative error of the solutions found is very small (around 1%, as Figure 6.5 shows) and thus, the presented GA achieves very good

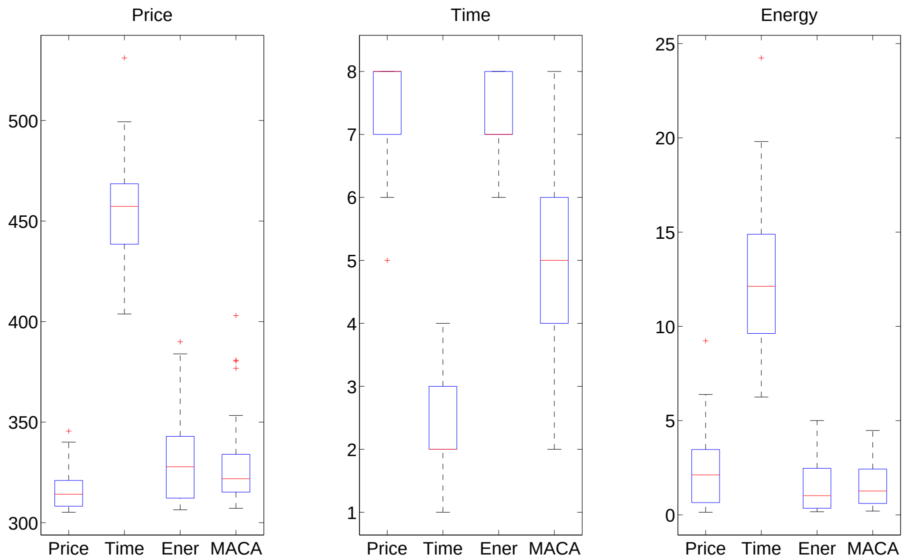

Figure 6.6: Values of the attributes of the winning bids when a single attribute (monetary cost, time or energy) or the aggregation of all of them (horizontal axis) is optimised. Y axis: (left) price, (centre) time, (right) energy

results when it deals with the e-MPSP.

Finally it is worth pointing out that the initialisation of chromosomes is not constrained to only feasible solutions. The solutions happen to be feasible but feasibility constraints are not imposed: basically it is just luck. In this case, the algorithm should check the constraints at each computation and assign an infinite value to the objective function if the solution is infeasible. However, it is expected that for more complex problems, GA would have some difficulties finding feasible solutions.

Further research should study the applicability of mechanisms that increase the drop rate of infeasible solutions, or even avoid the algorithm to consider them.

6.2.3 MACA

This section analyses the performance of the multi-agent approach based in multi-attribute combinatorial auctions as presented in Section 3.2.3. First, it explains the experimental set up and then it presents the results of the experimentation.

The experimentation aims to show the effect of considering energy issues in a business process and the benefits of using a methodology that merges multi-attribute and combinatorial

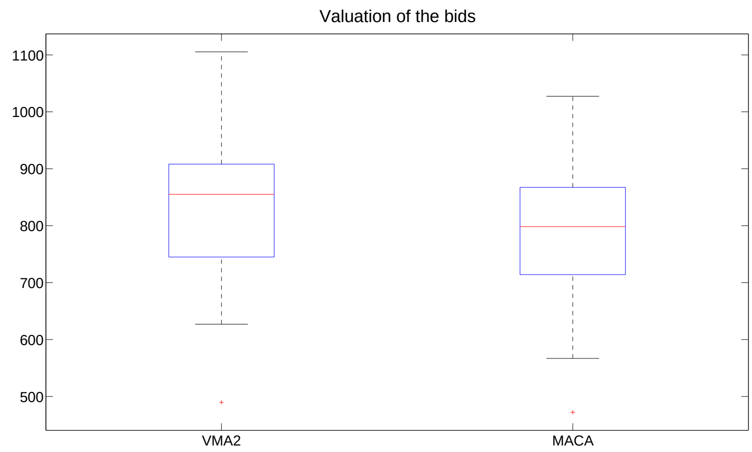

Figure 6.7: Comparison of the average aggregated cost of the winning bids when using MACA or VMA2.

auctions instead of using a sequential auction mechanism.

Experimental set up

The experimentation was conducted using a multi-agent simulator [Pla et al., 2012a] and real based data (see Section 6.2.1). Tasks were managed by an agent (auctioneer) that outsourced tasks to 7 other agents (bidders) with different skills. Each task required a particular skill and conveyed an economic cost, a particular execution time and an energy consumption. Each bidder had assigned a particular energy tariff which conveyed variable energy prices. Agents' behaviour was modelled as competitive and greedy.

The considered scenarios are the following:

Scenario 1: The goal of the experiment is to point out the importance of aggregating all the objectives that an organisation needs to consider, especially when they cannot be optimised simultaneously. Then the use of aggregation functions provides solutions with a trade-off between the objectives.

For that purpose, this scenario aims to compare the allocation of the tasks of a single day considering uni-criteria (combinatorial auctions) and multi-criteria valuation functions (MACA). The resulting task allocation was computed using a uni-attribute approach of the MACA auction mechanism (considering only the price, or the delivery time, or the energy consumption of the bids in Equations (3.24) and (3.28)) and using MACA

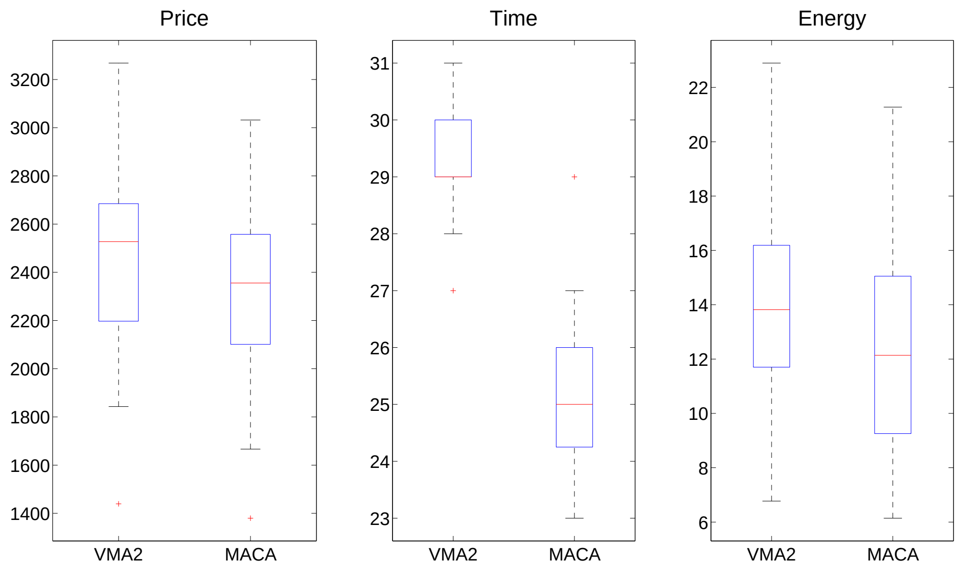

Figure 6.8: Comparison of the values of the attributes of the winner bids when using MACA or VMA2. The values for VMA2 consist of the aggregation of the results of auctioning the same tasks one after the other rather than in MACA.

(determining the auction winner using aggregation function V). The experiment was conducted over 50 sets of tasks.

Scenario 2: this scenario aims to compare the performance of VMA2 and MACA. VMA2 [Pla et al., 2014] auctions one task at a time (sequential auction). Therefore, the order in which tasks are auctioned could affect the results. On the other hand, in MACA all the tasks are auctioned at the same time (combinatorial). Although the benefits of combinatorial auctions as compared to sequential ones are very well known, both VMA2 and MACA consider multi-attribute auctions. In particular, scenario 2 is used to point out the cost differences when using each method.

For that purpose, the allocation of the tasks of a single day was computed using MACA and a multi-attribute sequential auction approach (VMA2). Experiments were also repeated 50 times to obtain meaningful results. To compare VMA2 and MACA the same tasks were auctioned, but VMA2 auctioned them sequentially and MACA auctioned them concurrently. To compare the results, VMA2 results were aggregated. The makespan for VMA2 was calculated as the difference between the ending of the last task and the auction time of the first task. MACA computes the makespan as the difference between the end time of the last task performed and the auction time.

Scenario 1: uni-attribute versus multi-attribute combinatorial auctions

Figure 6.6 shows the box plot of the attributes of the winning bids when the auctioneer wants to optimise a single attribute (price, or time, or energy) or the aggregation of them all. It points out that in this experiment, it is impossible to optimise all the attributes, i.e. the optimisation of time greatly increases the price and energy consumption. However, when all attributes are aggregated, the obtained allocation is a trade-off between the objectives. Such trade-off is determined by the aggregation function. For example, Figure 6.6 shows that optimising the aggregation of all attributes, produces a solution in terms of price and energy very close to the optimal; and in terms of time the solution is between the optimal and the solutions obtained when it is optimised only by either price or energy (which are far worse than when only time is optimised).

ANOVA analysis over the values of price, time and energy of Figure 6.6 shows that the results obtained by optimising different attributes can be considered that come from different distributions with p-values lower than 10^{-73}. Even the results from optimising either price, energy, or the aggregation (MACA) are different, with p-values lower than 10^{-2}. Even paired-response tests show that with a significance value of 0.05 one can consider that the values of either price or time or energy, obtained when it is optimised by price or time or energy respectively, are better than when it is optimised another objective.

Scenario 2: multi-attribute sequential versus multi-attribute combinatorial auctions

Figures 6.7 and 6.8 show the results obtained in this scenario. As it was expected, MACA outperforms VMA2 in terms of aggregated cost (price, time and energy) because it is able to consider bundles of tasks and is therefore, able to provide better allocation. Pair-response tests were conducted and showed that it can be assumed that the aggregated cost of the winning bids when using MACA is lower than when using VMA2 at the significance level of 0.05. ANOVA analysis also discards that both collection of values come from a population with the same mean with a p-value of 0.0472.

Regarding the values of the attributes, pair-response tests also show that with a significance level of 0.05 it can be assumed that the values of the attributes using MACA and GA are better than VMA2. ANOVA analysis also discard that results of MACA and VMA2 regarding the values of the attributes come from populations with the same mean with p-values of 0.0417 (for price), $1.25 \cdot 10^{-35}$ (for makespan) and 0.012 (for energy consumption).

6.2.4 trust-MACA

This section analyses the benefits of extending MACA in order to take into account agent's trust during the auction protocol. Furthermore, it compares the performance of the trust model provided in Section 3.2.4 with two other trust models of the state-of-the-art, aiming to present the advantages of including trust but also modelling trust according to that model.

Experimental set up

For the experimentation, 6 couples of competitive and greedy bidders were modelled. Their time and energy values (for executing tasks) were randomly distributed according to real probability distributions (see Section 6.2.1). Each couple of bidders consists of two equal bidders regarding time and energy distributions, but one of them is able to exactly estimate the values of time and energy it needs to perform the tasks whilst the other one is only able to estimate the values according to the mean of the distributions. Thus, there are 6 *reliable* bidders and their *unreliable brothers*.

Regarding incentive compatibility, bidders follow an adaptive strategy: they adapt their offers (increase or decrease their economic pretensions) according to the resulting allocations in order to increase their chances of winning the auction and maximizing their benefits [Lee and Szymanski, 2005].

Finally, to study the behaviour of trust, the following models were tested:

- *No trust*: no trust model is used.
- *T-Trust model*: this is the trust learning method proposed in Section 3.2.4 with the learning algorithm of the previous section.
- *Schillo model*: the trust learning method is taken from [Schillo et al., 2000] and consists of calculating the honesty of a bidder by checking what it claimed and what it finally did. The estimated probability of a bidder of being honest is then $\frac{h}{n}$ where h is the times it has been honest (regarding time or energy) in the past and n is the number of tasks delivered.
- *Dirichlet models*: the trust learning method is described in [Jø sang et al., 2007] and consists of rating the task delivered by the bidders according to a discrete and finite set (e.g. {*very bad, bad, average, good, very good*}). The auctioneer then calculates a

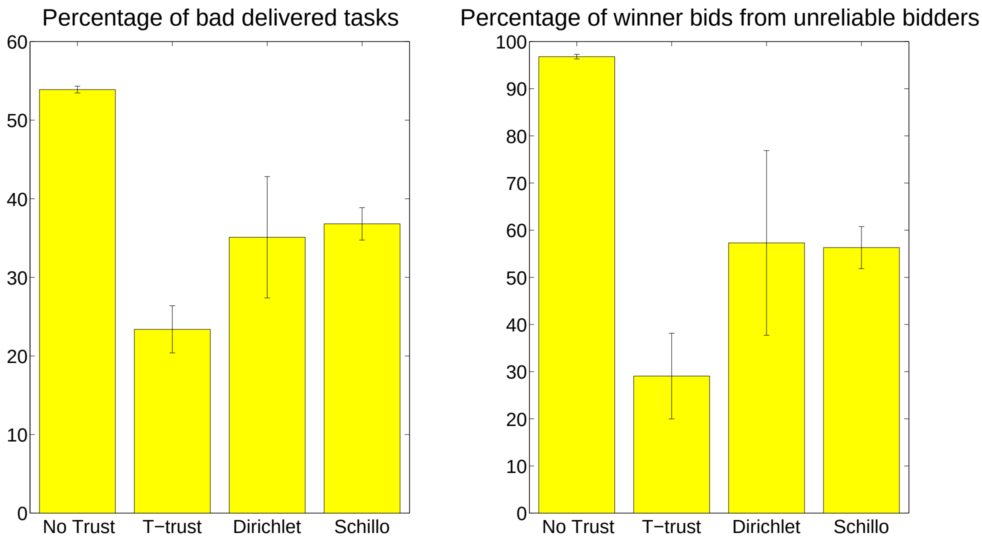

Figure 6.9: On the left, percentage of tasks delivered in worse conditions than the agreed using different trust models and not using trust (20 repetitions). On the right, percentage of winner bids from unreliable bidders using different trust models and not using trust (20 repetitions). All trust values have been initialized to 0.5. Bid attributes from unreliable bidders are equal to the average. Bid attributes from reliable bidders are equal to the average plus 1.5 times the standard deviation.

probability distribution according to this set, which represents the probability that the bidder has to act as stated in each one of the categories.

The performed experiments are evaluated using the percentage of bad delivered tasks (tasks with at least one attribute delivered in worse conditions than agreed) and the percentage of winner bids from unreliable bidders. The first metric evaluates the reliability of the resulting allocations, where a high percentage of bad delivered tasks implies poor reliability on the resulting allocations (the auctioneer cannot rely that its tasks will be successfully performed). The second metric is useful to evaluate whether, for a bidder, it is important or not to be reliable, indicating if a bidder wins more auctions when it is or when it is not reliable.

Results: Trust versus no trust

Figure 6.10 shows the percentage of bad delivered tasks (tasks delivered without the agreed conditions) and the percentage of winner bids from inaccurate bidders using different trust methods and not using trust. The initial trust value used in all the models was 0.5 while α_t and β_t values of T-trust were set to 0.1. As expected, the results tell us that the use of trust reduces the number of winner bids from unreliable bidders (inaccurate bidders), and therefore,

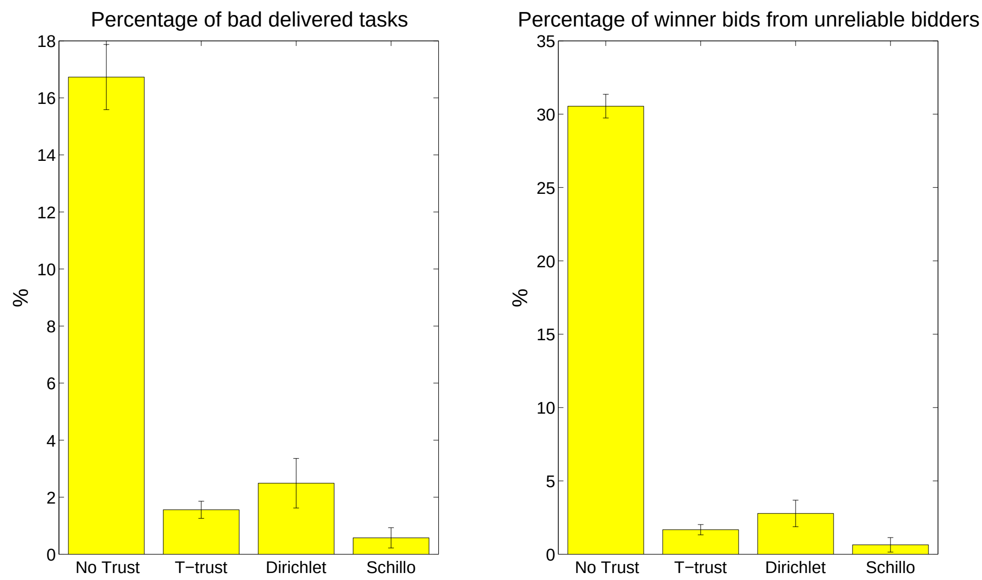

Figure 6.10: On the left, percentage of tasks delivered in worse conditions than the agreed using different trust models and not using trust (20 repetitions). On the right, percentage of winner bids from unreliable bidders using different trust models and not using trust (20 repetitions). All trust values have been initialized to 0.5.

the number of tasks badly delivered. These results show the improvement respecting the previous work of [Pla et al., 2014]. However, the improvement depends on the trust model. Figure 6.9 presents the results obtained repeating the latter experiment, as explained in the previous section *Experimental set up*, but any bidder is capable of accurately estimating its attributes. Instead, accurate bidders are those that send attribute values that are the average plus a security margin (1.5 times the standard deviation), and inaccurate bidders are those that bid according to the average. The figure shows that when trust is not used, most of the winner bids are from the bidders that do not apply a security margin. Therefore, the percentage of bad delivered tasks is very high. However, the use of trust reduces by a great deal the amount of winner bids from unreliable bidders, especially when the model presented in Chapter 3 (T-trust) is used.

Results: Trust models comparison

According to Figure 6.10, the best results are obtained using the Schillo model. For example, the Schillo model obtains the best results according to Figure 6.10 because its simple model is able to quickly discriminate between reliable and unreliable bidders. On the other hand,

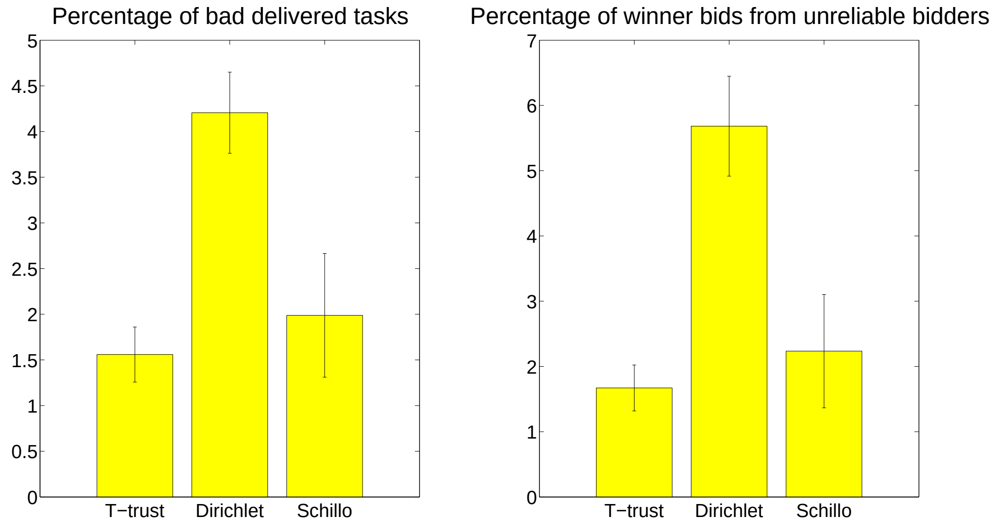

Figure 6.11: On the left, percentage of tasks delivered in worse conditions than the agreed using different trust models (20 repetitions). On the right, percentage of winner bids from unreliable bidders using different trust models (20 repetitions). All trust values have been initialised to 0.5 but the Schillo and Dirichlet mechanism has an initial memory of 10 values (half of them good) for each bidder.

T-trust and Dirichlet models obtain worse results because they are slower. Dirichlet model needs more information to make up the probability distribution function because it considers more states (bad, neutral and good). T-trust answer time depends on α_t and β_t and the values used make it slower than the Schillo model without memory.

An important issue of the Dirichlet and Schillo models is that they use all the past information without emphasising the most recent. This conveys a problem of rigidity when agents change their behaviour. To tackle this problem Schillo and Dirichlet approaches can use a memory parameter that will determine how many of the last auctions should be considered to compute the trust. Conversely, the trust model proposed in Chapter 3 does not need such parameter as it automatically gives more relevance to the most recent auctions. Figure 6.11 shows the same information as Figure 6.10 regarding the different trust models analysed in this section, but Schillo and Dirichlet models have been initialised with a memory of 10 values from each bidder, of which five were *good* delivered tasks and the others were *bad* (*very bad* for Dirichlet) delivered tasks. Note that this models a change of behaviour of the agents respecting their last 10 actions. T-trust model was also initialised with a value of 0.5 for each bidder and 0.1 for the (α_t and β_t values). Regarding Schillo and Dirichlet models, the results obtained with these initializations are worse than the results of Figure 6.10. This proves the drawback these models have with respect the T-trust model. Comparing the Schillo model with the Dirichlet model, it can be said that Schillo model again outperforms the Dirichlet model because it needs less instances to re-shape the probability distribution function of each agent.

The experiment has also been repeated with all trust values initialised to 1.0 and Schillo and Dirichlet models with an initial memory of 10 good delivered tasks for each bidder.

The best results are obtained by the model presented in Chapter 3 confirming that it is more robust to bad initialisations and changes in agents' reliability. Figures 6.10 and 6.11 show that the three models are sensible to the initialisation values. That fact was expected because they are based on past experience and, therefore, if the initialisation values do not correspond to the behaviour of the agents, the performance will be worse. However, the important point is the flexibility of the models.

Results presented in Figure 6.9 confirm the point that the T-trust model is capable of better adjusting trust when the behaviour of the agents is not static. In that experiment unreliable bidders provide 50% of good deliveries but randomly distributed. However, reliable bidders sometimes deliver tasks in worse conditions than the agreed. In such a scenario, T-trust clearly outperforms the other two trust models, reducing by half the percentage of winner bids from unreliable bidders.

6.2.5 Discussion

This section has analysed the results of running the single and multi-agent approaches presented in Chapter 3 for solving the e-MPSP. Although the three methods aim to solve the same problem, results of the single-agent and multi-agent approaches are not generally comparable because of the different context where they are applied. For example, the single-agent approach considers a context where an agent manages all the resources and, therefore, has its own energy consumption profile, while multi-agent approaches consider that tasks are outsourced (through auctions) to external agents, and these are responsible of their own energy consumption profiles. However, the auctioneer takes into account energy issues since every task has its own energy (or environmental) footprint.

Although approaches are thought to run over different contexts, results state the importance of considering energy consumption in business processes and how aggregating the different objectives achieves good trade-off among them. Also, results show an increase of complexity when variable prices are considered. Results regarding the single-agent approach justify the use of meta-heuristics (particularly GA) when tackling large instances of e-MPSP. According to this statement, multi-agent approaches use also GA for solving the WDP. Furthermore, MACA experimentation shows that the use of GA for solving the WDP on combinatorial auctions obtains better results, in a similar amount of time, than sequential auctions which avoid the complexity of the WDP.

Including trust in the bid valuation according to the trust-MACA methodology highly reduces the percentage of bad delivered items because it reduces the chances any unreliable bidder has of winning an auction. Nevertheless, the results are strongly linked to the model of trust and its initialization. In this regard, the Schillo model is the one that obtains better results when agents have a constant reliability. However, when the reliability of the agents is not constant, the performance of this model, as well as the Dirichlet model, drops compared to the trust model proposed in this thesis. This problem can be solved by adding a sliding window to the model or by weighting the past values according to time, but this adds a complexity to these simple and easy models. On the other hand the T-trust model becomes a simple and robust solution against changes in the reliability of the agents.

Summing up, the results state the importance of taking into account energy issues in business processes and that the aggregation of objectives enables multi-criteria optimisation. Furthermore, it can be stated that meta-heuristics such as GA become very appropriate methods for tackling the high complexity of scheduling problems with variable prices. Also, incentive compatibility mechanisms are not sufficient in multi-agent systems where agents are not able to accurately estimate their abilities. In this context, the use of trust, and in particular the T-trust model presented in Section 3.2.4, reduces the probability of allocating tasks to unreliable agents.

6.3 Power re-allocation

This section deals with the experimental evaluation of the PRA methods proposed in Section 3.3, which manage the maximum power demand peaks. It aims to demonstrate and quantify the potential cost reduction that the method can achieve. The section first explains the experimental set up over which the experimentation has been conducted. Then it analyses the performance of the methodology and reallocation strategies presented in Section 3.3.

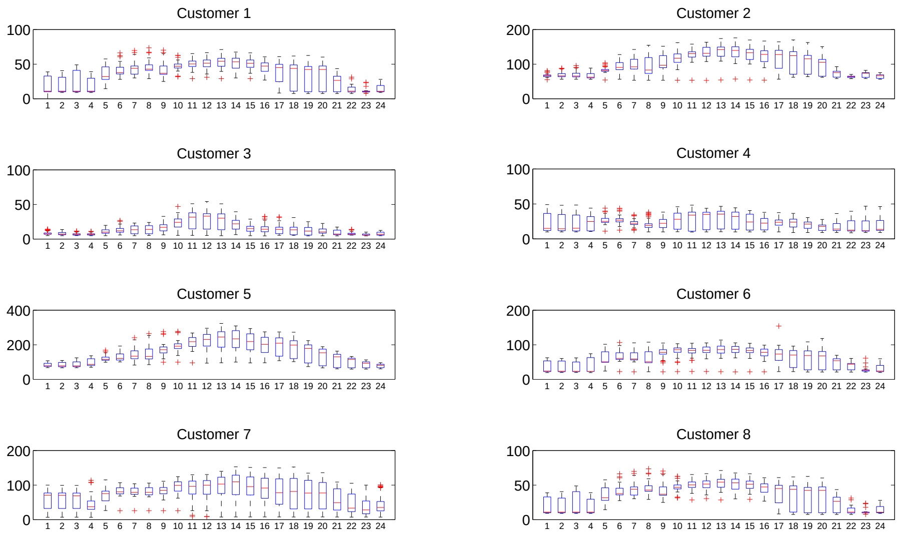

Figure 6.12: Box plots of the demanded power of each customer throughout workdays.

6.3.1 Experimental set up

The data on which the experimentation has been conducted is based on the real electric energy consumptions of eight business buildings (office and teaching buildings of the University of Girona) ($N_c = 8$). The data has been analysed in order to estimate the probability distributions of the power consumptions in a day (differentiating between workdays and vacations/weekend)[2]. From that distribution is obtained the $p_{i,k,t}$ of each consumer. Figure 6.12 shows the box plot of the demanded power of each customer on workdays. It has been set $N_p = 3$ because this is the current number of periods of the Spanish model.

The contracted power of each customer ($c_{i,k}$) has been set to the optimal one, which can be obtained since all the historical information of the simulated companies is known. That is, for each period k, it is possible to know what is the maximum demanded power of a consumer, and then to assign that as the contracted power, meaning than the derived cost will be the best according to Equation (3.45). Of course this is the optimal power regarding the consumers work in isolation; this value is expected to improve when consumers work in coalition. Dealing with the optimal contracted power ensures that the results of the different methods are comparable. Regarding the $\alpha_{i,k}$ and $\beta_{i,k}$, they have been set to 0.85 and 1.05 correspondingly.

Regarding power prices, three different periods for all customers and the same prices for

[2]Probability density functions available at http://eia.udg.es/˜ftorrent/powerProfiles.pdf

each customer have been considered: 3.31 €/kW for $k = 1$, 1.98 €/kW for $k = 2$ and 1.32 €/kW for $k = 3$. These prices have been taken from current companies' bills.

In order to analyse PRA and the reallocations strategies, experimentation over two different scenarios has been conducted:

Scenario 1: Analysis and comparison of costs regarding the benefits of using PRA. To this end, three configurations are considered,

- no-PRA: the consumers manage power by themselves
- Aggregation: an unconstrained umbrella entity, which pays for all of the consumers, and proportionally shares the power.
- PRA: an umbrella entity with PRA using the proportional strategy

Simulations are run for one month of the electric consumption of each customer. The hypothesis is that either the use of PRA or the aggregation will convey a reduction of the cost compared with no-PRA. Moreover, with PRA, consumers are guaranteed that they will never pay more than they would alone.

Scenario 2: This second scenario is used to study the implications of using different reallocation strategies. Experimentation for one simulated year has been conducted because one month is a too short period of time to achieve significant differences concerning the amount of power or how many times customers receive power from others. In addition to the RAP, the RFP and the proportional priority strategy has been defined as a random priority strategy as a baseline.

6.3.2 Results and Discussion

Results are analysed on the basis of the following measures:

- Global costs (€): the sum of the power costs of all customers according to Equation (3.28),

$$\sum_{i,k} cost(m_{i,k}) \tag{6.1}$$

- Customer costs (€): the sum of the power costs for a customer i inside a time window,

$$\sum_k cost(m_{i,k}) \tag{6.2}$$

- Final power profile (kW): the power required by a particular customer i as a result of the method (final p_i)

- Gini coefficient: to evaluate the fairness of each strategy, the Gini coefficient [Gini, 1912, Gastwirth, 1972] is used taking as wealth the savings of each customer, and as size of the population the mean power that each customer receives from others. Thus the Gini coefficient has been calculated weighting the saving of each customer by the power it has received from others. This means that the index is a measure of fairness regarding the benefits of each customer with respect to how useful it has been to the other customers.

Results are provided in average after 100 repetitions of the simulations.

Scenario 1: Benefits of using PRA. As a first example, Figure 6.13 shows the target power of four customers ($\tau_{i,k}$) and the final power profile of each one throughout a day when using PRA and when not[3]. Figure 6.13 shows how demanded power for those customers that exceed their contracted power, is re-allocated to other customers. For example, at $t = 20$ customers one and seven demand a power of 61kW and 113kW. If no re-allocation is performed, demanded power will exceed contracted power (and target power); but when using PRA, they can reduce demanded power to 47kW and 96kW respectively, which keeps them below their power target. On the other hand, customers four and six have a demanded power of 11kW and 35kW respectively, but after re-allocation their demanded power increases to 19kW and 57kW. Therefore, PRA follows a peak shaving and valley-filling strategy for the power required by each customer but it does not change the overall demand.

Note that customers that receive power from others never surpass their target power and therefore they do not increase their own power costs.

Figure 6.14 shows the global costs of eight customers with their optimal contracted power (x=1.0), and other costs resulting from adjusting the contracted power upwards (1.05*optimal power, 1.10 * optimal power, ...) and downwards (0.95 *optimal power, ...). Figure 6.14 shows that in general, using PRA or the aggregation configuration achieves a great reduction in the cost of the whole demand, with respect to the case where each customer has its own contracted power and there is not a re-allocation of the demanded power (non-PRA). Comparing PRA with the aggregation configuration, as was expected, the aggregation obtains the

[3]At $t = 20$ the other customers give or receive small amounts of power and they are not showed.

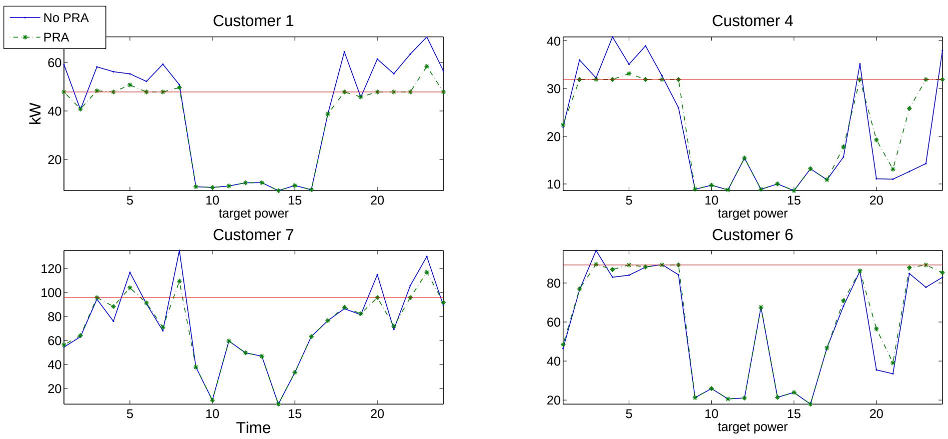

Figure 6.13: Power profiles throughout a day of four customers using PRA and without PRA compared with the target power of each one (flat line)

minimum possible cost for each possible contracted power. However, when customers have their optimal contracted power for their demand, the difference between PRA and the aggregation is negligible ($5.1 \cdot 10^3$ and $5.05 \cdot 10^3$ correspondingly). This means that PRA is able to achieve the minimal possible cost when customers have their optimal contracted power. In other situations, it is important to note that the aggregation does not guarantee that the consumer will pay less than in an individual way, whereas PRA does.

Focusing on each customer, Figure 6.15 shows the cost each customer would pay for each method (PRA, no-PRA and aggregation). According to this, PRA guarantees that any customer will not increase their cost, while aggregating the demands does not guarantee it. For example, customers five and seven achieve their lowest cost when PRA is used. The cost reduction for each customer goes from 14.63% (customer five) to 24.29% (customer eight). Thus each customer achieves an important reduction of the cost.

It is worth pointing out that PRA has been tested with eight different customers that share a similar power profile (the highest peaks are approximately at the same time each day, and they have vacations, valleys, at the same time). However PRA is more effective if profiles are complementary (peaks of one customer correspond to a valley of another). Even in such conditions the cost of reduction is very important, around 20% in average. Thus the savings achieved by PRA may be an incentive for industrial parks or other communities of customers to tend to complementary profiles.

Results in Figure 6.14 also show that PRA becomes useless when the contracted power of each customer is sufficiently high (worse case for x=1.50 of the optimal contracted power) and no re-allocation is needed. It also shows a trend indicating that for very low contracted powers (worse case for x=0.50 of the optimal contracted power) the cost increases and tends to be equal to the cost with No-PRA. This is because most of the time the customers' demands exceed their contracted power, and power re-allocation is not possible.

The main benefit of PRA comes from the fact that it returns information regarding the possibility of reducing contracted power. According to Figure 6.14, the cost curve reaches the minimum when using PRA at $x = 0.80$, meaning that all customers could propose a new contract power for that value to the company. Comparing the minimum No-PRA cost with the minimum PRA cost, there is a 20% reduction. In the real case under study, this means a saving of around 1300€ per month for the overall cost. The investment and costs required by PRA is the implantation of smart meters (300€ per unit) to all consumers (which are currently being implanted in many countries) and additional one for the umbrella entity to be able to measure the aggregated consumption. The cost of managing the umbrella entity is considered negligible if it is managed by an electricity trade company. Given these costs and these experimental results, it can be said that the benefits of using PRA widely surpass its costs.

On the other hand, the reduction of the contracted power not only benefits consumers, but also electricity companies. When a consumer has a particular contracted power, the electricity distribution company has the duty of satisfying a power demand of this value at any time. Thus, an increase of the contracted power by the consumers (or an increase of the number of consumers) conveys an adjustment of the grid, even if this grid is underutilised most of the time. In this regard, a reduction of the contracted power by the consumers, without reducing the demand, increases the utilisation of the grid, benefiting electricity companies because they can make the most of their infrastructure.

Scenario 2: Priority trade-off. Experimentation with Scenario 2 showed us that global costs do not depend on the priority strategy used. This was an expected result because the priority strategies are only used to decide the amount of energy each customer can give when it is impossible to keep all of them below their target power. Thus, it is important to have a strategy that guarantees some fairness, not in terms of equity, but in terms of benefiting those customers that are active receivers.

Figure 6.16 shows the Gini coefficient (the mean and the standard deviation) achieved by each priority strategy. It shows that the use of RFP or RAP reduces the Gini coefficient. Since the Gini index is calculated taking as the wealth the relative savings of each consumer, and the size of each population as the amount of received power by each customer, the index indicates the fairness of each strategy. According to this index a fair strategy is the one that provides,

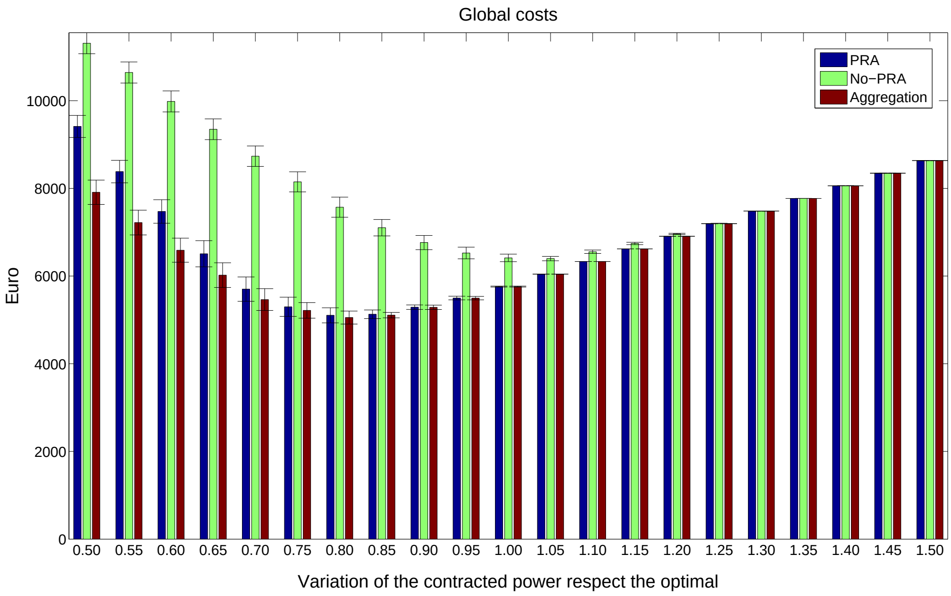

Figure 6.14: Average and standard deviation of the sum of power costs of all customers modifying all $c_{i,k}$ proportionally respecting the contracted power, $c^o_{i,k}$, that minimizes PRA power costs.

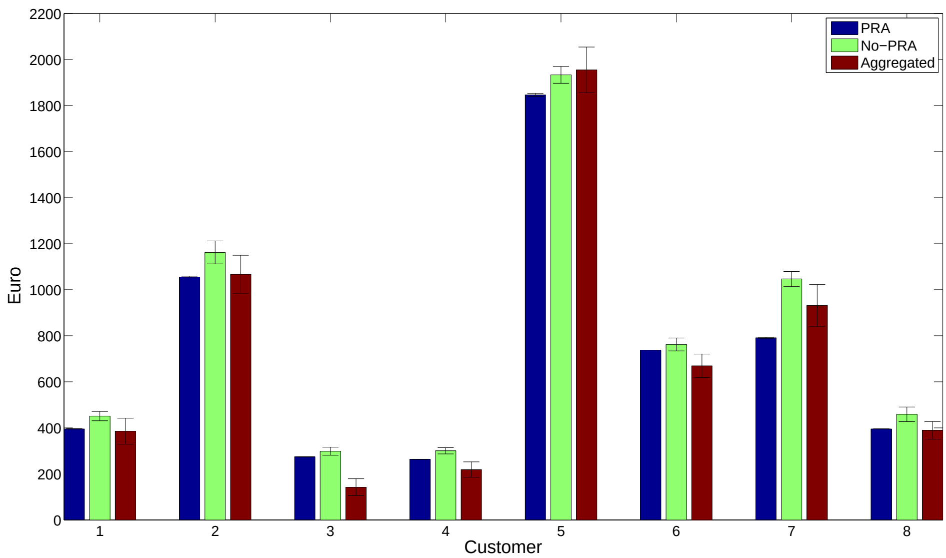

Figure 6.15: Power cost of each customer.

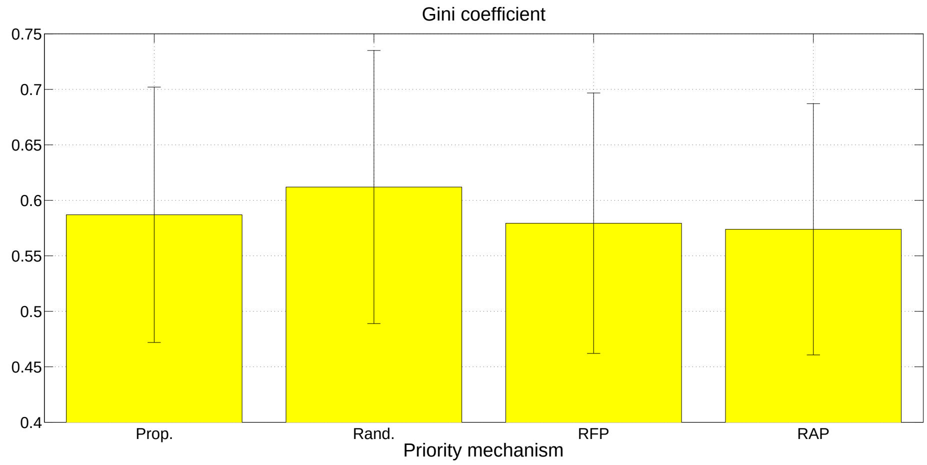

Figure 6.16: Gini coefficient achieved by each priority strategy. On the left the wealth was set as the savings achieved by each consumer and the population size was set as the amount of received power. On the right the wealth was set as the savings and the population size was set as the number of times each customer received power.

each consumer with a relative saving proportional to the amount of received power. In this way, Figure 6.16 shows that RFP and RAP strategies are fairer than the others. In particular, RAP is the fairest strategy.

Paired-response (with a significance level of 5%) tests of the Gini indices with 100 repetitions of the experiment have been computed, and these tests show that the RAP strategy does achieve the lower Gini index, followed by RFP. Pair-response tests also conclude that using random priorities performs worse than using the proportional method.

6.4 Energy demand allocation

This section presents the experimentation conducted and the results obtained regarding the energy demand allocation method presented in Chapter 4 in order to analyse its performance. Thus, the presented approach is compared with other two allocation methods, one based on canon f_{1b} which seeks egalitarian allocations and another one based on canon f_3 which seeks to maximise the reliability of the allocation.

6.4.1 Experimental set up

The experiments were conducted over Presage2 [Macbeth et al., 2012], modelling agents as DERs of different types (CHP, PV, wind turbines or batteries) and sizes. DERs were intercon-

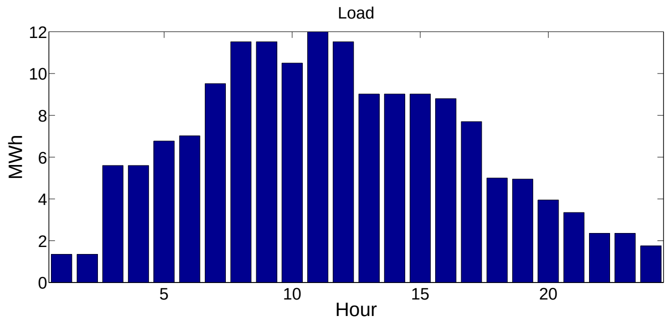

Figure 6.17: Time-dependent load

nected in a 14-bus grid with the global electricity load of Figure 6.17, which was periodically repeated throughout time. The load was distributed among all the buses. Time-dependent electricity prices have been also considered. Simulations consisted of 1000 rounds, representing each round a time-step of one hour.

Results are measured regarding DERs' benefits (payments received τ_i minus costs) and agents satisfaction (measured according to Equation (4.4.1)) in order to analyse whether the use of the allocation methods is beneficial or not. Furthermore, the reliability of the system, percentage of delivered energy respecting the allocated demand, is also analysed in order to examine the performance of the whole system. The fairness of DERs' benefits and satisfaction (benefit and satisfaction) is analysed using the Gini index [Gini, 1912, Gastwirth, 1972] (note that the lower the better) as it is pursued by a distributive justice approach. Finally the claims' weights are analysed, showing that they evolve according to the VPP composition and context (including external interferences).

DERs are modelled as greedy agents that want to produce the amount of energy that maximises their benefits. Their features are:

- CHP plants: they can produce energy whenever they want, considering their up and down ramp limits (2MW/h). Their production cost is 37€ /MWh and their start up and shut down costs are 20€ and 25€ respectively. They only demand to produce energy if the payment they will receive compensates its cost. They produce 390 kg/MWh of CO_2.
- PV plants: they can only produce energy depending on solar radiation (it has been considered via the average meteorological data in Catalunya[4]). Their production cost is zero, so they need to produce as much energy they can considering the weather forecast. They have an average prediction relative error of 25% [Pelland et al., 2013].

[4]Data from Servei Meteorològic Català (Catalan Meteorological Service).

- Wind turbines: they can produce energy depending on the wind speed[4]. Their production cost is zero, so, as PV plants, they need to produce as much energy as they estimate they can according to the weather forecast. Their average prediction error is 0.85m/s [Soder, 2004]. They are the most inaccurate DERs.

- Batteries: they do not produce energy, but they can buy energy and sell it later, complementing those DERs that cannot produce energy whenever they want. Thus, they buy energy when it is very cheap and demand to sell it when it is more expensive. They cannot exceed their storage capacity and their charge/discharge ramp limits (1.5MW/h). They have an associated CO_2 emissions factor of 240 kg/MWh, which corresponds to the average Spanish electricity emissions factor.

Two test scenarios have been defined over two VPP configurations with scarcity of electric load:

- Case 1: all DERs have the same capacity $C = 10.0$MW. There are two CHP plants, two PV plants, two wind turbines and two batteries.

- Case 2: there are four PV plants and four batteries with $C = 2.0$MW, two wind turbines with $C = 2.0$MW and one CHP plant with $C = 20$MW.

Therefore, results are comparing a homogeneous VPP (all DERs with the same size) with a heterogeneous VPP (composed by different sizes of DERs).

To test the performance of the approach presented in Chapter 4, the following configurations regarding the methods used are distinguished:

SO: the method as explained in Chapter 4, self-organisation with legitimate claims

f1b: a non self-organised approach where the equity claim f_{1b} is the only one used. This situation is equivalent to other fair mechanisms in the literature based on a single measure (fairness) [Pla et al., 2015].

f3: a non self-organised approach with the productivity claim f_3 alone. This scenario means to favour reliable DERs in regard to the others, minimising unbalance problems in the grid.

Finally, to test the challenges regarding external interferences, three forms of green quotas (percentage of green energy that has priority in the allocation process) are considered: Q of

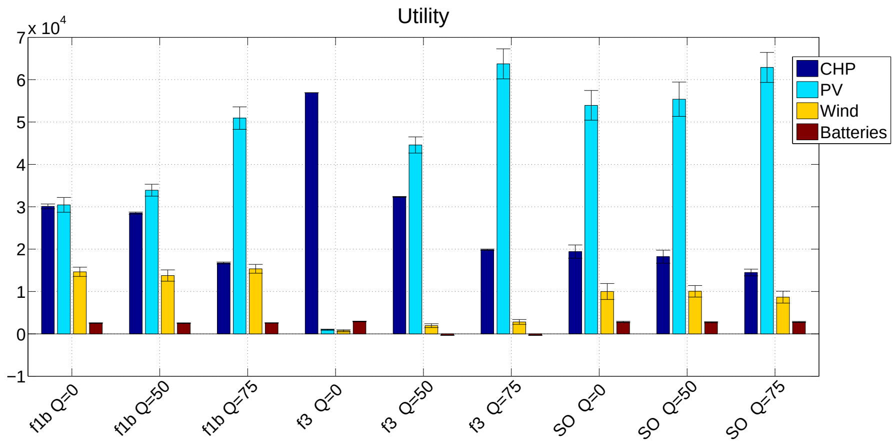

Figure 6.18: Average and standard deviation of the benefits of each type of DER for case 1.

0%, 50% and 75%. These percentages state that the corresponding percentage of the load has to be covered by green energy if possible.

6.4.2 Results on DERs benefits

Focusing on DERs' benefits at the end of the simulations (see Figures 6.18 and 6.19), as was expected, the increase of Q conveys an increase of the overall benefits of green DERs (especially PV plants which are the most promoted by the most voted canons) in exchange for a reduction of the benefits of the rest of DERs. Comparing allocation methods, f_{1b} provides the highest equity in terms of benefits for case 1 (see Figures 6.18 and 6.20). However, if there is a much bigger CHP plant than the others, SO obtains better values of equity because DERs foster canons of equity and needs.

Analysing in depth the results with the Gini index, for case 1, SO obtains worse results because despite allocating similar amounts to CHP and PV plants, CHP plants obtain lower benefits due to its lower profit margin. To obtain better equity values, a canon of equity should have been added, considering profit margins. However, this is an internal information of each DER and it is not likely to be verifiable. Therefore it has been decided to not use such information. On the other hand, f_3 is highly unfair (see Figure 6.20) because it tries to allocate all demand to CHP plants and when $Q > 0$ it allocates the demand imposed by the green quota to PV plants and the rest to CHP plants, omitting wind turbines and batteries (batteries are useless when producers can guarantee energy whenever it is needed as CHP does).

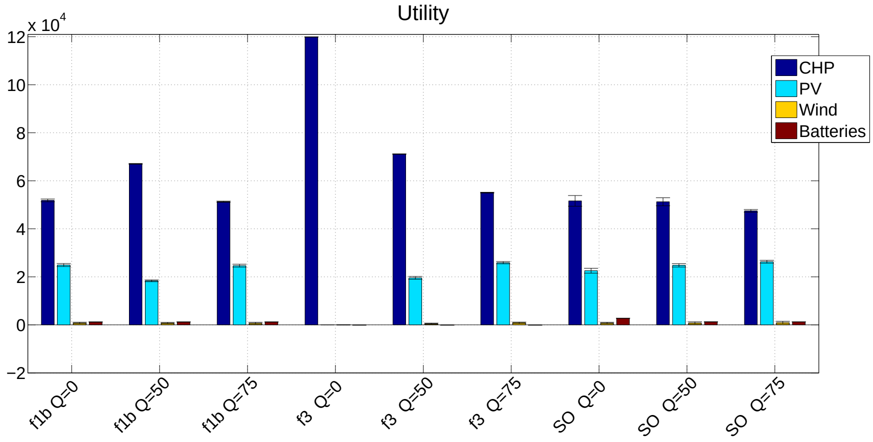

Figure 6.19: Average and standard deviation of the benefits of each type of DER for case 2.

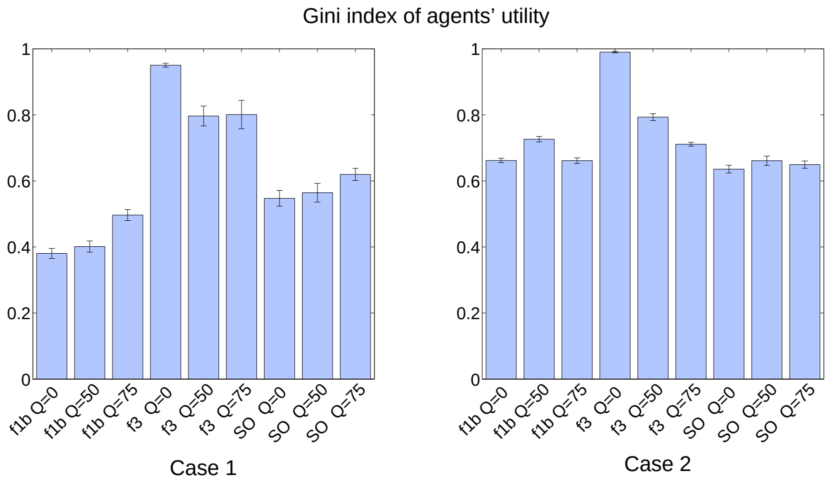

Figure 6.20: Gini index of the accumulated benefits by the DERs.

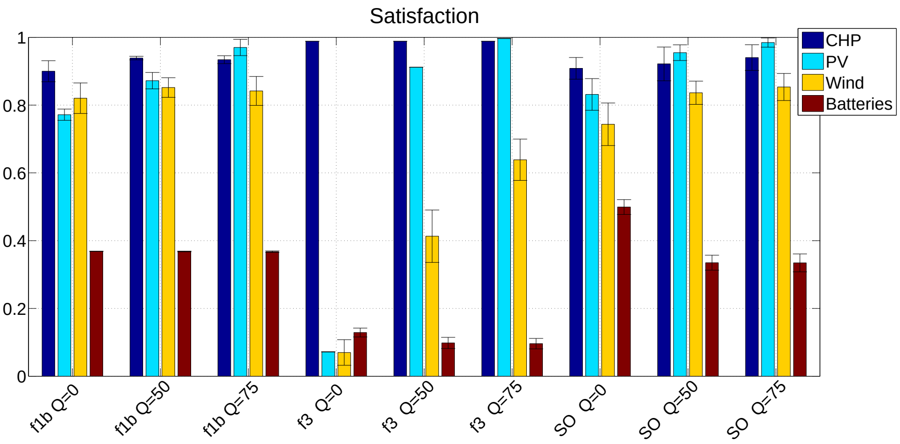

Figure 6.21: Average and standard deviation of the satisfaction of each type of DER for case 1.

6.4.3 Results on DERs satisfaction

Regarding satisfaction, f_{1b} and SO results are comparable and, as in terms of wealth, it depends on the configuration of the VPP. Thus SO obtains similar results to f_{1b} in terms of equity when it takes account of other claims such as productivity or social utility. On the other hand, Figures 6.21 to 6.23 illustrate the unequal allocation provided by f_3 reaching satisfaction levels lower than 0.2 for DERs other than CHP. These low wealth and satisfaction values convey the risk of depopulating the VPP (unsatisfied DER may leave the VPP) and reduce the diversity of energy resources with their associated problems such as oligopolies, contamination, etc.

Although SO and f_{1b} report good results in terms of equity, f_3 obtains the best results in terms of reliability. Figure 6.24 shows the part of the allocated load that is finally uncovered by the corresponding DER. It shows that f_3 obtains the lowest uncovered amounts because it allocates all the load it can to CHP plants, but with corresponding drawbacks like CO_2 emissions (see Figure 6.25). However, this uncovered demand does not correspond to an imbalance in the power grid between load and generation, it corresponds to typical imbalances due to beforehand (i.e. day ahead) estimations of the load and generations schedules. Obviously, a reduction of the prediction error of stochastic DERs will convey an improvement of the credibility values of the results, as well as, an increase of the storage capacity in the VPP.

Given these results it can be said that the proposed energy demand allocation method provides distributive justice dealing with the plurality of legitimate claims according to [Pitt et al., 2012]. Furthermore, the presented method has been proved to be robust against external au-

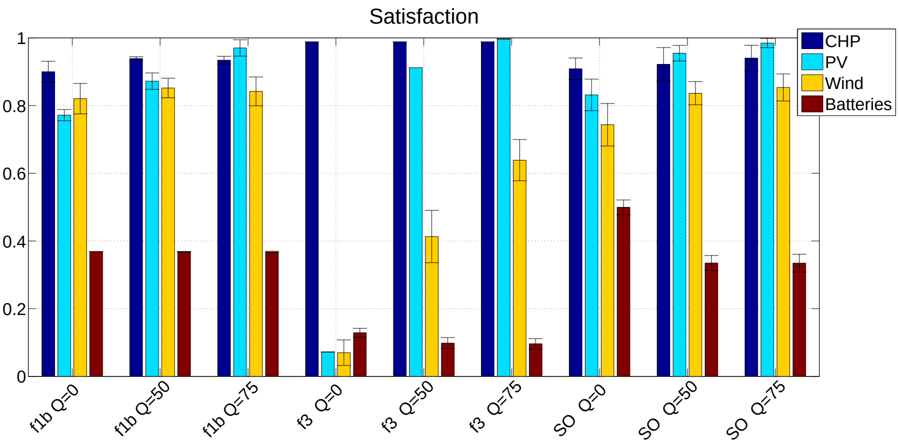

Figure 6.22: Average and standard deviation of the satisfaction of each type of DER for case 2.

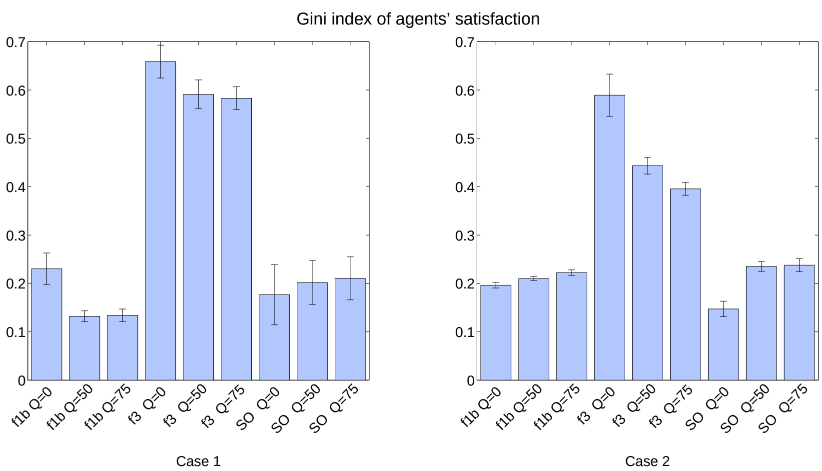

Figure 6.23: Gini index of the final satisfaction of the DERs.

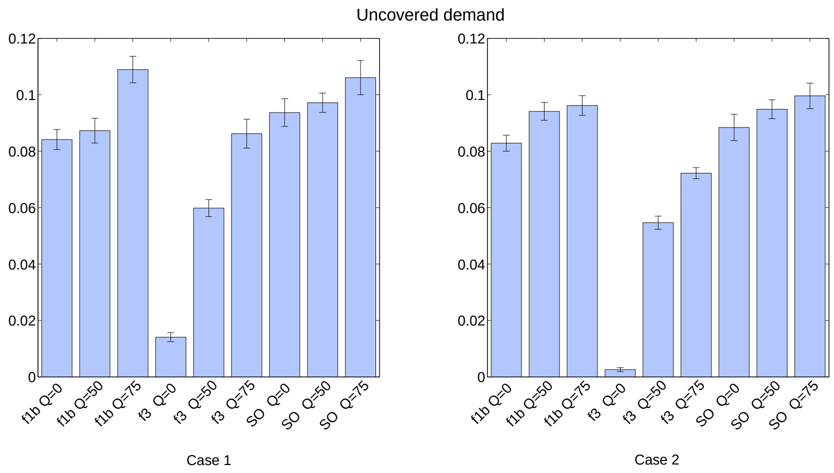

Figure 6.24: Part of the allocated load that, in the end, cannot be covered by the corresponding DER it was allocated.

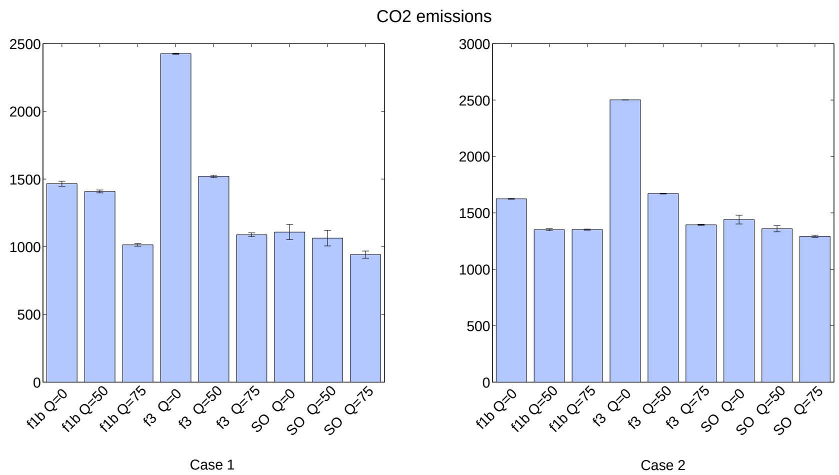

Figure 6.25: CO_2 emissions

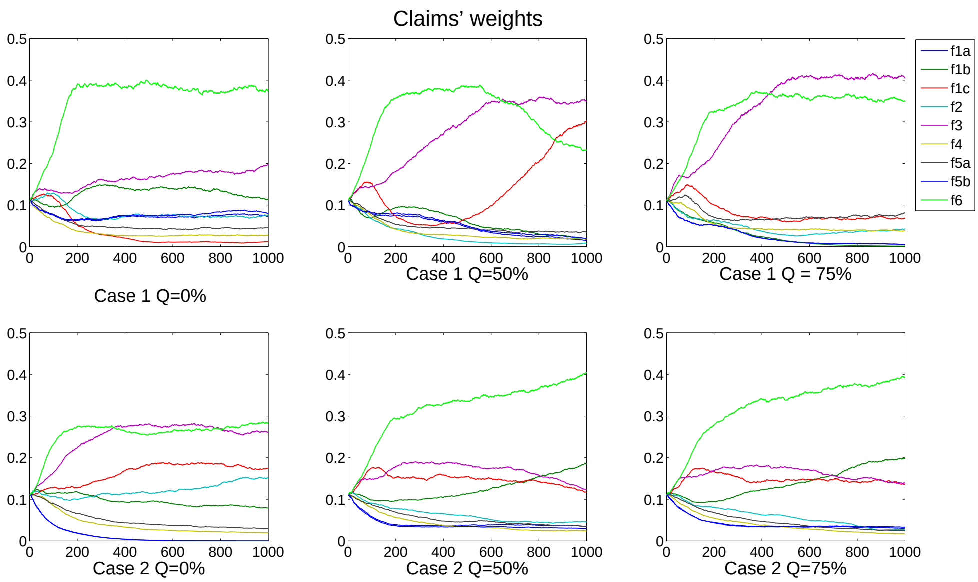

Figure 6.26: Claims' weights for cases 1 and 2 and with green quotas of 0%, 50% and 75%.

thorities (green quotas). Nevertheless, an allocation method designed to optimise a particular canon or minimise a particular interference will usually obtain better results regarding the optimised target than a plurality approach, but it will err of rigidity when tackling other situations. Also, with SO, DERs have more power to decide how the allocations are done, which they cannot do with the other mechanisms.

6.4.4 Results on weight claims

Figure 6.26 shows the evolution of the claims' weights for cases 1 and 2 and for different values of Q. It shows that f_6 (supply & demand), which promotes DERs that can produce energy when others cannot, is usually the most preferred weight. Considering a scenario with different types of DERs, this result is not surprising. Furthermore, for case 1, f_3 has a very important weight, and it increases when $Q > 0$. In this regard, when an external interference appears, weights evolve to minimise its effect. Thus, if energy from green DERs, which are at the same time DERs with the lowest productivity success rate, is prioritised, then weights prioritise DERs with a high productivity success rate. Note that for case 1 $Q = 50\%$ they also increase the weight of f_{1c} (equity in payments) but this is also a way to prioritise CHP plants and batteries since they have a lower wealth (see Figure 6.18) because they receive smaller allocations.

When there are differences among DERs' capacities (there are bigger DERs than others), the weights of claims of equity and need are increased (see differences between case 1 and 2 with $Q = 0\%$). However, f_3 and f_6 are still important claims. Thus, there is a balance between claims that promote equity, diversity and productivity. Nevertheless, when Q is increased for case 2, DERs respond by reducing equity claims, because green DERs are more satisfied (all green DERs get most of the allocation they demand), so they reduce their votes for claims of equity and need. But f_6 becomes predominant, which benefits the big CHP plant but at the same time prioritises PV plants over wind turbines (which usually get allocated most of their demand). In this regard, they find, again, a balance between all claims that benefits all them (or at least the majority).

6.4.5 Discussion

In electrical power systems, the energy generation has to perfectly match the load in order to keep the system running and avoid blackouts. Therefore, the reliability of the generators is crucial in order to avoid mismatches. However, the process of determining the amount of energy each generator should produce is done through several steps spaced throughout time, and each step allows a particular range of uncertainty or unreliability. When the constraint of matching the load and the generation of energy is relaxed, other objectives of the energy demand allocation (i.e. CO_2 emissions) can be achieved in a higher degree. Therefore, the self-organised approach presented to deal with the energy demand allocation problem allows the aggregation of different objectives expressed as canons of *distributive justice*. These canons are aggregated through voting functions allowing DERs to participate in the decision process. The principle that DERs vote canons at each round enables the system speed to adapt itself to new situations. This, added to the great variety of objectives posted by distributive justice, makes the system dynamic and adaptable to new situations. Then the system is able to achieve an appropriate trade-off among the canons to each situations, i.e. minimising the impact of external circumstances or reducing differences between big and small DERs. Then, when the proposed approach is compared with other methods (i.e. f_{1b} or f_3), it provides a trade-off among the different posed objectives (canons) but at the same time it achieves a dynamic robustness to new situations.

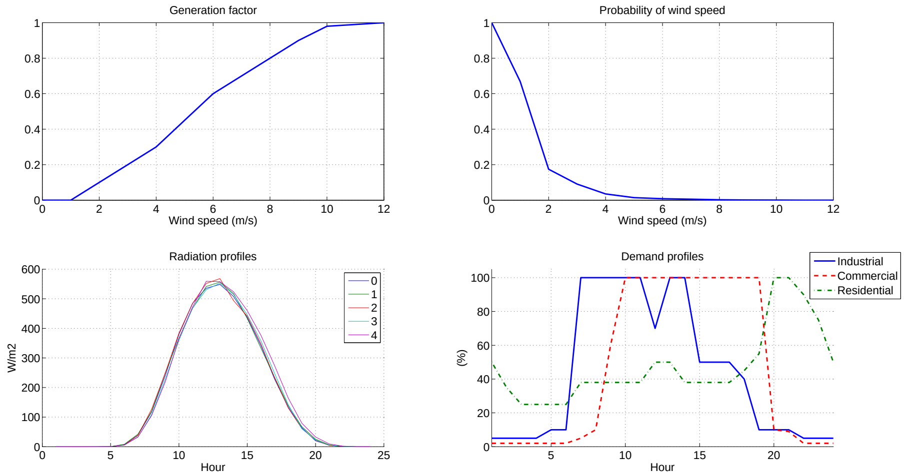

Figure 6.27: Wind energy generation curve, probability of wind speed, daily radiation profiles and daily load profiles

6.5 DG Location and Sizing

This section explains the experimentation conducted regarding the methods presented in Chapter 5 for supporting the planning of the integration of new DERs in the smart grid.

It is expected that population-based methods outperform single point methods. It is also expected that the combination of SA with population-based algorithms outperforms the sole algorithms.

6.5.1 Experimental set up

Experimentation has been conducted using two different power systems: the IEEE 14-bus (see Figure 6.28) and 57-bus systems[5]. Line data and bus voltage and power limits have been considered. The generators already present in the system have not been considered; instead a single generator is considered, connected to the slack bus able to provide sufficient energy to cover the internal demand in case the placed DG could not. Furthermore, the loads at each bus are replaced by time-dependent loads with residential, commercial and industrial profiles as shown in Figure 6.27, where the percentage respect the maximum load at each hour is represented. Table 6.7 shows the maximum active load demand for each profile for each bus (note that index i indicates the bus number).

[5]Data available at `http://www.ee.washington.edu/research/pstca`

i mod 7	Industrial (MW)	Commercial (MW)	Residential (MW)
1	0.8	0.8	0.8
2	0.8	1.2	0.95
3	1.5	1.5	1.5
4	0.8	0.8	0.8
5	0.5	1.5	0.7
6	0.8	0.8	0.8
7	1.0	0.5	1.5

Table 6.7: Buses load profiles.

	Investment (1000×€ /MW)	Fixed maintenance cost (€ /MW year)	Variable operating cost (€ /MWh)
Wind	1570	11000	6.45
PV	2550	32000	0.00

Table 6.8: Generators' costs considering an amortisation horizon of 10 years for PV generators and 20 for Wind turbines. Information from Open Energy Information (OpenEI).

The types of generators considered in the experimentation are on-shore wind turbines and photovoltaic generators. Investment, fixed maintenance cost and variable operating cost are $1570 \cdot 10^3$€ /MW, 11000€ /MW year and 6.45€ /MWh for wind turbines; and $2550 \cdot 10^3$€ /MW, 32000€ /MW year and 0.00€ /MWh for PV generators. An amortisation horizon of 20 years for the wind DERs and 10 years for the PV DERs has been considered. Table 6.8 summarises the considered costs.

Wind statistical information and radiation profiles considered in this experimentation have been extracted from the Catalan Meteorological Service[6] and are detailed in Figure 6.27. This shows the energy generation curve of the wind DERs depending on the wind speed. The final throughput is obtained by multiplying by the size of the DER. An efficiency of 0.33 for PV was considered.

For calculating the fitness of each candidate solution it is necessary to define a production schedule of each DG unit considering its location, type and size ($P^t_{i,k} \forall t$). The approach proposed in Chapter 5 calculates $P^{max}_{i,k}$ but the scheduling is out of the scope of the chapter. Instead, a naive system is used to simulate the power system operator. Given $P^{max}_{i,k}$ for all i and k, it calculates a power generation schedule where the load of the grid is proportionally

[6]Catalan Meteorological Service: http://www.meteo.cat

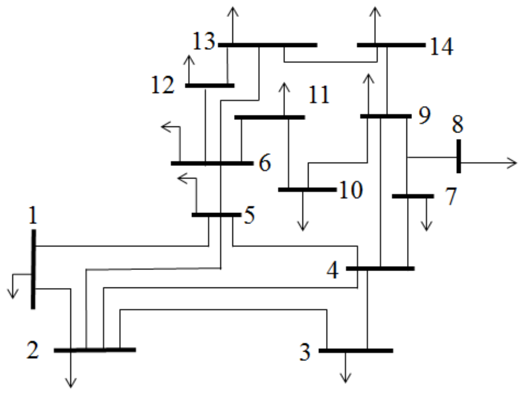

Figure 6.28: 14-bus diagram from University of Washington.

shared with all the generators considering their availability and physical constraints. If the DERs cannot cover the demand, it injects energy from the *main grid* through the slack bus (bus 1).

For simplicity and without loss of generality the energy price is used as the estimation of the cost of the energy produced at each time ($\pi^t = \rho^t$). This is an overestimation of the cost of the energy. Moreover, the size of new DERs is limited to $SIZE_{i,k}^{max} = 2.0$MW for all i, k, corresponding to a solar farm of 45000 m^2 approximately. The types of DER are constrained to wind and photovoltaic power. The parameter K of algorithms SAacc and SA+LRS has been set to $K = 4$.

The next sections present the results obtained from the experimentation and are based on the values obtained in the objective function represented in Equation (5.14).

6.5.2 14-bus system results

Figure 6.29 shows the box plot of the solutions' fitness achieved by the algorithms presented in Chapter 5 regarding the IEEE 14-bus system. Table 6.9 shows the results obtained after conducting paired-response tests (they examine the distributions of the difference between the performances on the same problem values) where 1s indicate that the corresponding row algorithm outperforms the column algorithm. According to the results it can be concluded that the worst option for solving the DGLS problem is the use of SA with a neighbour function that assigns random values (SAran). The performance can be improved by combining SA with LRS, however, SA with the accumulative neighbour function (SAacc) outperforms SAran and SA+LRS. Thus, the combination of SA and LRS does not achieve a great improvement and the performance of SAran is usually worse than SAacc, even combined with other algorithms

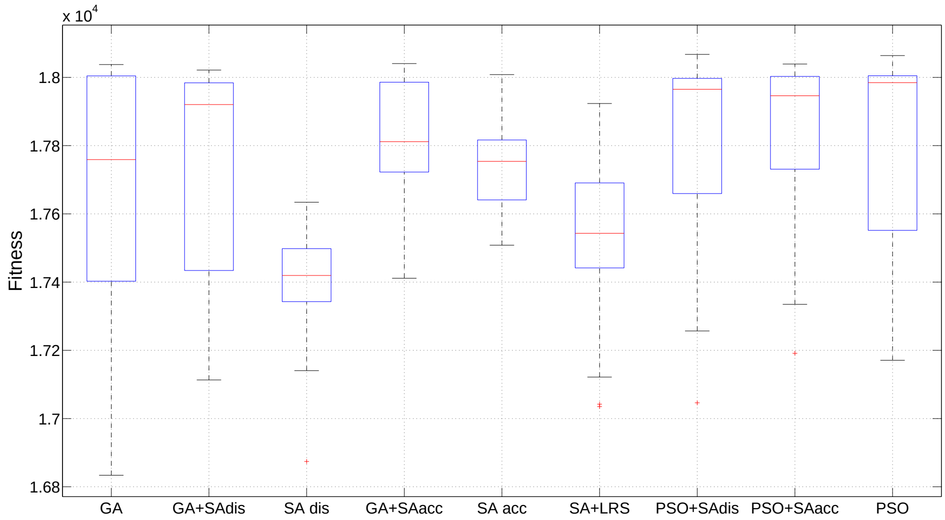

Figure 6.29: Fitness of the solutions found by different meta-heuristic algorithms in the 14-bus. Box plot over 50 solutions of each case.

(GA+SAacc is better than GA+SAran). Another conclusion that comes from Figure 6.29 is that the use of SAacc combined with another algorithm (PSO or GA) reduces the variance of the solutions. In the particular case of GA+SAacc the reader can see that it outperforms GA. Also, approaches that combine PSO with SA beat more algorithms, according to Table 6.9, than PSO alone. However, paired-response tests are not able to determine which algorithm is the best (there is not any algorithm that outperforms all others). There is a trend indicating that combining GA or PSO with SA improves the performance, but also indicating that using SA after either PSO or GA improves the performance more than using only SA. Thus, it seems a good point to start the search using a population-based algorithm such as GA or PSO and then polish it using SA.

Another point from Table 6.9 is that paired-response tests are not able to distinguish any difference between the results from the three approaches using PSO. Even carrying out an ANOVA analysis between the results of these three approaches concludes that it cannot be assumed that the results come from different distributions with a p-value of 0.9246. Such a p-value tells us that with a probability of 92.46% the results obtained by the three approaches come from the same distribution. Thus, if the three approaches share the use of PSO, it means that the PSO dominates over SA regarding the final solutions found.

Table 6.10 shows the location, type and size of the DG units of a solution found by each method for the 14-bus system and the value of the three objectives. The best solutions (given

	GA	GA+SAran.	SAran.	GA+SAacc.	SAacc.	SA+LRS	PSO+SAran.	PSO+SAacc.	PSO
GA	-|-	0|0	1|1	0|1	0|1	1|1	0|0	0|0	0|0
GA+SA ran.	0|0	-|-	1|1	0|0	0|1	1|1	0|0	0|0	0|0
SA ran.	0|0	0|0	-|-	0|0	0|0	0|0	0|0	0|0	0|0
GA+SA acc.	1|0	1|0	1|1	-|-	1|1	1|1	0|0	0|0	0|0
SA acc.	0|0	0|0	1|1	0|0	-|-	1|1	0|0	0|0	0|0
SA+LRS	0|0	0|0	1|1	0|0	0|0	-|-	0|0	0|0	0|0
PSO+SA ran.	1|0	1|1	1|1	0|1	0|1	1|1	-|-	0|0	0|0
PSO+SA acc.	1|1	1|1	1|1	0|1	1|1	1|1	0|0	-|-	0|0
PSO	1|0	0|1	1|1	0|1	0|1	1|1	0|0	0|0	-|-

Table 6.9: Paired-response tests from the 14-bus and 57-bus system (14-bus|57-bus). 1 indicates that the row algorithm obtains better solutions than the column algorithm. 0 indicates that it cannot be assumed that the row algorithm is better than the column algorithm.

by GA and PSO based methods) are those which propose the installation of a few units with a total power around 1.5MW. Furthermore, it can be seen that the preferred DG type is PV (21 DERs of 30), which was expected since wind of more than 4m/s is very rare (see Figure 6.27). Regarding the preferred location, the most repeated bus is bus number 5, which according to Figure 6.28 is one of the most centric buses. Indeed all solutions on Table 6.10 propose bus number 5 as the best location to install the biggest DG unit, except PSO that proposes bus 6 (which is next to bus 5 and it is also very centric) and SAacc that also locates a big DG unit (0.864MW) at bus 5 but not the biggest. Thus, in general, all given solutions share best locations, best DG type and the total installed power.

6.5.3 57-bus system results

Regarding the 57-bus system, Figure 6.30 shows the box plot of the solutions found by all the approaches. Apparently, the approaches which use PSO obtain the best results followed by those using GA. Figures 6.29 and 6.30 show that SAran is the worst approach for 14-bus and 57-bus cases. This mean that the use of an SA approach that determines the size of the DERs by adding/subtracting random values to the current sizes of the generators obtains better results than simply selecting new random sizes. That is consistent with the fact that PSO-based approaches obtain slightly better solutions than GA-based approaches.

Furthermore, SA+LRS outperforms SAran but not SAacc meaning it is better to use a good SA algorithm than combining it with LRS.

Table 6.9 shows that PSO+SAacc obtains better results than all other approaches except that of PSO+SAran and PSO, from which it cannot be assumed that one is better than the

Method	f_1	f_2	f_3	Bus no.	DG type	DG size (MW)
GA	18280.67	562.12	2.28	5	PV	0.592
				13	PV	0.545
				14	PV	0.488
GA+SA ran.	18385.56	461.51	2.58	1	Wind	0.003
				1	PV	0.511
				4	Wind	0.042
				5	PV	1.000
SA ran.	15674.67	401.13	1.21	1	PV	0.486
				5	Wind	1.701
				8	Wind	1.378
				10	Wind	0.951
				11	PV	1.255
				12	PV	0.878
				14	PV	1.656
GA+SA acc.	18399.40	445.26	1.97	1	PV	0.526
				5	PV	1.000
				11	Wind	0.022
SA acc.	18150.72	492.39	2.07	1	PV	0.881
				5	PV	0.864
				11	Wind	1.202
SA+LRS	17700.07	465.91	2.71	1	PV	1.026
				5	PV	1.691
				8	Wind	1.379
				12	Wind	0.671
PSO+SA ran.	18430.47	427.62	1.90	1	PV	0.215
				5	PV	1.367
PSO+SA acc.	18438.29	440.25	2.65	2	PV	0.445
				5	PV	1.113
PSO	18042.22	1207.20	1.88	6	PV	1.171
				13	PV	0.973

Table 6.10: DG installation found by each method for 14-bus system.

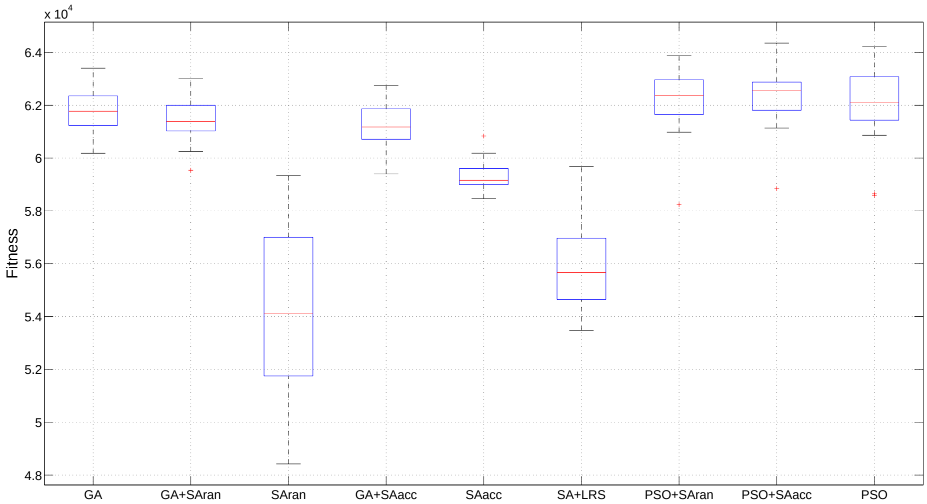

Figure 6.30: Fitness of the solutions found by different meta-heuristic algorithms in the 57-bus. Box plot over 50 solutions of each case.

others. Specifically, an ANOVA analysis of the results obtained by these three approaches returns a p-value of 0.5771, meaning that it cannot be assumed that the results are from different distributions. So the use of any of such techniques is equivalent for building a decision support tool for aiding grid planners.

6.5.4 Discussion

Figure 6.31 shows a graph where a line $p \longrightarrow q$ indicates that algorithm p outperforms algorithm q, meaning that, according to Table 6.9, algorithm p outperforms q in both cases, or at least in one case, and in the other it is not outperformed by q. A dotted line between two algorithms p and q states that either p does not outperform q in any case and q does not outperform q, or p outperforms q in one case, and in the other, q outperforms p, meaning that it cannot be assumed that one of the algorithms is better than the other.

According to Figure 6.31 it can be said that population-based algorithms such as GA or PSO obtain better solutions for the DGLS problem than SA, which is an algorithm based on improving a single candidate solution. It can also be observed that PSO-based approaches obtain better results than GA-based approaches, and approaches using SAacc usually obtain better results than those using SAran. These results lead us to conclude that those algorithms which perform the search modifying the candidate solution in a *continuous* way (PSO modifies

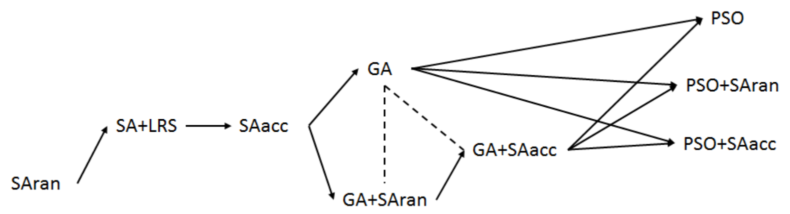

Figure 6.31: Graph indicating which algorithms outperform others. A line $p \longrightarrow q$ indicates that algorithm q outperforms p, and a dotted line between two algorithms states that it cannot be said that one algorithm outperforms the other.

the position of each particle according to a velocity that depends on its past velocity and two gravity centres and SAacc modifies the DERs' size of the candidate solution adding/subtracting small random values) obtain better results than those that present more *discontinuities* in the search process. This conclusion is also reinforced by the point that SA+LRS outperforms SAran.

Besides the comparison between the approaches proposed in Chapter 5 to solve the DGLS problem, it is worth pointing out that the DGLS problem is very complex, especially when there are so many variables to determine (location of the generators, type, size, etc.). It is also very time consuming because of the need to evaluate the power flow of each candidate solution, which at the same time is not an easy problem. However, the possibility of tackling it using meta-heuristic algorithms has been demonstrated. In particular, a decision support system based on a PSO+SAacc could provide recommendations to grid planners, as in the solution shown in Table 6.10.

6.6 Summary

Chapters 3, 4 and 5 present different methods to efficiently solve each resource location and/or allocation problem posed in this dissertation regarding energy management problems due to the smart grid. This chapter has presented the experimentation conducted to test and analyse these methods and has discussed the results obtained.

The first part of the chapter focuses on evaluating the advantages of considering the energy consumption in task scheduling and resource allocation problems (i.e. the e-MPSP) in a context of DSM strategies. In such scenarios, it is crucial to provide consumers with a certain demand response capacity. Hence, this chapter initially analyses the complexity of the e-MPSP and how difficult it is to solve large instances of it using exact methods such as B&B. Next, it studies the capacity of a GA to solve different instances of the e-MPSP, pointing out that there is a small loss of optimality in the solutions obtained. However, the improvement in terms of computational time makes up for this loss of optimality.

After analysing the e-MPSP for the single-agent approaches, the performance of multi-agent approaches, which coordinate the use of energy consuming resources, is analysed. First, MACA mechanism using GA to determine optimal allocation of resources to tasks has been shown to provide better results, for a similar computational effort, than sequential auctions. Thus, obtained results conclude that GA enables the resolution of large allocation problems in a small amount of time.

The consideration of independent bidders that could misdeliver the allocated tasks is an additional problem. Trust-MACA extends MACA, presenting a methodology that enables the consideration of agent's trust during the auction. The results show that the use of trust highly reduces the percentage of allocated bids to untruthful bidders, and as a consequence, the percentage of bad delivered tasks due to involuntary errors. For example the number of bad delivered tasks is 15% lower using T-trust than without trust. In the worst case analysed,the percentage of bad delivered tasks is 30% lower using T-trust than without trust. Furthermore, the T-trust model presented in this dissertation is more robust to initial trust values and changes in the behaviour of the bidders than the other tested models. Therefore it is easier to use in practice.

The second part of the chapter analyses the PRA methodology. It takes advantage of coalitions of consumers to re-allocate the power consumption of all of them in order to minimise power costs related to consumers' power demand peaks. According to the presented results, which are based on a real case scenario, the system achieves an average power costs reduction of 20%. Next, the different fairness mechanisms are tested and analysed, showing that the presented methods achieve lower Gini index values. However the differences shown from the experimentation are small because consumers are assumed to behave honestly, and have reasonable contracted powers, i.e. contracted power not far from their power demand peak.

The third part of the chapter tests and analyses the presented methodology in Chapter 4 to tackle the energy demand allocation problem based on the fairness concept of distributive justice through self-organisation. In this regard, unlike in the first two parts of the chapter, this one is not related to demand response methods. The analysed methodology includes the fairness concept of self-organisation through self-organisation. Thus, the agents (the DERs) decide the relative importance of each canon of distributive justice when carrying out the allocation of the energy demand. The proposed methodology has been compared with the other two (non self-organised) methods, an egalitarian method and another one that prioritises the most reliable generators. The experimentation has shown that, as was expected, optimising a particular objective, i.e. the reliability, obtains better results regarding this objective than seeking a balance between a set of canons that implement the distributive justice in the self-organised institution. However, according to the results, the proposed self-organised methodology achieves an interesting balance between all the objectives because it is dynamically adjusted according to a VPP context. In this regard, if the presence of a big and reliable generator puts in danger the satisfaction of the rest of DERs, the consensus achieved regarding the different canons promotes the most needed DERs. Furthermore, when an external interference appears that affects the allocation, violating the sixth Ostrom's principle, and therefore jeopardising the VPP (see Chapter 4 or [Ostrom, 1990]), the methodology is capable of adjusting the weights of the canons in order to minimise the effect of the interference. The strong points of this method are its robustness against external interferences and its capacity to rapidly adjust itself to new contexts or situations.

Finally, the chapter focuses on the DGLS problem and the proposed algorithms in Chapter 5 regarding the planning of new generators. It presents the experimentation to test the proposed algorithms in two different power networks with the corresponding load and weather conditions. The results show an important difference between the single point search methods and the population based methods, to the benefit of the latter ones (the median of the worst population based method is 3.4% better than the best single point method for the same computational effort on the 57-bus system). It can also be said that combining a population-based algorithm, i.e. PSO, and a single point search method, i.e. SA, seems to improve the performance. However, in general, the differences achieved are not relevant with respect to the population-based algorithm alone. Finally, the results obtained by GA are outperformed by those achieved by PSO, i.e. the best PSO is 0.36% and 1.25% better than the best GA (median) for the 14-bus and 57-bus systems respectively. Similarly, the best PSO is 1.3% and 5.73% better than the best SA (median) for the 14-bus and 57-bus systems respectively. This shows the latter to be more appropriate to solve the DGLS problem.

Summing up, results experimentally show the need for considering energy issues and variable prices in business processes and the increase of complexity of this. Despite the complexity, these problems can be tackled using meta-heuristics algorithms like GA, even when multi-agent systems, such as auctions, are used. Results also showed the benefits of using multi-attribute combinatorial auctions in business processes and the importance of using trust in situations where agents cannot accurately estimate their abilities or the attributes of the delivered tasks. Regarding PRA, experimentation showed that it is a good demand response method to handle DSM strategies based on charging consumers for their peak of power demand, providing important savings to consumers. Next, is studied how to tackle energy demand allocation problems through self-organised methods, which do not have scalability problems, and that combining them with different canons of justice makes the method dynamic and adaptable to new situations. Finally, the complete DGLS problem is defined enabling the utilisation of off-the-shelf optimisation methods to support the planning of placing new renewable generators in a smart grid.

CHAPTER 7

CONCLUSIONS

This final chapter summarises the goals, methodologies and the most relevant results presented in this thesis. It describes the contributions of this thesis to the field of optimisation methods in the smart grid context. Finally, it proposes possible lines of research derived from this work.

7.1 Summary

The aim of this thesis was to study several problems posed by the smart grid which can be modelled as optimisation problems. Given the great range of topics posed by the smart grid, the focus of the thesis was the resource allocation in the scope of energy consumption and generation including the planning of the placement of new generators. The aim of this thesis was to provide methods to solve these optimisation problems in order give the capacity to consumers to adapt their consumption profile to the energy generation according to some stimuli (i.e. variable energy prices), and to the energy production the capacity to adapt to the energy demand.

To that end, this dissertation first deals with the activities of a consumer (i.e. business process) to support it in obtaining an activity schedule that takes into account the energy required by the resources in charge of the activities. Therefore this thesis poses the optimisation problem of allocating resources to tasks and scheduling them considering energy issues such as the load profiles and variable energy prices, called e-MPSP. Next, the thesis presents some approaches to solving this problem while considering two different contexts: (i) when all resources are managed by the same organisation, and (ii) when the resources are managed by external agents and tasks are outsourced to them inside a multi-agent framework, proposing new coordination mechanisms (MACA and trust-MACA). For both contexts, genetic algorithms

(GA) were proved to efficiently solve the optimisation problems. Besides, the trust-MACA approach, presented as an alternative for the second context, has proved that the integration of agent's trust reduces the percentage of allocation to agents that may be considered as unreliable, and therefore, the number of misdelivered tasks. Thus, trust incentivises agents to add security margins when they are not able to accurately estimate their abilities.

Beyond the quality of the allocations provided by the presented approaches, it is worth pointing out their capacity to consider variable energy prices, load shapes agreed by the consumers and the capacity of the methods to keep the consumption profiles of the consumers within these load shapes as modelled in the e-MPSP. This capacity is becoming important in business processes since the costs (economic, social, environmental, etc.) derived from energy consumption become more significant. Optimisation methods have been proved to be useful tools in such challenge.

Despite the individual capacity of consumers to adjust their consumption profiles to the energy production, demand side strategies are also considered for collections of consumers. According to that, it is reasonable to develop methods to agglutinate consumers to respond to these stimuli as a single organisation. In this context PRA is a new method presented in this dissertation, which proposes to re-allocate power demand among a coalition of consumers in order to reduce their contracted power, and thus, the derived costs and the utilisation index of the grid through flatter power profiles. PRA is a specific optimisation method towards that end.

After proposing consumer-oriented optimisation methods, the next goal of the thesis was to study the problem of allocating the energy demand among the distributed generators. A distributed allocation method has been proposed that responds to the real ownership of DERs by different agents, while enabling the scalability of the smart grid operation. Accordingly, this thesis presented a self-organised method, which aggregates different optimisation objectives such as DERs reliability, CO_2 emissions, equity, and so on, through the concept of distributive justice. In other words, the objectives are implemented as canons (principles) which vote and rank DERs. Due to DERs ability to vote and update the importance of each canon and to the variety of canons, the proposed method achieves a significant dynamic robustness able to adapt itself to new situations and minimise the effects of external interferences, i.e. imposed by external or superior authorities, which contributes to enduring the coalition of DERs.

However, adapting electricity production to demand is not only about making the best of the available generators, but also about making an appropriate planning for placing new generators to the network. This problem, called the DGLS problem, is studied and tackled using meta-heuristics. Although this problem has been studied throughout the literature, it has been poorly studied while joining the different questions that make up the problem: how many DERs to place, where to place them, which type of DER should be placed and how big should they be. Therefore, this thesis aimed to cover this gap in the literature and jointly tackle all the questions of the DGLS problem. Unlike the energy demand allocation problem, it was decided to tackle the DGLS problem through centralised methods due to the nature of the planning problem, where it is expected that an organisation studies the potential benefits of placing new DERs to a given grid in order to identify the most promising options for itself or for advising possible DER owners. The performance of different meta-heuristics representing a wide range of the state-of-the-art has been analysed when solving the complete DGLS problem. The conclusions reached state that population-based algorithms are the most effective methods for solving the complete DGLS problem and that PSO is the most suitable algorithm among those tested. This may lead to the conclusion that swarm intelligence methods are more appropriate than evolutionary operators to solve this kind of optimisation problem.

7.2 Future work

This thesis has studied different optimisation problems posed by the smart grid, and it has proposed and analysed different useful methods for solving them.

Further interesting research regarding the e-MPSP may be the study of how delays on the finishing of some tasks can affect future tasks and to consider this fact in the allocation method. Following this idea and according to the proposed auction based approaches it would be interesting to study what to do when the delivery of a task is delayed because of problems that pop up in the delivery of another task assigned to another agent. Obviously, the use of trust-MACA will minimise the frequency of this kind of problems, but when they occur, there will be the need to solve them.

Regarding the energy demand allocation problem, it remains open in which electricity markets (day-ahead, spot market, ancillary services, etc.) a VPP operated using the proposed method based on self-organisation could participate (or would be profitable to participate in). Obviously this question is tied to the reliability of the allocations and this, at the same time, is tied to the composition of the VPP. Thus, it would be interesting to study the applicability of the proposed method in real case studies. Furthermore, the advantages of having the self-organised method should be compared with methods able to provide short- or mid-term schedules of the energy production of DERs.

Finally, the DGLS has been solved by different meta-heuristics comparing their performance but further research should include more algorithms. Furthermore, the problem solving of the DGLS problem involves the resolution of the energy demand allocation problem. This thesis has solved such a problem, but for the DGLS problem, it was decided to determine the energy production of each generator according to a naive proportional method due to the computational complexity. However, a demonstration is needed, that, in general, the influence of the energy demand allocation method is not significant in the solution of the DGLS problem.

APPENDIX A

NOTATION GUIDE

This appendix summarises the notation used in equations of Chapters 3, 4 and 5.

A.1 Demand Response

Notation used in Chapter 3 Section 3.2 which refers to e-MPSP:

- T_i Task i
  Task or activity defined by a start time interval $\left[\underline{s_i}, \overline{s_i}\right]$, an end time interval $\left[\underline{et_i}, \overline{et_i}\right]$ and a list of required skills $\mathbf{RQ}_i$.

$$T_i = \left\langle \left[\underline{s_i}, \overline{s_i}\right], \left[\underline{et_i}, \overline{et_i}\right], \mathbf{RQ}_i \right\rangle \tag{A.1}$$

- R_m Resource m
  Resource cable to execute tasks according to the skills S_k it masters.
- S_k Skills k
  Resource's skills determine the tasks the resource is capable to carry out.
- $p_{i,m}$ Processing time for carrying out task i by resource m.
- $c_{i,m}$ Cost of using resource m for executing task i.
  This does not include the energy-related cost.
- $e_{i,m}$ Energy consumed by resource m for executing task i.
- $z_{i,m}$ Binary variable used to indicate whether resource resource m is assigned to perform task i or not.

$z_{i,m} = 1$ means that resource m executes task i and $z_{i,m} = 0$ indicates that resource m is does not.

- $\mathscr{Z}$ Group of variables $z_{i,m}$ which indicates the resources in charge of all tasks.
- s_i Start time of task i
- $\mathscr{S}$ Group of variables s_i which indicates the start time of all tasks.
  $\mathscr{S}, \mathscr{Z}$ is used to define an schedule.
- $\mathscr{P}_i$ Set of predecessor tasks of task i.
  Task i cannot start before all the tasks in $\mathscr{P}_i$ are finished.
- ρ_t Energy consumption at time t
  $\rho_t \; \forall t$ defines the power profile.
- Σ Load shape.

$$\Sigma = \left\langle \underline{P_t}, \overline{P_t}, \underline{\rho_t}, \overline{\rho_t} \right\rangle_{\forall t} \tag{A.2}$$

- $\underline{P_t}$ Minimum energy consumption at time t.
- $\overline{P_t}$ Maximum energy consumption at time t.
- $\underline{\rho_t}$ Compromised minimum energy consumption at time t.
  $\rho_t < \underline{\rho_t}$ involves augmented energy prices.
- $\overline{\rho_t}$ Compromised maximum energy consumption at time t.
  $\rho_t > \overline{\rho_t}$ involves augmented energy prices.
- Γ Energy tariff.

$$\Gamma = \left\langle \pi_t, \underline{\pi_t}, \overline{\pi_t}, \underline{f_t}, \overline{f_t} \right\rangle_{\forall t} \tag{A.3}$$

- π_t energy price at time t.
- $\underline{\pi_t}$ Energy price at time t when $\rho_t < \underline{\rho_t}$.
- $\overline{\pi_t}$ Energy price at time t when $\rho_t > \overline{\rho_t}$.
- $\underline{f_t}$ Fine for $\rho_t < \underline{\rho_t}$ at time t.
- $\overline{f_t}$ Fine for $\rho_t > \overline{\rho_t}$ at time t.

- $C_T(\mathscr{S},\mathscr{Z})$ Makespan of the schedule defined by $(\mathscr{S},\mathscr{Z})$.

$$C_T(\mathscr{S},\mathscr{Z}) = \max_{i,j}\left(s_i + \sum_{m=1}^{M} z_{i,m}p_{i,m} - s_j\right), \quad \forall i,j\ 1 \leq i,j \leq N \tag{A.4}$$

- $C_E(\mathscr{S},\mathscr{Z})$ Energy consumption derived from schedule $(\mathscr{S},\mathscr{Z})$.

$$C_E(\mathscr{S},\mathscr{Z}) = \sum_{t=1}^{T_{max}} \rho_t(\mathscr{S},\mathscr{Z}) \tag{A.5}$$

- $C_M(\mathscr{S},\mathscr{Z})$Economic cost of schedule $(\mathscr{S},\mathscr{Z})$.

$$C_M(\mathscr{S},\mathscr{Z}) = \sum_{i=1}^{N}\sum_{m=1}^{M} z_{i,m}c_{i,m} + \sum_{t=1}^{T_{max}} \Phi(\rho_t(\mathscr{S},\mathscr{Z}),\Sigma,\Gamma) \tag{A.6}$$

- $\Phi(\rho_t,\Sigma,\Gamma)$Economic cost due to the energy consumption.

$$\Phi_t(\rho_t,\Sigma,\Gamma) = \begin{cases} \rho_t\pi_t + \left(\underline{\rho_t} - \rho_t\right)\underline{\pi_t} + \underline{f_t} & \rho_t < \underline{\rho_t} \\ \rho_t\pi_t & \underline{\rho_t} \leq \rho_t \leq \overline{\rho_t} \\ \rho_t\pi_t + (\rho_t - \overline{\rho_t})\overline{\pi_t} + \overline{f_t} & \rho_t > \overline{\rho_t} \end{cases} \tag{A.7}$$

- $B_{i,j,k}$ kth bid send for bidder j for performing task i.

$$B_{i,j,k} = \left\langle T_i@s_{i,j,k} : \left(\mu_{i,j,k},\epsilon_{i,j,k},\delta_{i,j,k}\right), M_{i,j,k}, E_{i,j,k}, \Delta_{i,j,k}\right\rangle \tag{A.8}$$

- $s_{i,j,k}$ Start time proposed by $B_{i,j,k}$ for task i.
- $\mu_{i,j,k}$ Price of $B_{i,j,k}$.
- $\epsilon_{i,j,k}$ Energy consumption according to $B_{i,j,k}$.
- $\delta_{i,j,k}$ Duration of the task performance according to $B_{i,j,k}$.
- $M_{i,j,k}$ Vector which indicates price changes for $B_{i,j,k}$ if bidder j is in charge of other tasks.

- $E_{i,j,k}$ Vector which indicates energy consumption changes for $B_{i,j,k}$ if bidder j is in charge of other tasks.

- $\Delta_{i,j,k}$ Vector which indicates duration changes for $B_{i,j,k}$ if bidder j is in charge of other tasks.

- $b_{i,j,k}$ Price of $B_{i,j,k}$ considering all tasks assigned to bidder j.

$$b_{i,j,k} = \mu_{i,j,k} + \sum_{l=1}^{N_j} M_{i,j,k}(l) \cdot x_{i,j,l} \tag{A.9}$$

- $e_{i,j,k}$ Energy consumption according to $B_{i,j,k}$ considering all tasks assigned to bidder j.

$$e_{i,j,k} = \epsilon_{i,j,k} + \sum_{l=1}^{N_j} E_{i,j,k}(l) \cdot x_{i,j,l} \tag{A.10}$$

- $t_{i,j,k}$ Execution time according to $B_{i,j,k}$ considering all tasks assigned to bidder j.

$$t_{i,j,k} = s_{i,j,k} + \delta_{i,j,k} + \sum_{l=1}^{N_j} \Delta_{i,j,k}(l) \cdot x_{i,j,l} \tag{A.11}$$

- $x_{i,j,k}$ Binary variable used to indicate the winner bids.
- $u\left(T_i, B_{i,j,k}\right)$ Auctioneer's utility for outsourcing task i according to $B_{i,j,k}$.
- $V\left(B_{i,j,k}\right)$ Auctioneer's evaluation function for $B_{i,j,k}$.

  Alternatively, it is also represented as $V(a_1, \ldots, a_n)$ being $a_1, \ldots, a_n$ the attributes of the corresponding bid (i.e. $b_{i,j,k}$, $t_{i,j,k}$ and $e_{i,j,k}$).

- $p_{i,j,k}$ Corresponding payment to bidder j for executing task i according to $B_{i,j,k}$
- $\tau^t_{j,r}$ Trust on bidder j at round r about delivery time.
- $\tau^e_{j,r}$ Trust on bidder j at round r about energy consumption.
- α_t Trust learning coefficient for delivery time (for positive reinforcement).
- β_t Trust learning coefficient for delivery time (for negative reinforcement).
- α_e Trust learning coefficient for energy consumption (for positive reinforcement).

- β_e Trust learning coefficient for energy consumption (for negative reinforcement).

Following it is summarised the notation used in Section 3.3

- W Time duration between two electricity bills (usually a month).
- N_p Number of periods which divide a day.
- $c_{i,k}$ Contracted power.
- W Time duration between two electricity bills (usually a month).
- $\alpha_{i,k}$ Under-power demand parameter of consumer i for period k.
- $\beta_{i,k}$ Over power demand parameter of consumer i for period k.
- $\rho_{i,k,t}$ Demanded power for consumer i, period k at time t.
- ρ_i Power profile of consumer i.

$$\rho = \left\{\rho_{i,k,t}\ \forall k, t\right\} \tag{A.12}$$

- $m_{i,k}$ Maximum demanded power of consumer i in period k.

$$m_{i,k} = \max_t \left(\rho_{i,k,t}\right) \tag{A.13}$$

- $\pi_{i,k}$ Power price of consumer i in period k.
- c_k^u Contracted power by the umbrella entity.
- m_k^u Maximum demanded power by the umbrella entity.

$$m_k^u = \max_t \left(\sum_i \rho_{i,k,t}\right) \tag{A.14}$$

- $\tau_{i,k}^n$ Target power of consumer i for period k on iteration n.

$$\max\left(\alpha_{i,k} c_{i,k}, \max_{\forall t \mid \rho_{i,k,t} < \max_t\left(\rho_{i,k,t}\right)} \left(\rho_{i,k,t}\right)\right) \tag{A.15}$$

- $APR_{k,t}$ Accumulated power rights at period k and time t.
- $ADP_{k,t}$ Accumulated demanded power at period k and time t.
- $PS_{k,t}$ Power sharing at period k and time t.

A.2 Energy demand allocation

Notation used in Chapter 4 which refers to energy demand allocation:

- p_i^{min} Minimum available production of DER i.
- p_i^{max} Maximum available production of DER i.
- $p_i^{forecast}(t)$ Expected energy production conditioned to the weather forecast of DER i at time t.
- s_i^u Up ramp limit of DER i.
- s_i^d Down ramp limit of DER i.
- $p_i^{min}(t)$ Minimum available production of DER i at time t.

$$p_i^{min}(t+1) = \max\left\{p_i^{min}, p_i(t) - s_i^d\right\} \tag{A.16}$$

- $p_i^{max}(t)$ Maximum available production of DER i at time t.

$$p_i^{max}(t+1) = \min\left\{p_i^{max}, p_i^{forecast}(t+1), p_i(t) + s_i^u\right\} \tag{A.17}$$

- N_{DER} Number of DERs in the VPP.
- $P^{min}(t)$ Minimum available energy production of the VPP at time t.
- $P^{max}(t)$ Maximum available energy production of the VPP at time t.
- $L(t)$ Load of the VPP at time t.
- $d_i(t)$ Desired energy production of DER i at time t.
- $\underline{d}_i(t)$ Minimum desired energy production of DER i at time t.
- $\overline{d}_i(t)$ Maximum desired energy production of DER i at time t.
- $I_i(t)$ Also I_i. Desired energy production interval of DER i.

$$I_i(t) = \left[\underline{d}_i(t), \overline{d}_i(t)\right] \tag{A.18}$$

- $D(t)$ Total demanded energy production of the VPP.
- $a_i(t)$ Assigned energy production to DER i at time t.
- $\tau_i(t)$ Received payment for DER i for producing energy at time t.
- $r_i(t)$ Delivered energy by DER i at time t.
- $T_i(t)$ Also T_i. Time-range during DER i has been active in the VPP.
- $\sigma_i(t)$ Satisfaction of DER i at time t.
- α, β Satisfaction learning coefficients.
- $LR(t)$ Remaining load to allocate of the VPP at time t.
- f_* Canon implementation function $*$ (i.e. f_{1a}).
- w_* Weight of the canon implementation function f_*.
- $\rho_{i,*}^{DER}$ Borda points assigned to DER i by function f_*.
- $\rho_{i,*}^{c}$ Borda points assigned to canon function f_* by DER i.
- $Borda(f_*, VPP)$

  Borda points received by f_* from all DERs.

$$Borda(f_*, VPP) = \sum_{i=1}^{N_{DER}} \rho_{i,*}^{c} \tag{A.19}$$

- $AvgBorda$

  Average Borda points received by all functions.

$$AvgBorda = \frac{1}{m} \sum_{\forall f_*} Borda(f_*, VPP) \tag{A.20}$$

- $TotalBorda$

  Total Borda points received by all functions.

$$AvgBorda = \sum_{\forall f_*} Borda(f_*, VPP) \tag{A.21}$$

A.3 Allocation of new generators

Notation used in Chapter 5:

- t Time index.
- i Bus index.
- j Bus index.
- k Generator type index
- $t_{N_{DGtypes}}$ Number of DER types.
- N_{bus} Number of buses.
- $K_{i,j}^{t}$ Power loss factor between bus i and j at time t.
- $S_{i,j}^{t}$ Apparent power flow from bus i to bus j at time t.
- $S_{i,j}^{max}$ Upper limit for apparent power flow from bus i to bus j.
- $R_{i,j}$ Resistance of line from i to j.
- $Y_{i,j}$ Admittance of line from i to j.
- $\theta_{i,j}$ Phase angle of $Y_{i,j}$.
- V_{i}^{t} Voltage magnitude in bus i at time t.
- V_{i} Desired voltage magnitude in bus i at time t.
- V_{i}^{min} Lower limit for voltage of bus i.
- V_{i}^{max} Upper limit for voltage of bus i.
- δ_{i}^{t} Voltage phase in bus i at time t.
- $P_{i,k}^{t}$ Active power output of DER type k at bus i.
- $Q_{i,k}^{t}$ Reactive power output of DER type k at bus i.
- $L_{P,i}^{t}$ Active power demand in bus i at time t.
- $L_{Q,i}^{t}$ Reactive power demand in bus i at time t.

- $P_{i,k}^{max}$ Upper limit for active power output of DER type k in bus i.
- $r_{i,k,forecast}^{t}$
  Expected resource availability for DER type k in bus i.
- $C_{i,k}$ Generation costs of DER type k in bus i (€ /MWh).
- $C_{i,k,amortisation}$
  Amortisation of installing DER type k in bus i (€ /MW).
- $C_{i,k,maintenance}$
  Yearly fixed maintenance cost of DER type k in bus i (€ /MW).
- $SUC_{i,k}$ Start up cost of DER type k in bus i (€ .
- $SDC_{i,k}$ Shut down cost of DER type k in bus i (€ .
- π^t Energy price at time t (€ /MWh).
- ρ^t Estimated cost of the energy produced at time t.
- $\beta_{i,k}^{t}$ Binary decision variable which indicates whether DER type k in bus i starts up at time t.
- $\gamma_{i,k}^{t}$ Binary decision variable which indicates whether DER type k in bus i shuts down at time t.

Bibliography

[Ackermann et al., 2001] Ackermann, T., Andersson, G., and Söder, L. (2001). Distributed generation: a definition. *Electric Power Systems Research*, 57(3):195–204.

[Alcaraz and Maroto, 2001] Alcaraz, J. and Maroto, C. (2001). A robust genetic algorithm for resource allocation in project scheduling. *Annals of Operations Research*, 102(1-4):83–109.

[Aman et al., 2014] Aman, M., Jasmon, G., Bakar, A., and Mokhlis, H. (2014). A new approach for optimum simultaneous multi-DG distributed generation Units placement and sizing based on maximization of system loadability using HPSO (hybrid particle swarm optimization) algorithm. *Energy*, 66:202–215.

[Ameli et al., 2014] Ameli, A., Bahrami, S., Khazaeli, F., and Haghifam, M.-R. (2014). A Multiobjective Particle Swarm Optimization for Sizing and Placement of DGs from DG Owner's and Distribution Company's Viewpoints. *IEEE Transactions on Power Delivery*, 29(4):1831–1840.

[Apt, 2003] Apt, K. (2003). *Principles of constraint programming*. Cambridge University Press.

[Atwa and El-Saadany, 2010] Atwa, Y. and El-Saadany, E. (2010). Optimal renewable resources mix for distribution system energy loss minimization. *IEEE Transactions on Power Systems*, 25(1):360–370.

[Ausubel and Cramton, 2010] Ausubel, L. M. and Cramton, P. (2010). Virtual power plant auctions. *Utilities Policy*, 18(4):201–208.

[Baños et al., 2011] Baños, R., Manzano-Agugliaro, F., Montoya, F., Gil, C., Alcayde, A., and Gómez, J. (2011). Optimization methods applied to renewable and sustainable energy: A review. *Renewable and Sustainable Energy Reviews*, 15(4):1753–1766.

[Bakari and Kling, 2010] Bakari, K. E. and Kling, W. L. (2010). Virtual power plants: An answer to increasing distributed generation. In *2010 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe)*, pages 1–6. IEEE.

[Beheshti et al., 2013] Beheshti, Z., Mariyam, S., and Shamsuddin, H. (2013). A Review of Population-based Meta-Heuristic Algorithms. *International Journal of Advances in Soft Computing Applications*, 5(1):1–35.

[Bellenguez-Morineau and Néron, 2007] Bellenguez-Morineau, O. and Néron, E. (2007). A branch-and-bound method for solving multi-skill project scheduling problem. *RAIRO-Operations Research*, 41(2):155–170.

[Binding et al., 2010] Binding, C., Gantenbein, D., Jansen, B., Sundstrom, O., Andersen, P. B., Marra, F., Poulsen, B., and TrÃholt, C. (2010). Electric vehicle fleet integration in the Danish EDISON project-a virtual power plant on the island of Bornholm. In *Power and Energy Society General Meeting, 2010 IEEE*, pages 1–8.

[Birattari et al., 2001] Birattari, M., Paquete, L., Stiitzle, T., and Varrentrapp, K. (2001). ClassiïňĄcation of Metaheuristics and Design of Experiments for the Analysis of Components. Technical report, Darmstadt University of Technology.

[Blum and Roli, 2003] Blum, C. and Roli, A. (2003). Metaheuristics in Combinatorial Optimization: Overview and Conceptual Comparison. *ACM Computing Surveys*, 35(3):268–308.

[Bose and Pal, 2012] Bose, I. and Pal, R. (2012). Do green supply chain management initiatives impact stock prices of firms? *Decision Support Systems*, 52(3):624–634.

[Boutaba and Won-Ki Hong, 2010] Boutaba, R. and Won-Ki Hong, J. (2010). Near optimal demand-side energy management under real-time demand-response pricing. In *2010 International Conference on Network and Service Management*, pages 527–532.

[Bradley et al., 1977] Bradley, S., Hax, A., and Magnanti, T. (1977). *Applied mathematical programming*. Addison-Wesley.

[Brounen et al., 2013] Brounen, D., Kok, N., and Quigley, J. M. (2013). Energy literacy, awareness, and conservation behavior of residential households. *Energy Economics*, 38:42–50.

[Cai and Gong, 2004] Cai, Z. and Gong, T. (2004). Advance in research on immune algorithms. *Control and decision*, 19:841–846.

[Cavazzuti, 2013] Cavazzuti, M. (2013). *Optimization Methods*. Springer Berlin Heidelberg.

[Celli et al., 2005] Celli, G., Ghiani, E., Mocci, S., and Pilo, F. (2005). A Multiobjective Evolutionary Algorithm for the Sizing and Siting of Distributed Generation. *IEEE Transactions on Power Systems*, 20(2):750–757.

[Chalkiadakis et al., 2011] Chalkiadakis, G., Robu, V., and Kota, R. (2011). Cooperatives of distributed energy resources for efficient virtual power plants. In *The 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 2. International Foundation for Autonomous Agents and Multiagent Systems*, pages 787–794.

[Che, 1993] Che, Y. (1993). Design competition through multidimensional auctions. *The RAND Journal of Economics*, 24(4):668–680.

[Clerc and Kennedy, 2002] Clerc, M. and Kennedy, J. (2002). The particle swarm-explosion, stability, and convergence in a multidimensional complex space. *IEEE Transactions on Evolutionary Computation*, 6(1):58–73.

[Collins et al., 2002] Collins, J., Demir, G., and Gini, M. (2002). Bidtree ordering in IDA combinatorial auction winner-determination with side constraints. *Agent-Mediated Electronic Commerce IV. Designing Mechanisms and Systems*, 2531:17–33.

[Dantzig and Thapa, 1997] Dantzig, G. B. and Thapa, M. N. (1997). *Linear Programming*. Springer Series in Operations Research and Financial Engineering. Springer-Verlag.

[de Castro, 2002] de Castro, L. (2002). Immune, swarm, and evolutionary algorithms. part i: basic models. In *Proceedings of the 9th International Conference on Neural Information Processing. ICONIP '02*, volume 3, pages 1464–1468.

[Dijkstra, 1959] Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische Mathematik*, 1(1):269–271.

[Dimeas and Hatziargyriou, 2007] Dimeas, A. L. and Hatziargyriou, N. D. (2007). Agent based control of virtual power plants. In *Intelligent Systems Applications to Power Systems, 2007. ISAP 2007. International Conference on*, pages 1–6.

[Dorigo, 1992] Dorigo, M. (1992). *Optimization, learning and natural algorithms*. PhD thesis, Politecnico di Milano.

[Dréo et al., 2006] Dréo, J., Pétrowski, A., Siarry, P., and Taillard, E. (2006). *Metaheuristics for Hard Optimization*. Springer-Verlag, Berlin/Heidelberg.

[Elnashar et al., 2010] Elnashar, M. M., El Shatshat, R., and Salama, M. M. (2010). Optimum siting and sizing of a large distributed generator in a mesh connected system. *Electric Power Systems Research*, 80(6):690–697.

[Emami and Noghreh, 2010] Emami, A. and Noghreh, P. (2010). New approach on optimization in placement of wind turbines within wind farm by genetic algorithms. *Renewable Energy*, 35(7):1559–1564.

[Emerson, 2007] Emerson, P. (2007). *Designing an All-inclusive Democracy: Consensual Voting Procedures for Use in Parliaments, Councils and Committees*. Springer.

[Erol-Kantarci and Mouftah, 2011] Erol-Kantarci, M. and Mouftah, H. T. (2011). Wireless Sensor Networks for Cost-Efficient Residential Energy Management in the Smart Grid. *IEEE Transactions on Smart Grid*, 2(2):314–325.

[Faria et al., 2011] Faria, P., Vale, Z., Soares, J., and Ferreira, J. (2011). Demand response management in power systems using a particle swarm optimization approach. *IEEE Intelligent Systems*, 28(4):43–51.

[Gastwirth, 1972] Gastwirth, J. (1972). The estimation of the Lorenz curve and Gini index. *The Review of Economics and Statistics*, 54(3):306–316.

[Gautam and Mithulananthan, 2007] Gautam, D. and Mithulananthan, N. (2007). Optimal DG placement in deregulated electricity market. *Electric Power Systems Research*, 77(12):1627–1636.

[Gellings, 2009] Gellings, C. W. (2009). *The smart grid: enabling energy efficiency and demand response*. The Fairmont Press, Inc.

[Ghosh et al., 2010] Ghosh, S., Ghoshal, S., and Ghosh, S. (2010). Optimal sizing and placement of distributed generation in a network system. *International Journal of Electrical Power & Energy Systems*, 32(8):849–856.

[Gini, 1912] Gini, C. (1912). *Variabilità e mutabilità. Contributi allo studio dele relazioni e delle distribuzioni statistiche (variability and mutability. contribution to the study of the statistic distributions and relations)*. PhD thesis, Tipogr. di P. Cuppini.

[Glover, 1989] Glover, F. (1989). Tabu search-part I. *ORSA Journal on Computing*, pages 190–206.

[Glover, 1990] Glover, F. (1990). Tabu searchâĂŤpart II. *ORSA Journal on computing*, pages 4–32.

[Glover and Kochenberger, 2003] Glover, F. and Kochenberger, G. A., editors (2003). *Handbook of Metaheuristics*, volume 57 of *International Series in Operations Research & Management Science*. Kluwer Academic Publishers.

[González et al., 2010] González, J., Rodriguez, A., and Mora, J. (2010). Optimization of wind farm turbines layout using an evolutive algorithm. *Renewable Energy*, 35(8):1671–1681.

[Gonzalez, 2007] Gonzalez, T. (2007). *Handbook of approximation algorithms and metaheuristics*. Chapman & Hall/CRC.

[Gottwalt et al., 2011] Gottwalt, S., Ketter, W., Block, C., Collins, J., and Weinhardt, C. (2011). Demand side management - A simulation of household behavior under variable prices. *Energy Policy*, 39(12):8163–8174.

[Ha et al., 2006] Ha, L., Ploix, S., Zamai, E., and Jacomino, M. (2006). Tabu search for the optimization of household energy consumption. In *2006 IEEE International Conference on Information Reuse & Integration*, pages 86–92.

[Hansen and Mladenović, 2001] Hansen, P. and Mladenović, N. (2001). Variable neighborhood search: Principles and applications. *European Journal of Operational Research*, 130(3):449–467.

[Hart et al., 1968] Hart, P. E., Nilsson, N., and Raphael, B. (1968). A formal basis for the heuristic determination of minimum cost paths. *IEEE Transactions on Systems Science and Cybernetics*, 4(2):100–107.

[Hartmann and Briskorn, 2010] Hartmann, S. and Briskorn, D. (2010). A survey of variants and extensions of the resource-constrained project scheduling problem. *European Journal of Operational Research*, 207(1):1–14.

[Haupt and Haupt, 2004] Haupt, R. L. R. and Haupt, S. S. E. (2004). *Practical genetic algorithms*. Wiley-Interscience.

[Helal et al., 2012] Helal, A., Amer, M., and Eldosouki, H. (2012). Optimal location and sizing of distributed generation based on gentic algorithm. In *2nd International Conference on Communications Computing and Control Applications*, pages 1–6.

[Holland, 1975] Holland, J. (1975). *Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence.* U Michigan Press.

[Horling and Lesser, 2005] Horling, B. and Lesser, V. (2005). A survey of multi-agent organizational paradigms. *The Knowledge Engineering Review*, 19(04):281.

[International Energy Agency, 1997] International Energy Agency (1997). Energy technologies for the 21st century.

[Jarboui et al., 2008] Jarboui, B., Damak, N., Siarry, P., and Rebai, A. (2008). A combinatorial particle swarm optimization for solving multi-mode resource-constrained project scheduling problems. *Applied Mathematics and Computation*, 195(1):299–308.

[Jia et al., 2012] Jia, W., Kang, C., and Chen, Q. (2012). Analysis on demand-side interactive response capability for power system dispatch in a smart grid framework. *Electric Power Systems Research*, 90(0):11–17.

[Jø sang et al., 2007] Jø sang, A., Ismail, R., and Boyd, C. (2007). A survey of trust and reputation systems for online service provision. *Decision support systems*, 43(2):618–644.

[Jongen et al., 2004] Jongen, H. T., Meer, K., and Triesch, E. (2004). *Optimization theory*. Kluwer Academic Publishers.

[Jurca and Faltings, 2003] Jurca, R. and Faltings, B. (2003). Towards incentive-compatible reputation management. *Trust, Reputation, and Security: Theories and ...*, 2631:138–147.

[Kash et al., 2014] Kash, I., Procaccia, A. D., and Shah, N. (2014). No agent left behind: dynamic fair division of multiple resources. *Journal of Artificial Intelligence Research*, 51:579–603.

[Kennedy, 2010] Kennedy, J. (2010). Particle swarm optimization. In *Encyclopedia of Machine Learning*, pages 760–766. Springer US.

[Kennedy and Eberhart, 1995] Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of IEEE International Conference on neural networks (ICNN'95)*, volume 4, pages 1942–1948.

[Kirkpatrick et al., 1983] Kirkpatrick, S., Gelatt, C., and Vecchi, M. (1983). Optimization by simmulated annealing. *Science*, 220(4598):671–680.

[Kishore and Snyder, 2010] Kishore, S. and Snyder, L. V. (2010). Control Mechanisms for Residential Electricity Demand in SmartGrids. In *2010 First IEEE International Conference on Smart Grid Communications*, pages 443–448.

[Kongnam and Nuchprayoon, 2010] Kongnam, C. and Nuchprayoon, S. (2010). A particle swarm optimization for wind energy control problem. *Renewable Energy*.

[Korf, 1985] Korf, R. (1985). Depth-first iterative-deepening An optimal admissible tree search. *Artificial Intelligence*, 27(1):97–109.

[Kornelakis and Marinakis, 2010] Kornelakis, A. and Marinakis, Y. (2010). Contribution for optimal sizing of grid-connected PV-systems using PSO. *Renewable Energy*, 35(6):1333–1341.

[Kota et al., 2012] Kota, R., Chalkiadakis, G., Robu, V., Rogers, A., and Jennings, N. R. (2012). Cooperatives for demand side management. In *The Seventh Conference on Prestigious Applications of Intelligent Systems*, pages 969–974.

[Land and Doig, 1960] Land, A. H. and Doig, A. G. (1960). An automatic method of solving discrete programming problems. *Econometrica: Journal of the Econometric Society*, pages 497–520.

[Lee and Szymanski, 2005] Lee, J.-S. and Szymanski, B. K. (2005). A novel auction mechanism for selling time-sensitive e-services. In *E-Commerce Technology, 2005. CEC 2005. Seventh IEEE International Conference on*, pages 75–82.

[Lerner et al., 2009] Lerner, J., Wagner, D., and Zweig, K. A., editors (2009). *Algorithmics of Large and Complex Networks*, volume 5515 of *Lecture Notes in Computer Science*. Springer Berlin Heidelberg, Berlin, Heidelberg.

[Li et al., 2011] Li, D., Jayaweera, S. K., and Naseri, A. (2011). Auctioning game based Demand Response scheduling in smart grid. In *2011 IEEE Online Conference on Green Communications*, pages 58–63.

[Li et al., 2013] Li, J., Guo, Y., Platt, G., and Ward, J. K. (2013). Renewable energy aggregation with intelligent battery controller. *Renewable Energy*, 59:220–228.

[Lopez et al., 2014] Lopez, B., Ghose, A., Savarimuthu, B. T. R., Nowostawski, M., Winikoff, M., and Cranefield, S. (2014). Towards Energy-Aware Optimisation of Business Processes. In *Proceedings of the 3rd International Workshop on Smart Grids and Green IT Systems (Smartgreens2014)*, Barcelona.

[López and Galán, 2008] López, P. and Galán, S. (2008). A method for particle swarm optimization and its application in location of biomass power plants. *International Journal of Green Energy*, 5(3):199–211.

[López et al., 2008] López, P., Jurado, F., and Reyes, N. (2008). Particle swarm optimization for biomass-fuelled systems with technical constraints. *Engineering Applications of Artificial Intelligence*, 21(8):1389–1396.

[Luke, 2013] Luke, S. (2013). *Essentials of metaheuristics*. Lulu, 2nd edition. available for free at http://cs.gmu.edu/˜sean/book/metaheuristics/.

[Macbeth et al., 2012] Macbeth, S., Pitt, J., Schaumeier, J., and Busquets, D. (2012). Animation of Self-Organising Resource Allocation Using Presage2. In *2012 IEEE Sixth International Conference on Self-Adaptive and Self-Organizing Systems*, pages 225–226.

[MacKie-Mason and Varian, 1994] MacKie-Mason, J. K. and Varian, H. R. (1994). Generalized vickrey auctions. Technical report, School of Public Policy, Gerald R. Ford.

[Martín García and Gil Mena, 2013] Martín García, J. A. and Gil Mena, A. J. (2013). Optimal distributed generation location and size using a modified teachingâĂŞlearning based optimization algorithm. *International Journal of Electrical Power & Energy Systems*, 50:65–75.

[Mashhour and Moghaddas-Tafreshi, 2011] Mashhour, E. and Moghaddas-Tafreshi, S. M. (2011). Bidding strategy of virtual power plant for participating in energy and spinning reserve market Part I: Problem formulation. *IEEE Transactions on Power Systems*, 26(2):949–956.

[Maskin and Riley, 2003] Maskin, E. and Riley, J. (2003). Uniqueness of equilibrium in sealed high-bid auctions. *Games and Economic Behavior*, 45(2):395–409.

[Meir and Pearlmutter, 2010] Meir, I. A. and Pearlmutter, D. (2010). Building for climate change: planning and design considerations in time of climatic uncertainty. *Corrosion Engineering, Science and Technology*, 45(1):70–75.

[Meir et al., 2012] Meir, I. A., Peeters, A., Pearlmutter, D., Halasah, S., Garb, Y., and Davis, J.-M. (2012). An assessment of regional constraints, needs and trends. *Advances in Building Energy Research*, 6(2):173–211.

[Mitchell, 2002] Mitchell, J. E. (2002). Branch-and-cut algorithms for combinatorial optimization problems. In *Handbook of applied optimization*, pages 65–77. Oxford University Press.

[Mitchell, 1998] Mitchell, M. (1998). *An introduction to genetic algorithms*. MIT press.

[Mohsenian-Rad and Leon-Garcia, 2010] Mohsenian-Rad, A.-H. and Leon-Garcia, A. (2010). Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments. *IEEE Transactions on Smart Grid*, 1(2):120–133.

[Mohsenian-Rad et al., 2010] Mohsenian-Rad, A.-H., Wong, V. W., Jatskevich, J., and Schober, R. (2010). Optimal and autonomous incentive-based energy consumption scheduling algorithm for smart grid. In *2010 Innovative Smart Grid Technologies (ISGT)*, pages 1–6.

[Molderink et al., 2010] Molderink, A., Bakker, V., Bosman, M. G. C., Hurink, J. L., and Smit, G. J. M. (2010). Management and Control of Domestic Smart Grid Technology. *IEEE Transactions on Smart Grid*, 1(2):109–119.

[Moradi and Abedini, 2012] Moradi, M. and Abedini, M. (2012). A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems. *International Journal of Electrical Power & Energy Systems*, 34(1):66–74.

[Moscato et al., 2004] Moscato, P., Cotta, C., and Mendes, A. (2004). Memetic algorithms. In *New Optimization Techniques in Engineering*, volume 141 of *Studies in Fuzziness and Soft Computing*, pages 53–85. Springer Berlin Heidelberg.

[Murillo Espinar, 2010] Murillo Espinar, J. (2010). *Egalitarian behaviour in multi unit combinatorial auctions*. PhD thesis, University of Girona.

[Nerves and Roncesvalles, 2009] Nerves, A. C. and Roncesvalles, J. C. K. (2009). Application of evolutionary programming to optimal siting and sizing and optimal scheduling of distributed generation. In *TENCON 2009 - 2009 IEEE Region 10 Conference*, pages 1–6. IEEE.

[Nguyen et al., 2012] Nguyen, H. K., Song, J. B., and Han, Z. (2012). Demand side management to reduce Peak-to-Average Ratio using game theory in smart grid. In *2012 Proceedings IEEE INFOCOM Workshops*, pages 91–96.

[Office of Electric Transmission and Distribution, 2003] Office of Electric Transmission and Distribution (2003). 'GRID 2030' A national vision for electricity's second 100 years. Technical report, US Department of Energy.

[Ostrom, 1990] Ostrom, E. (1990). *Governing the Commons*. Cambridge University Press.

[Oyarzabal et al., 2009] Oyarzabal, J., Martí, J., Ilo, A., Sebastian, M., Alvira, D., and Johansen, K. (2009). Integration of DER into power system operation through Virtual Power Plant concept applied for voltage regulation. In *Integration of Wide-Scale Renewable Resources Into the Power Delivery System, 2009 CIGRE/IEEE PES Joint Symposium*, pages 1–7.

[Paquete, 2006] Paquete, L. F. (2006). *Stochastic local search algorithms for multiobjective combinatorial optimization : methods and analysis*. Akademische Verlagsgesellschaft Aka.

[Parkes and Kalagnanam, 2005] Parkes, D. C. and Kalagnanam, J. (2005). Models for Iterative Multiattribute Procurement Auctions. *Management Science*, 51(3):435–451.

[Pedrasa et al., 2010] Pedrasa, M. A. A., Spooner, T. D., and MacGill, I. F. (2010). Coordinated Scheduling of Residential Distributed Energy Resources to Optimize Smart Home Energy Services. *IEEE Transactions on Smart Grid*, 1(2):134–143.

[Peik-Herfeh et al., 2013] Peik-Herfeh, M., Seifi, H., and Sheikh-El-Eslami, M. (2013). Decision making of a virtual power plant under uncertainties for bidding in a day-ahead market using point estimate method. *International Journal of Electrical Power & Energy Systems*, 44(1):88–98.

[Pelland et al., 2013] Pelland, S., Remund, J., Kleissl, J., Oozeki, T., and De Brabandere, K. (2013). Photovoltaic and Solar Forecasting : State of the Art. Technical report, International Energy Agency.

[Perea et al., 2008] Perea, E., Oyarzabal, J. M., and Rodríguez, R. (2008). Definition, evolution, applications and barriers for deployment of microgrids in the energy sector. *e & i Elektrotechnik und Informationstechnik*, 125(12):432–437.

[Piagi and Lasseter, 2006] Piagi, P. and Lasseter, R. (2006). Autonomous control of microgrids. In *2006 IEEE Power Engineering Society General Meeting*, page 8 pp.

[Pinyol and Sabater-Mir, 2013] Pinyol, I. and Sabater-Mir, J. (2013). Computational trust and reputation models for open multi-agent systems: a review. *Artificial Intelligence Review*, 40(1):1–25.

[Pirsiavash et al., 2011] Pirsiavash, H., Ramanan, D., and Fowlkes, C. C. (2011). Globally-optimal greedy algorithms for tracking a variable number of objects. In *2011 IEEE conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1201–1208.

[Pisica et al., 2009] Pisica, I., Bulac, C., and Eremia, M. (2009). Optimal Distributed Generation Location and Sizing Using Genetic Algorithms. In *2009 15th International Conference on Intelligent System Applications to Power Systems*, pages 1–6.

[Pitt et al., 2012] Pitt, J., Schaumeier, J., Busquets, D., and Macbeth, S. (2012). Self-Organising Common-Pool Resource Allocation and Canons of Distributive Justice. In *2012*

IEEE Sixth International Conference on Self-Adaptive and Self-Organizing Systems, pages 119–128.

[Pla et al., 2012a] Pla, A., Gay, P., Meléndez, J., and López, B. (2012a). Petri net-based process monitoring: a workflow management system for process modelling and monitoring. *Journal of Intelligent Manufacturing*, 25(3):539–554.

[Pla et al., 2012b] Pla, A., Lopez, B., and Murillo, J. (2012b). Multi criteria operators for multi-attribute auctions. *Modeling Decisions for Artificial Intelligence*, 7647:318–328.

[Pla et al., 2015] Pla, A., López, B., and Murillo, J. (2015). Multi-dimensional fairness for auction-based resource allocation. *Knowledge-Based Systems*, 73:134–148.

[Pla et al., 2014] Pla, A., López, B., Murillo, J., and Maudet, N. (2014). Multi-attribute auctions with different types of attributes: Enacting properties in multi-attribute auctions. *Expert Systems with Applications*, 41(10):4829–4843.

[Pla Planas, 2014] Pla Planas, A. (2014). *Multi-attribute auctions: application to workflow management systems*. PhD thesis, University of Girona.

[Poli et al., 2007] Poli, R., Kennedy, J., and Blackwell, T. (2007). Particle swarm optimization. In *Swarm intelligence*, pages 33–57. Springer US.

[Pudjianto et al., 2007] Pudjianto, D., Ramsay, C., and Strbac, G. (2007). Virtual power plant and system integration of distributed energy resources. *Renewable power generation, IET*, 1(1):10–16.

[Ramchurn and Mezzetti, 2009] Ramchurn, S. and Mezzetti, C. (2009). Trust-based mechanisms for robust and efficient task allocation in the presence of execution uncertainty. *Journal of Artificial Intelligence Research*, 35(1):119.

[Rescher, 1966] Rescher, N. (1966). *Distributive justice*. Bobbs-Merrill.

[Robu et al., 2012] Robu, V., Kota, R., Chalkiadakis, G., Rogers, A., and Jennings, N. R. (2012). Cooperative Virtual Power Plant Formation Using Scoring Rules. In *Proceedings of the 26th AAAI Conference on Artificial Intelligence*, pages 370–376.

[Rose et al., 2012] Rose, H., Rogers, A., and Gerding, E. H. (2012). A scoring rule-based mechanism for aggregate demand prediction in the smart grid. In *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems - Volume 2*, AAMAS '12, pages 661–668.

[Rothlauf, 2011] Rothlauf, F. (2011). *Design of Modern Heuristics*. Natural Computing Series. Springer Berlin Heidelberg.

[Rózycki and Weglarz, 2012] Rózycki, R. and Weglarz, J. (2012). Power-aware scheduling of preemptable jobs on identical parallel processors to meet deadlines. *European Journal of Operational Research*, 218(1):68–75.

[Ruiz et al., 2009] Ruiz, N., Cobelo, I. n., and Oyarzabal, J. (2009). A direct load control model for virtual power plant management. *IEEE Transactions on Power Systems*, 24(2):959–966.

[Russell et al., 2010] Russell, S., Norvig, P., Canny, J., Malik, J., and Edwards, D. (2010). *Artificial intelligence: a modern approach*. Pearson, 3rd edition.

[Saad et al., 2012] Saad, W., Han, Z., Poor, H., and Basar, T. (2012). Game-Theoretic Methods for the Smart Grid: An Overview of Microgrid Systems, Demand-Side Management, and Smart Grid Communications. *IEEE Signal Processing Magazine*, 29(5):86–105.

[Sandholm, 1996] Sandholm, T. (1996). Limitations of the Vickrey auction in computational multiagent systems. *Proceedings of the Second International Conference on Multiagent Systems (ICMAS-96)*, pages 299–306.

[Schienbein and Dagle, 2001] Schienbein, L. A. and Dagle, J. E. (2001). Electric Power Dstribution Systems. In *Distributed Generation: The Power Paradigm for the New Millennium*, pages 295–322. CRC press.

[Schillo et al., 2000] Schillo, M., Funk, P., and Rovatsos, M. (2000). Using trust for detecting deceitful agents in artificial societies. *Applied Artificial Intelligence*, 14(8):825–848.

[Schneider and Kirkpatrick, 2006] Schneider, J. J. and Kirkpatrick, S. (2006). *Stochastic optimization*. Springer.

[Shoham and Leyton-Brown, 2009] Shoham, Y. and Leyton-Brown, K. (2009). *Multiagent Systems*. Cambridge University Press.

[Simonis and Hadzic, 2011] Simonis, H. and Hadzic, T. (2011). *A Resource Cost Aware Cumulative*, pages 76–89. Recent Advances in Constraints. Springer Berlin Heidelberg, lecture notes edition.

[Soder, 2004] Soder, L. (2004). Simulation of wind speed forecast errors for operation planning of multiarea power systems. In *8th International Conference on Probabilistic Methods Applied to Power Systems*, pages 723–728.

[Stentz, 1994] Stentz, A. (1994). Optimal and efficient path planning for partially-known environments. In *Proceedings of the 1994 IEEE International Conference on Robotics and Automation*, pages 3310–3317.

[Torrent-Fontbona, 2012] Torrent-Fontbona, F. (2012). Decision support methods for global optimization. Master's thesis, University of Girona.

[Torrent-Fontbona et al., 2013] Torrent-Fontbona, F., Muñoz, V., and López, B. (2013). Solving large immobile locationâĂŞallocation by affinity propagation and simulated annealing. Application to select which sporting event to watch. *Expert Systems with Applications*, 40(11):4593–4599.

[US Environmental Protection Agency, 2012] US Environmental Protection Agency (2012). Chapter 2. Trends in Greenhouse Gas Emissions. In *US Greenhouse Inventory Report*, pages 33–81. US Environmental Protection Agency.

[Vale et al., 2010] Vale, Z. A., Morais, H., and Khodr, H. (2010). Intelligent multi-player smart grid management considering distributed energy resources and demand response. In *2010 IEEE Power and Energy Society General Meeting*, pages 1–7.

[Černý, 1985] Černý, V. (1985). Thermodynamical approach to the traveling salesman problem: An efficient simulation algorithm. *Journal of Optimization Theory and Applications*, 45(1):41–51.

[Veit et al., 2013] Veit, A., Xu, Y., Zheng, R., Chakraborty, N., and Sycara, K. (2013). Demand side energy management via multiagent coordination in consumer cooperatives. Technical Report CMU-RI-TR-13-27, Robotics Institute.

[Vinyals et al., 2012] Vinyals, M., Bistaffa, F., and Rogers, A. (2012). Stable coalition formation among energy consumers in the smart grid. In *Proceedings of the 3rd International Workshop on Agent Technologies for Energy Systems (ATES 2012)*, Valencia.

[Wang et al., 2014] Wang, R., Wang, P., Xiao, G., and Gong, S. (2014). Power demand and supply management in microgrids with uncertainties of renewable energies. *International Journal of Electrical Power & Energy Systems*, 63:260–269.

[Weiss, 1999] Weiss, G., editor (1999). *Multiagent Sytems*. The MIT Press.

[Wille-Haussmann et al., 2010] Wille-Haussmann, B., Erge, T., and Wittwer, C. (2010). Decentralised optimisation of cogeneration in virtual power plants. *Solar Energy*, 84(4):604–611.

[Working Group III, 2007] Working Group III (2007). Climate change 2007 - mitigation. Technical report, Intergovernmental Panel of Climate Change.

[Working Groups I, II and III, 2007] Working Groups I, II and III (2007). Working groups i, ii and iii to the fourth assessment. Technical report, Intergovernmental Panel of Climate Change.

[Yang, 2010] Yang, X. (2010). *Nature-inspired metaheuristic algorithms*. Luniver press.

[You et al., 2010] You, S., Træ holt, C., and Poulsen, B. (2010). *Developing virtual power plant for optimized distributed energy resources operation and integration*. PhD thesis, Technical University of Denmark.

[Yu et al., 2011] Yu, Y., Pan, M., Li, X., and Jiang, H. (2011). Tabu search heuristics for workflow resource allocation simulation optimization. *Concurrency and Computation: Practice and Experience*, 23(16):2020–2033.

[Zhang et al., 2013] Zhang, Z., Kusiak, A., and Song, Z. (2013). Scheduling electric power production at a wind farm. *European Journal of Operational Research*, 224(1):227–238.