Università degli Studi di Cagliari

DOTTORATO DI RICERCA

IN FISICA

Ciclo XXVII

TITOLO

A NOVEL COMPLEX SYSTEM APPROACH FOR THE DETERMINATION OF RENEWABLE ENERGY SOURCES IMPACT ON ELECTRICITY INFRASTRUCTURES

FIS/02

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Esame finale anno accademico 2013 – 2014

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Introduction

The increasing environmental awareness, associated with the increase in demand and price for fossil fuels, is leading to the implementation of novel energy models based on **renewable energy sources (RES)**. Until 2014, over 69.68 GW of PV and 250 GW of wind power generation is installed worldwide [49] and the amount of installed power is expected to rise in the near future [93]. The technological advances in this field have made possible the installation of RES generators of a great variety of scales, from private users to the great power company ones. For this reason, RES generation is already capillary distributed in the power network trough both big size generators (nowadays, the typical scale of large RES generators is about to 10 MW, but integrated plants can reach a size of hundred of MW) and small size ones, typically distributed over the entire system. This kind of energy production represents a totally new approach in energy generation, called **distributed generation** [94].

The implementation of such energy generation technologies has produced great benefits in terms of energy production and environmental impact. However, RES generation strongly depends on climatic conditions; this introduces into the system an high variability in terms of active and reactive power production, output frequency and voltage. Such variability determines a difficult integration of large-scale wind and solar photovoltaic (PV) energy generation into the existing infrastructures [32, 36, 53, 58, 95]. Due to this variability, major issues has been pointed out in term of energy security and access, inspiring changes in methods and paradigms associated to energy supply management in order to add flexibility to the system.

Until now, the management of electrical energy system has been done with deterministic approaches [8, 12, 38, 98], allowing his proper functioning by virtue of an accurate profile management of generation and of an high degree of accuracy in loads prediction. The high reliability of the Electric Energy Management System and its typical top-down control structure, associated with the presence of systems of centralized production, has been tackled by introducing an electricity market whose function is to define the energy price and the generation profiles in relation to supply and demand laws [97]. However, the fast development of renewable energy sources and in particular of non-programmable ones introduces in this system a non-deterministic variable that is changing both the electricity market behaviour and the electric energy system management, pointing out the need to change the methodologies used for their modeling.

The switch from fully programmable energy supply towards a time and space fluctuating one needs to change the technical and economic models on which those systems are based on [76]. In particular, the migration from strict deterministic based dispatching and planning rules towards a more flexible statistical description of the system is needed, in order to obtain a methodology able to describe the increasing intrinsic variability of the system. In order to describe and model power systems with an high RES generation, is important to point out that such systems are made by a great number of microscopical interacting elements who behave in a stochastic way. For this reason, these systems can not be easily described in a deterministic way, but must be described by a statistical representation of the system observables. In this thesis, a novel methodology based on a **statistical mechanics approach** is presented in order to describe on a statistical basis the effect of renewable energies on both electricity energy systems and electricity balancing markets. This has been done by perturbing the system on a microscopic scale, and creating a realistic set of unbalanced states that can be studied statistically in order to obtain the expected distribution of global system variables that measure the system stability. This approach wants to be the core finding of this thesis, and is presented in the following into two different papers. In the first one [80], the impact of RES generation on power grid voltage stability is studied. In the second one (citazione paper mercato) the impact of RES generation over the global network power balance has been quantified in terms of physical size and economic cost.

Clean energy production and CO_2 emission reduction are strictly connected with the concept of sustainable mobility [33]. About 15% of total CO_2 emissions comes from transportation, and a promising solution to this issue is given by electric vehicles (EV) technologies [6]. Integration between RES and EV mobility is a perfect way to ensure sustainable mobility. Moreover, Grid to Vehicle (G2V) and Vehicle to Grid (V2G) [87] concepts allows to use EV as distributed controllable loads or charging systems over the network. In relation to that, the EV charging infrastructure can be used to limit the fluctuations caused by RES providing at the same time a clean energy source to mobility, in a positive virtue feedback [52, 77]. In order to build an optimized EV charging infrastructure, a good planning methodology is needed, able to distribute in space the necessary amount of charging stations and charging plugs crucial for guaranteeing the charging needs of the expected EV fleet. In relation to this, in this thesis, two papers are proposed. In these two works, two topics are covered; the first one [35] studies the existing mobility infrastructure, by using a newly proposed methodology based on complex networks theory [23], whereas the second one [65] is based on an **Agent Based Modelling (ABM)** that allows to simulate the behaviour of an EV fleet into a medium size city, yielding the spatial and time distribution of the fleet charging needs.

In the following, an outline of the thesis is given. In part I, a brief overview of the used methods is given: complex networks theory [23], agent based modelling [75] and power flow method [46, 89, 90] are described. In part II, a novel methodology able to describe the effects of RES generation on power grids is introduced. After a brief description, two papers are presented; in the first one, a novel statistical based method is presented, able to understand the possible effects of distributed RES in terms of power grid voltage quality. In the second one, after a brief introduction about electricity markets, a similar methodology is used to forecast the amount of unexpected power produced by distributed RES. Moreover, a new ABM methodology is proposed for the simulation of an energy market session carried out for network balancing purposes, the electricity balancing market. In part III, EV mobility charging needs are studied by means of two research papers. In the first one [35], a complex networks approach for the evaluation of existing mobility infrastructure is presented. In this paper, an extension of the Louvain methodology [14] of community detection is proposed for the evaluation of the most critical and important sites into the commuting network. In the second one [65], an agent based model of the traffic flow is implemented in order to describe the charging needs of a medium sized city EV fleet. Using these results, a charging infrastructure planning procedure is proposed, together with an EV charging strategy.

Part I

Methods

Overview

This part is intended to describe the main methodologies used to study power grids and traffic infrastructures, such as complex networks theory [23], agent based modelling [75] and power flow method [46, 89, 90]. The first two ones are the main methods used for complex systems description, and has been used in the papers proposed in parts II and III in order to enhance the understanding of the studied systems. A brief overview of such methods, together with some important references is given in chapter 1.
Power flow method is one of the main methods used for the study and characterization of power grids operational parameters, and it is based on the numerical solution of a non-linear set of equations, called power flow equations. An introduction to such method is given in chapter 2

Chapter 1

Complex networks theory and agent based modeling

The complex networks theory is based on a mathematical formulation called graph theory. A very good introduction to Complex Networks science, together with the main definitions associated to graph theory are given in the book of Guido Caldarelli, *Scale-Free Networks* [23].

1.1 Graph theory definition

Graphs are described by a set of vertices (or nodes) and a set of connections between them, called edges (or links). The number of edges connected to each vertex is called degree, often addressed as k. Edges can have a direction or not. In the first case the graph is called oriented graph. Also, at each edge can be assigned a value, called weight, that represents somehow the intensity of interaction between the connected edges. If this happens, the graph is called weighted graph. For example, in the special case of power grids, one possible graph representation can be obtained by choosing as weight the power that flows between edges, and as direction of the links the direction of such flow.

A graph is often indicated as $G(n; m)$, where n is the number of vertices (called also order) and m is the number of edges (called also size). The maximum number of edges m_{max} is dependent from the number of vertices of the graph. In particular, for undirected graphs it is $m_{max} = \frac{n(n-1)}{2}$. This number can be easily obtained by noticing that the number of edges that each node can have is exactly $(n-1)$; taking into account this number for each node and dividing by two in order to avoid double counting, his computation is straightforward. In case of directed graphs, the division by two is not needed and the maximum number of links become $m_{max}^{dir} = n(n-1)$.

The topological characteristics of a graph $G(n; m)$ can be represented by means of a adjacency matrix $A(n; n)$ whose entries a_{ij} are 0 if vertices $i; j$ are not connected and 1 otherwise. The adjacency matrix is symmetric only in the case of undirected graph; in case of directed graph, this assumption is generally false. In case of weighted graphs each matrix entry a_{ij} is equal to the corresponding link weight, if link exists, and 0 otherwise.

Starting from the adjacency matrix, some graph characteristics can be computed. In particular, the degree k_i of each vertex i is calculated by equation 1.1 in case of undirected graphs, and by equations 1.2 and 1.3 for directed graphs, where a in-degree and a out-degree can be defined.

$$k_i = \sum_{j=1}^{n} a_{ij} \tag{1.1}$$

$$k_i^{in} = \sum_{j=1}^{n} a_{ij} \tag{1.2}$$

$$k_i^{out} = \sum_{j=1}^{n} a_{ji} \tag{1.3}$$

A path $\mathcal{P}_{ij}$ on a graph is an ordered set of links that allows to go from vertex i to vertex j. At each path is associated a length $l(\mathcal{P})$ defined in equation 1.4. Among all the possible paths that can connect vertices i and j, the minimum length ones are called shortest paths, and are often addressed as σ_{ij}. Notice that there can be more then one shortest paths for each couple of nodes.

Another important measure on graphs is the distance d_{ij} between nodes i and j; it is defined as the length of the shortest path between node i and j, or alternatively as shown in equation 1.5. The largest distance between two vertices in the graph is often called graph diameter.

$$l_{ij} = \sum_{m,k \in \mathcal{P}_{ij}} a_{mk} \tag{1.4}$$

$$d_{ij} = \min\{\sum_{m,k \in \mathcal{P}_{ij}} a_{mk}\} \tag{1.5}$$

The clustering coefficient C_i of vertex i is an important measure of the level of how much the graph is connected around vertex i. C_i is given by the average fraction of pairs of neighbours that are also neighbours of each other, formally:

$$C_i = \frac{1}{(ki)(ki-1)/2} \sum_{j,k} a_{ij} a_{ik} a_{jk}. \tag{1.6}$$

The average of clustering coefficient around all nodes of the graph is often taken as a measure of how much the vertices of the graph are connected among them.

1.2 Complex network theory

A lot of natural and artificial systems shows the possibility to be described by means of a graph. Such high interacting systems can be abstracted in a way that represents how their components are related among them, and these relations patterns can improve a lot our knowledge of them. By the time that this thesis has been written, a lot of work has been done in order to understand, for example, the interaction of proteins among some biological processes [91], the way in which epidemics spread around the world [50], and how the World Wide Web behaves [74]. By describing these systems components and the way in which they interact, is possible to understand a lot of behaviours that are really difficult to explain using standard methods. This methodology is called complex networks theory, and aims to provide a theoretical background to the study of such systems, by studying the properties of their graphs.
All these systems, in fact networks, show non-trivial topological features, that includes heavy tail in the degree distribution, high clustering coefficient, community and/or hierarchical structure that are not highlighted in past studied regular networks such as lattices and random graphs. Many of these features can be obtained by the study of the topological properties of the networks, such as their community and hierarchical structure and resilience to attacks. Another important information, crucial in this thesis, is the concept of topological centrality, that aims to characterize the network nodes in order to sort their importance in relation to precise phenomena like the identification of the most influential people in a social network or key infrastructure nodes in the Internet or power grids.

NetworkX

Computations related to networks and graphs has been performed using the software NetworkX [47]. NetworkX is a Python library for studying graphs and networks, a collection of libraries useful to calculate and represent a vast number of the possible calculations that can be performed on a graph. In particular, it has been used in this thesis for the calculation of betweenness centrality and RageRank over the studied networks. The calculation methods implemented by it are, for betweenness centrality, the one proposed by Brandes [18] and for PageRank the one described in [55].

1.3 Community detection

Most of the systems of interest, once represented as networks, are found to divide naturally into communities, subsets of nodes that share the same characteristics. Detection and characterization of community structures are one of the most important fields of study in network sciences. Understanding if and how a system can be divided in parts, called clusters or communities, can be a crucial point in improving his level of description [42]. One of the most effective approaches is the modularity optimization over the possible divisions of a network. The modularity is a quality function, that measures the density of links inside communities as compared to links between communities. This quantity, introduced by Newman [67] is defined as shown in equation 1.7, where A_{ij} is the adjacency matrix, s_i is the strength of node i, $m = \frac{1}{2}\sum_{ij} A_{ij}$ and $\delta(u, v)$ is a function that values 1 if $u = v$ and 0 otherwise.

$$Q = \frac{1}{2m}\sum_{i,j}\left[A_{ij} - \frac{s_i s_j}{2m}\right]\delta(c_i, c_j) \tag{1.7}$$

Computation of modularity is not an easy task, and several methods have been proposed to speed-up the optimization process. The most important and used one has been proposed by Blondel et al., and is often addressed as Louvain method [14]; in this paper, a methodology that shows the possibility to find high modularity partitions of large networks in short time and that unfolds a complete hierarchical community structure for the network is proposed, thereby giving access to different resolutions of community detection. The proposed method aims to optimize the modularity by an hierarchical iterative technique that aims to agglomerate communities at each iteration, speeding up the process. In chapter 5, a paper that propose an extension of the Louvain method able to identify the most important nodes of each community, called core nodes is attached.

1.4 Centrality measures

In complex networks, the topological position of nodes can affect their behaviour and influence among the system. As an example, in social networks, high degree nodes (the so-called hubs) have a primary role in information spreading and opinion formation. The same phenomena can be observed in epidemics where high flow places, such as airports and big cities, improve the infection spreading. The identification of these nodes by simple topological methodologies is an important branch of complex networks, that has led by far to important scientific results [23]. In this work, two different centrality measures have been used: the betweenness centrality, and the pagerank.

Betweenness centrality Betweenness centrality [44] is a centrality measure based on topological characteristics of the network, and assumes that edges that share the most shortest paths are somewhat more important in the network. This measure has been developed in social sciences, and is based on the assumption that information spreads faster when it passes among high betweenness nodes. Formally, the betweenness centrality of each node is defined as the normalized number of shortest paths that passes through it, and can be calculated by equation 1.8. Given his simple definition, betweenness centrality can be calculated for directed, undirected, weighted and unweighted graphs.

$$BC^i = \sum_{s,t \in \{V - \{i\}\}} \frac{\sigma_{st}^i}{\sum_{s,t} \sigma_{st}} \tag{1.8}$$

PageRank This centrality measure has been proposed in 1998 by Google search engine founders Brin and Page [70], together with Motswami and Winograd. This method introduces a new measure of importance for web pages, and has been for years the main algorithm used by Google to sort the web pages. PageRank formulation has been made in relation to the WWW hyperlink structure. Every hyperlink received by a web page increases her PageRank value by a quantity proportional to the PageRank of the sending one. The importance of each node is related to the probability that a user, randomly clicking on hyperlinks, will arrive at a particular page. A first definition of PageRank is given by the iteration of equation 1.9. Despite the simple definition, the calculation of PageRank is not straightforward. The presence of dangling nodes (i.e. nodes with only in-edges) makes calculation difficult without introducing a parameter that takes into account the probability of random jumping into the network; this parameter is called damping factor. A complete review of the PageRank calculation methods can be found in [55]. The PageRank algorithm can be easily extended to different kind of systems. In this thesis, in particular, it has been used for power networks nodes in the paper reported in chapter 3.

$$r_i = \sum_{j \to i} \frac{r_j}{k_j} \tag{1.9}$$

1.5 Agent based modelling

Agent-based modelling has seen a number of applications in the last few years [15]. It is a powerful simulation modelling technique often applied to real-world business problems like organizational simulation, diffusion simulation, market simulation and flow simulation.

A perfect (in my opinion) description of ABM has been proposed by Bonabeau et al. in [15]: "In agent-based modelling (ABM), a system is modelled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. Agents may execute various behaviours appropriate for the system they represent, for example, producing, consuming, or selling. Repetitive competitive interactions between agents are a feature of agent-based modelling, which relies on the power of computers to explore dynamics out of the reach of pure mathematical methods. At the simplest level, an agent-based model consists of a system of agents and the relationships between them. Even a simple agent-based model can exhibit complex behaviour patterns and provide valuable information about the dynamics of the real-world system that it emulates. In addition, agents may be capable of evolving, allowing unanticipated behaviours to emerge. Sophisticated ABM sometimes incorporates neural networks, evolutionary algorithms, or other learning techniques to allow realistic learning and adaptation."

Electricity markets have been widely studied during time due to their crucial role in terms of power grid overall stability. The complexity of electricity markets calls for rich and flexible modelling techniques in order to describe market dynamics, useful for designing appropriate regulatory frameworks. A growing number of researchers developed agent-based models for simulating electricity markets, aiming to describe the various electricity market phases, crucial for the definition of electrical energy price. The diversity of the proposed approaches shows an increasing interest in this field of study. A brief review of this methods is given in [97]. In this thesis, a new agent based methodology able to model the electricity balancing market is presented. The paper [64], submitted on Scientific Reports journal, can be found in chapter 4.

Chapter 2

Power flow method

The power-flow method, also called load-flow calculation, is one of the fundamental techniques used for power system simulation and management. This method, presented at first by Ward and Hale [96], aims to describe an electrical system in terms of bus voltages and branches power flows, in order to know the operational steady state of such systems.
The method is based on the numerical solution of a non-linear system of equations, called power-flow equations.
On the next sections, power grid modelling, mathematical formulation of the problem and his numerical solution will be described.

2.1 Network modelling

Power grids goal is to transmit and distribute electrical energy between producers, like power plants, and users, like industries or private houses.
Power grids can be described as interconnected networks, each of them working at a different voltage. Each network can be modelled by a set of nodes, often addressed as buses in electrical engineering, that represents electrical substations, and by a set of link, also called branches, that represents electrical connections between nodes.
In this model, active (P_i) and reactive (Q_i) power production and consumption is performed on nodes i, characterized by a voltage V_i, a phase φ_i and a frequency f whereas power flows through edges between nodes i and j, each of them characterized by an impedance of Z_{ij}. In order to understand the effect of power production or consumption changes into this system, is possible to perform a calculation called power flow method, (also called load flow method) [89, 90].

Power flow into and out of each of the buses can be calculated as the sum of power flows of all of the lines connected to the referred bus. Aim of the load flow method is to find the set of complex voltages $\mathbf{V}_i = V_i \cdot e^{i\varphi_i}$, described by magnitude V_i and angle φ_i, which, together with the network impedances, produces the load flows at the system terminals. At each bus i there is a production (or consumption) of complex power $S_i = P_i + iQ_i$. If such node is connected to the system, the complex power flow into the network at node i can be also written as:

$$S_i = \mathbf{V}_i \mathbf{I}_i^*, \tag{2.1}$$

where $\mathbf{I}_i = I_i e^{i\phi}$ is the complex current.
The power grid can be also viewed as a graph, and his topology can be described by the so-called incidence matrix A. This matrix, which has N columns and N_b rows, represents in matrix form the connections between the buses. Such matrix is defined, for directed graphs, as $A = a_{ij}$, where $a_{ij} = \pm$ if buses i and j are connected , 0 if not. The sign of the entry is given by the link direction that, in this case, can be decided *a priori*. If the network itself is

linear, interconnections between buses and between buses and ground can be described by the bus admittance matrix $\mathbf{Y} = \frac{1}{\mathbf{Z}}$, inverse of the bus impedance matrix $\mathbf{Z}$. $\mathbf{Y}$ is simple to obtain starting from the line admittance matrix Y_L, that can be obtained as follows. Considering a network with a number N_b of buses and another number N_l of lines, each of them characterized by a (generally complex) impedance Z, the line admittance matrix can be obtained by placing the admittance of each line on the main diagonal of an $N_L \times N_L$ matrix:

$$I = \begin{bmatrix} \frac{1}{Z_1} & 0 & 0 & 0 & \dots & 0 \\ 0 & \frac{1}{Z_2} & 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{Z_{N_L}} \end{bmatrix} \tag{2.2}$$

Knowing the lines admittance matrix Y_L and the incidence matrix A, the bus admittance matrix Y can easily be computed by eq. 2.3.

$$Y = A \cdot Y_L \cdot A \tag{2.3}$$

2.2 Power flow equations

Starting from the generalized Ohm's law (eq. 2.4, in subscript form in 2.5) is possible, in principle, to obtain voltages and currents of the systems, and to calculate powers from the power flow equations 2.6, one for each bus.

$$\mathbf{I} = \mathbf{YV} \tag{2.4}$$

$$I_k = \sum_{j=1}^{N} Y_{jk} V_j \tag{2.5}$$

$$S_k = V_k \sum_{j=1}^{N} Y_{jk}^* V_j^* \tag{2.6}$$

In order to do so, is necessary to limit the number of unknowns, fixing the value of some variables. Each of the complex equations reported in 2.6 carries 6 variables, 2 for complex voltage, current and power. However, these three quantities are related by eq. 2.1, so that any two of these can be specified by the other four, and the network itself provides two more constraints. The other two constraints for each equation are provided using some assumptions based on the physical properties of the buses. In relation to this, three types of buses are defined:

- Load buses (PQ): in these buses, consumed (or produced) active and reactive power P and Q can be easily obtained. For this reason, is a common practice to set these values as constraints for system solution. The remaining unknowns for this buses will be voltage magnitude V and angle φ.

- Generator buses (PV): In these buses is installed a major generator, that is supposed to work as an ideal voltage generator. For this reason, active power P and voltage V are considered as constraints, leaving as unknowns Q and φ.

- One slack bus (ref): this bus is often associated with the bus with the biggest generator, and for this bus voltage magnitude V and phase φ are taken as constraints, leaving active P and reactive Q power as unknowns.

The obtained non-linear system must be solved numerically, and the main methods used for its solution are described in [89, 90]. In particular, the calculations made for this thesis has been performed using the program MATPOWER [100]. MATPOWER is a MATLAB package used for solving power flow and optimal power flow problems with various solution algorithms. All the calculations performed in this thesis have been made using the Newton-Raphson method, described in [89].

Part II

Estimation of renewable energy sources effects on power grids

Overview

During last years, the amount of power produced by renewable energy sources has shown a really interesting increase in terms of installed power and economic investments. The worldwide availability of these energy sources and their relative pollution-free energy production are seen as fundamental for CO_2 emissions reduction.
Recently, technological advances have made possible to install RES generators at really different scales, from the private user one, where KW size PV generators can be installed on single households, to the big energy company one, where generators of the size of hundreds of MW can be installed. This difference has led to a total new approach in energy production, called distributed generation. By using this approach, energy generation is not anymore accounted exclusively to great energy companies, but even to small and medium size users; this allows to move the cost of the implementation of new energy generating systems toward a more private issue, improving at the same time the energetic independence of some geographical zones. However, this distributed, uncontrolled generation over the entire power system is difficult to control. Actual power systems are built for strictly hierarchical and programmed power production, and a complete change in infrastructure planning, both from technical and theoretical point of view, is needed in order to manage the increasing amount of RES energy production.

The presence of distributed RES generation introduces an high stochastic variability over the system, impossible to describe using the classic deterministic methods. For these reasons, a totally new method of description of such systems, inspired on statistical mechanics methods, is proposed; in such method, RES generators are represented by stochastic fluctuating power generation facilities over the entire grid. Due to this intrinsic variability of a large amount of power supply over the network, the system can not be found anymore in a single programmable state, but in a state that is susceptible of the random processes that can occur over the network. For this reason, the system must be studied in a statistical way. This has been done by using a numerical procedure able to produce an high number of possible states. in which the system can effectively be because of uncertainties in RES power production. The effects of such random fluctuations can now be described by means of a statistical representation of global system variables over the entire set.

In the next two papers, such new methodology is presented. In the first paper, **Distributed generation and Resilience in Power Grids**, found in chapter 3, the possible stability impact of increasing RES generation on Polish power grid is studied. As important result, has been found that a centrality oriented distribution of RES generators can improve or decrease stability. In chapter 4, after a brief introduction to electricity markets, the paper **Green power grids: how energy from renewable sources affects networks and markets** [64] is proposed. In this paper, submitted on scientific reports, the previously described statistical approach has been used to sample the expected distribution of deviations from network power balance due to the intrinsic variability of RES generation. Moreover, this information has been used for the development of a new agent based methodology able to forecast the economic cost associated to these fluctuations. This paper aims to propose a tool for the simulation of the electricity balancing market with the goal of developing an integrated approach to evaluate and analyse the

effects of RES on the power system. In order to be able to assess the economic issues associated with the electricity balancing market is necessary to define the size of the market during time. After this step, once the effective power balancing needs are known, the entire market session can be simulated. The first part of the work aim to determine (based on the output profile from the previous day-ahead market session) the dimension of balancing services required by the BM. To such purpose, a statistical analysis tool that allows to establish a georeferenced distribution of necessary balancing services has been developed. Basic assumption was to consider only the imbalances and not events such as failures or outages of lines, transformers and production units. Such imbalances has been obtained by the estimation of RES power generation uncertainties for each geographical area in which the electricity market is divided. Using such estimations, the geographical distribution and the time evolution of the size of the balancing market have been determined and given in statistical terms. Such information are a prerequisite in order to define market strategies and to make a comparative evaluation of different market models. Once information about the market size has been obtained, has been possible to simulate the real balancing market phase by means of an Agent Based Modeling With this method, every market operator has been described by an agent that learns to place a bid on the market, given the characteristics of the network and a previous learning phase.
ABM is a method widely used for the simulation of complex competitive market phases, and is based on the assumption that global systemic observables, like market size and price, depends in great place from the interaction between bidders. By using this methodology, has been possible to obtain the total cost related to the unbalancing effects caused by RES generation over the network, and the price at which the energy used for balancing purposes has been sold.

Chapter 3

Distributed Generation and Resilience in Power Grids

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Published on Lecture Notes in Computer Science, volume 7722, DOI 10.1007/978-3-642-41485-57

3.1 Abstract

The upcoming growth in renewable energy sources (RES) will introduce an high number of stochastic fluctuations on power grids. In order to find a way to describe and estimate the effects of such fluctuations, we study the effects of the allocation of distributed generation on the resilience of power grids. We find that an unconstrained allocation and growth of the distributed generation can drive a power grid beyond its design parameters. In order to overcome such a problem, we propose a topological algorithm derived from the field of Complex Networks to allocate distributed generation sources in an existing power grid.

3.2 Introduction

Distributed Generation from renewable sources is having a deep impact on our power grids. The difficult task of integrating of the stochastic and often volatile renewable sources into a the grid designed with a power-on-demand paradigm could perhaps solved leveraging on distributed storage [11]; nevertheless, massive and economic power storage is not yet readily available. In the meanwhile, power grids are nowadays required to be robust and smart, i.e. systems able to maintain, under normal or perturbed conditions, the frequency and amplitude supply voltage variations into a defined range and to provide fast restoration after faults. Therefore, many studies have concentrated on the dynamic behaviour of Smart Grids to understand how to ensure stability and avoid loss of synchronization during typical events like the interconnection of distributed generation. The large number of elements present into real grids call for simplifications like the mapping among the classic swing equations [88] and Kuramoto models [39–41] that has allowed to study numerically or analytically the synchronization and the transient stability of a power network.

Even simple models [37] akin to the DC power flow model [98] show that the network topology can dynamically induce complex blackout size probability distributions (power-law distributed), both when the system is operated near its limits [24] or when the system is subject to erratic disturbances [79]. New realistic metrics to assess the robustness of the electric power grid with respect to the cascading failures [99] are therefore needed.

Smart grids are going to insist on pre-existing networks designed for different purposes and tailored on different paradigms and new kind of failures are possible: therefore a careful transition is needed. One possible approach could be the use of advanced metering infrastructure (AMI) not only for implementing providers and customers services, but also to detect and forecast failures; nevertheless an ill-designed network will never be efficient.

Our approach will not concentrate on the instabilities but will focus instead on the condition under which, in presence of distributed generation, the system can either be operated controlled back within its design parameters, i.e. it is *resilient*. It is akin in spirit to the approach of [27], that by applying DC power flow analysis to a system with a stochastic distribution of demands, aims to understand and prevent failures by identifying the most relevant load configurations on the feasibility boundary between the normal and problematic regions of grid operation.

To model power grids, we will use the more computational intensive AC power flow algorithms as, although DC flows are on average wrong by a few percent [90], error outliers could distort our analysis.

To model distributed renewable sources, we will introduce a skewed probability distribution of load demands representing a crude model of reality that ignores effects like the correlations between different consumers or distributed producers (due for examples to weather conditions).

3.3 Methods

3.3.1 AC Power Flow

The AC power flow is described by a system of non-linear equations that allow to obtain complete voltage angle and magnitude information for each bus in a power system for specified loads [46]. A bus of the system is either classified as Load Bus if there are no generators connected or as a Generator Bus if one or more generators are connected. It is assumed that the real power PD and the reactive power QD at each Load Bus are given while for Generator Buses the real generated power PG and the voltage magnitude $|V|$ are given. A particular Generator Bus, called the Slack Bus, is assumed as a reference and its voltage magnitude $|V|$ and voltage phase Θ are fixed. The branches of the electrical system are described by the bus admittance matrix Y with complex elements Y_{ij}s.

The power balance equations can be written for real and reactive power for each bus. The real power balance equation is:

$$0 = -P_i + \sum_{k=1}^{N} |V_i|\,|V_k|\,(G_{ik}\cos\theta_{ik} + B_{ik}\sin\theta_{ik})$$

where N is the number of buses, P_i is the net real power injected at the i^{th} bus , G_{ik} is the real part and B_{ik} is the imaginary part of the element Y_{ij} and θ_{ik} is the difference in voltage angle between the i^{th} and k^{th} buses. The reactive power balance equation is:

$$0 = -Q_i + \sum_{k=1}^{N} |V_i| |V_k| (G_{ik} \sin\theta_{ik} - B_{ik} \cos\theta_{ik})$$

where $Q_i$is the net reactive power injected at the i^{th} bus .

Real and reactive power flow on each branch as well as generator reactive power output can be analytically determined but due to the non-linear character of the system numerical methods are employed to obtain a solution. To solve such equations, we employ Pylon [2], a port of MATPOWER [100] to the Python programming language.

A requirement for the stability of the load and generation requirements is the condition that all branches and buses operate within their physical feasibility parameters; going beyond such parameters can trigger cascades of failures eventually leading to black outs [71].

In the present paper a topological investigation on the power grid has been developed in order to evaluate the effects of distributed generation on the voltage and power quality. Hence a steady state analysis has been carried out and the transient phenomena connected to the power flow control has been neglected. Under this hypothesis the frequency variation connected to power flow control has been considered stabilized and the system has been considered characterized by a constant steady state supply voltage frequency. Therefore, if all the nodes are near their nominal voltage it is much easier to control the system and to avoid reaching unfeasible levels of power flow. Consequently, to measure the effects of power quality of a power grid under distributed generation we measure the fraction F of load buses whose tension goes beyond $\pm 5\%$ of its nominal voltage. Notice that real networks are often operated with some of the buses beyond such parameters so that (especially for large networks) it is expected to be $F \neq 0$. The maximum of the resilience for a power grid (intended as the capability of restoring full feasible flows) is therefore expected for $F = 0$.

3.3.2 Distributed Generation and Skew-normal distribution

We will consider distributed generation due to erratic renewable sources like sun and wind; therefore, we will model the effects of "green generators" on a power grid as a stochastic variation the power requested by load buses. Load buses with a green generator will henceforth called green buses. We will consider the location of green buses to be random; the fraction p of green buses will characterize the penetration of the distributed generation in a grid.

If the power dispatched by distribution generation is high enough, loads can eventually become negative: this effect can be related to the efficiency of green generators. We model such an effect by considering the load on green buses described by the skew-normal distribution [10], a pseudo-normal distribution with a non-zero skewness:

$$f(x, \alpha) = 2\phi(x)\, \Phi(\alpha x)$$

where α is a real parameter and

$$\phi(x) = \exp\left(-x^2/2\right)/\sqrt{2\pi} \qquad\qquad \Phi(\alpha x) = \int_{-\infty}^{\alpha x} \phi(t)\, dt$$

. The parameter α will characterize the level of the distributed generation: to positive α correspond loads positive on average, while for negative α green nodes will tend to dispatch power.

Our model grids will therefore consist of three kind of buses: N_G generators (fixed voltage), N_l pure loads (fixed power consumption) and N_g green buses (stochastic power consumption) with $N_G + N_l + N_g = N$ the total number of buses and $N_g + N_l = N_L$ the number of load nodes. The fraction $p = N_g/N_L$ measures the penetration of renewable sources in the grid.

3.3.3 Complex Networks and Page Rank

The topology of a power grid can be represented as a directed graph $G = (V, E)$, where to the i-th bus corresponds the nodes n_i of the set V and to the k-th branch from the i-th to the j-th bus corresponds the edge $e_k = (i, j)$ of the set E. In Power System engineering, it is custom to associate to the graph G representing a power networks its *incidence* matrix B whose elements are

$$B_{ik} = \begin{cases} 1 & if\, e_k = (i, \_) \in E \\ -1 & if\, e_k = (\_, i) \in E \\ 0 & otherwise \end{cases}$$

. An alternative representation of the graph much more used in other scientific fields is its *adjacency* matrix A whose element are

$$A_{ij} = \begin{cases} 1 & if\ (i, j) \in E \\ 0 & otherwise \end{cases}$$

.

While Graph Theory has an old tradition since Euler's venerable problem on Koenigsberg bridges [13], Complex Networks is the new field investigating the emergent properties of large graphs. An important characteristic of the nodes of a complex network is their centrality, i.e. their relative importance respect to the other nodes of the graph [23]. An important centrality measure is Page Rank, the algorithm introduced Brin and Page [19] to rank web pages that is at the hearth of the Google search engine. The Page Rank r_i of the i-th node is the solution of the linear system

$$r_i = \frac{1-\rho}{N} + \rho \sum \frac{A_{ij} r_j}{d_j^o}$$

where N is the number of buses (nodes), $d_i^o = \sum_i A_{ij}$ is the number of outgoing links (out-degree) and $\rho = 0.85$ is the Page Rank damping factor. In studying power grids, we will employ Page Rank as it is strictly related to several invariants occurring in the study of random walks and electrical networks [28].

3.4 Results

3.4.1 Effects of distributed generation

We have investigated the effects of our null model of distributed generation on the 2383 bus power grid of Poland, 1999. Starting from the unperturbed network, we have found an initial fraction $F_0 \cong 1.6\%$ of load buses beyond their nominal tension. We have therefore varied the penetration p at fixed distributed generation level α's; results are shown in Fig. 3.1.

We find that the behaviour of the fraction F of buses operating near their nominal tension does not follow a monotonic behaviour. Initially (low values of p), the penetration of distributed generation enhances resiliency (i.e. decreases F). At higher values of p, F grows and resilience worsens. Such an effect is particularly severe if green nodes introduce a surplus ($\alpha < 0$) of power respect to the normal ($p = 0$) operating load requests. On the other hand, keeping the levels of renewable energy production below ($\alpha > 0$) the normal load request delays the point beyond which the penetration of distributed generation worsens the resiliency.

Notice that when distributed generation is ancillary ($\alpha > 0$) and not predominant in the power supplied of the network, full penetration ($p = 1$) of renewable sources lead to more stable state than the initial ($p = 0$) one.

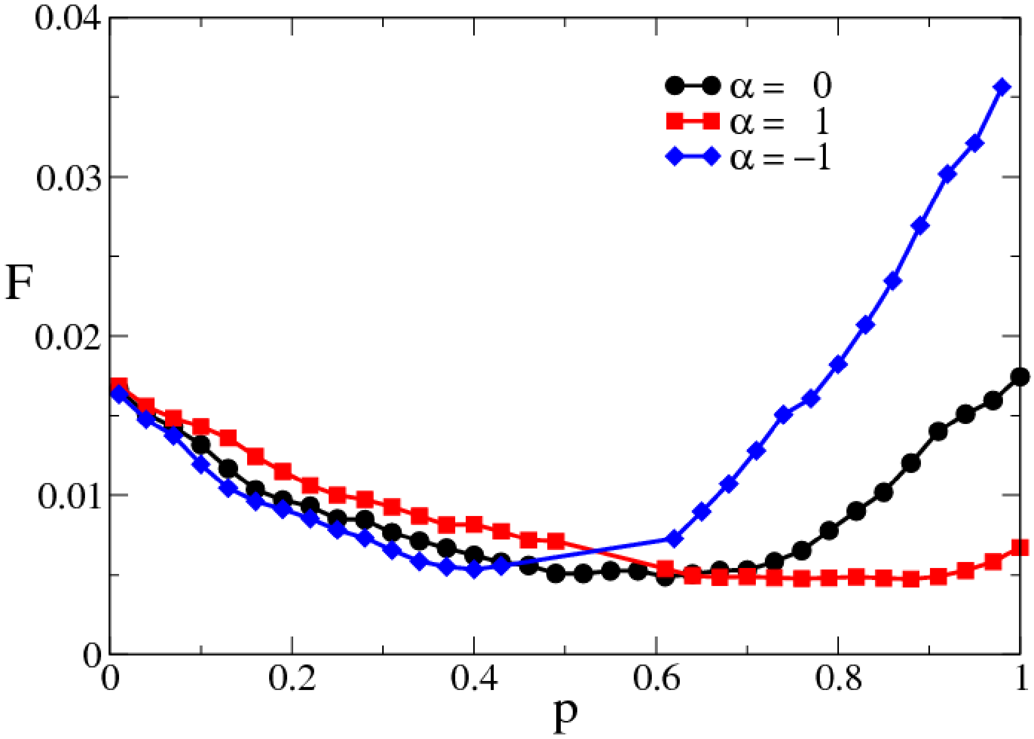

Figure 3.1: Effects of the penetration p of distributed generation on the resilience of the Polish power grid at different values α of the green generators. Notice that for $\alpha = 0$ renewable sources satisfy on average the load requested by the network, while for $\alpha < 0$ there is a surplus of renewable energy. Lower values of the fraction F of buses operating near their nominal tension correspond to a higher resiliency. Notice that the penetration of distributed generation initially enhances resiliency. At higher values of p, resilience worsens; in particular, it is severely impaired if distributed generation produces on average more energy than the normal load requests ($\alpha = -1$). It is therefore advisable to keep levels of renewable energy production below ($\alpha = 1$) the normal load request.

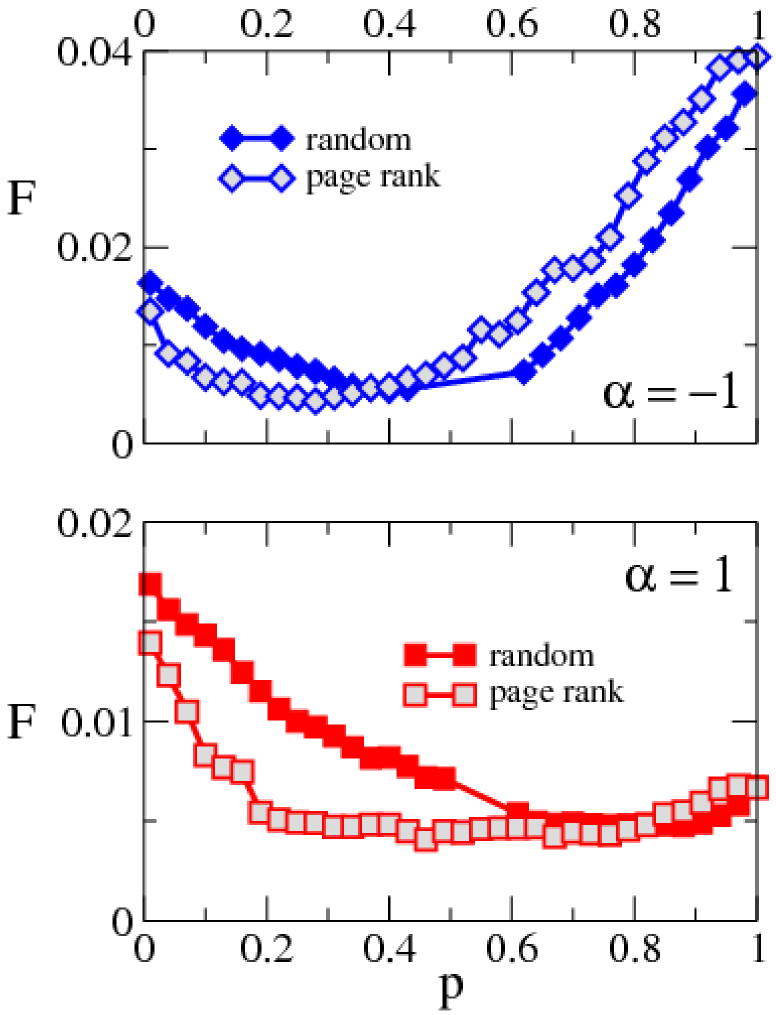

Figure 3.2: Comparison between random placement (filled symbols) and page-rank placement (empty symbols) of green nodes in the Polish grid, both for surplus production of renewable energy (upper panel, $\alpha = -1$) and for levels of renewable energy production below the normal load request (lower panel, $\alpha = 1$). The page-rank placement of renewable sources allows to attain lower values of the fraction F of buses operating near their nominal tension (and hence a higher resiliency) at lower values of the penetration p. The ideal situation is for levels of renewable energy production below the normal load request, where a plateau to low values of F is quickly attained.

3.4.2 Targeted distributed generation

Beside their natural application to web crawling, the Page Rank algorithm can be applied to find local partitions of a network that optimize conductance [9]. We therefore investigate what happens in a power network if distributed generation is introduced with a policy that accounts for the pagerank of load nodes. In other words, for a level of penetration p, we choose the first $n_g = pN_L$ load nodes in decreasing pagerank order to become green nodes. The effects of such a choice are shown compared to the random penetration policy in Fig. 3.2.

We find that, for low penetration levels, the pagerank policy reduces the number of nodes operating beyond their nominal tension both for positive and for negative α's. Again, the excess of power production ($\alpha < 0$) reduces the resilience of the network.

Preliminary results show that Page Rank is the best behaved among centralities in enhancing power grid resilience; such study will be the subject of a future publication.

3.5 Discussion

We have introduced a model base on the AC power flow equation that allows to account for the presence of erratic renewable sources distributed on a power grid and for their efficiency. By defining the resilience of the grid as a quantity related to the possibility of controlling the power flow via voltage adjustments (hence returning within the operating bounds of its components), we have studied the penetration of distributed generation on a realistic power grid.

We have found that while the introduction of few "green" generators in general enhances the resilience of the network by decreasing the number of nodes operating beyond their nominal voltage, a further increase of renewable sources could decrease the power quality of the grid. Anyhow, if distributed generation is ancillary and not predominant in the power supplied of the network, the grid at full penetration ($p = 1$) of renewable sources is in a more stable state than the starting grid ($p = 1$).

Our finding that a surplus of production from renewable sources is also a source of additional instabilities is an effect that is perhaps to be expected in general for networks that have been designed to dispatch power from their generators to their loads and not to locally produce energy. While we have found this possible increase in instability with the penetration in an isolated grid, what happens when more grids are linked together is an open subject. Power grids are typical complex infrastructural systems; therefore they can exhibit emergent characteristics when they interact with each other, modifying the risk of failure in the individual systems [25]. As an example, the increase in infrastructural interdependencies could either mitigate [20] or increase [21, 56] the risk of a system failure.

Finally, we find that a policy of choosing the sites where to introduce renewable sources according to Page Rank allows to increase the resilience with a minimal amount of green buses.

Chapter 4

Green power grids: how energy from renewable sources affects network and markets

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Submitted on Scientific reports

4.1 Abstract

The increasing attention to environmental issues is forcing the implementation of novel energy models based on renewable sources, fundamentally changing the configuration of energy management and introducing new criticalities that are only partly understood. In particular, renewable energies introduce fluctuations causing an increased request of *conventional* energy sources oriented to balance energy requests on short notices. In order to develop an effective usage of low-carbon sources, such fluctuations must be understood and tamed. In this paper we present a microscopic model for the description and the forecast of short time fluctuations related to renewable sources and to their effects on the electricity market. To account for the inter-dependencies among the energy market and the physical power dispatch network, we use a statistical mechanics approach to sample stochastic perturbations on the power system and an agent based approach for the prediction of the market players' behaviour. Our model is a data-driven; it builds on one day ahead real market transactions to train agents' behaviour and allows to infer the market share of different energy sources. We benchmark our approach on the Italian market finding a good accordance with real data.

Introduction

The increasing demand for energy, the improved sensitivity to environmental issues, and the need for a secure supply are all contributing to a new vision of energy resource management [8, 34]. This new awareness is contributing to the development of a novel approach in energy planning, based on the rational use of local resources [86]. In this contest, distributed energy management is considered one of the viable solutions to integrate local renewable sources and to promote rational use of energy [63]. Moreover, the recent emphasis on sustainability, also related to the climate change policies, asks for a fast development in the use of renewable resources in local energy systems. This determines a fast growth of distributed generation and co-generation at which does not correspond an equally fast upgrade of the electricity infrastructure. This inhomogeneous evolution of the different components of power systems is the consequence of the actual structure of the electricity network which, being characterised by strict dispatching and planning rules, hardly fits with the increasing demand of flexibility connected to the distributed generation [16].

Such scenario induces unavoidable effects on the electricity market which reveals an unexpected sensitivity to the enhancement of distributed generation based on Renewable Energy Sources (RES) [53, 58, 82]. In fact, due to their non-programmable characteristic and the widespread geographic distribution, the development of RES-based distributed generation is undermining the technical and economic models on which the electricity system are actually based on; in particular, they highlight problems in the classical management model of energy-flows. In fact, the classical hierarchical and deterministic methodologies used to (i) manage the power system, (ii) forecast the energy demands and production, (iii) balance the network, all show drawbacks which finally affect the electricity market price. An instructive example of such problems comes from the analysis of the effects of the subsidies policy granted by governments to promote the exploitation of RES and for implementing the climate change policies: in fact, such policies have played a major role in the magnification of critical market anomalies, like the negative and/or null price of electricity registered in the Germany and Italy. Therefore, to implement the new smart grid paradigms, it is necessary to change and renew the classical approaches for modeling and managing the electricity market. However, even if the production of energy from renewable sources introduces perturbations in the power system and in the electricity market [54], it constitutes a crucial value in emissions trading. Generators based on renewable sources have a great intrinsic forecast uncertainty, highly variable both in time and space. Hence, the increasing amount of REnewable-like (RE) generators induce a stochastic variability in the system; such variability could induce security issues like difficulties in voltage controlling [80] or unforeseen blackouts [72] and eventually causes a relevant error in the power flow forecasting that can give rise to extreme results on energy market, like very high prices or null/negative price sell. To understand such effects, we must describe not only the dynamics of the fluctuations in energy production/demand but also the functioning of electricity markets.

Actual electricity markets aim to reach efficient equilibrium prices at which both producers and distributors could sell electricity profitably. Typically, the electricity markets are hierarchically structured according to time-based criteria strictly connected to the power system's constrains. In particular, the Short Term Market (ST) is usually structured into One Day Ahead Market (ODA), Intraday Market (ID) and Ancillary Service, Reserve and Balancing Market (ASR) [51]. Almost all the simulation approaches for the electricity market are either based on stochastic [60, 69] or on game theoretical [85] studies based on past data series, while few models focus on market equilibrium as obtained from production and transmission constraints [45]. To the best of our knowledge, nobody yet addressed the effects of distributed generation not only in power balancing but also in balancing market prices taking into account the network constraints.

In this paper we present a simplified model that, taking into account the power system constraints, allows both the forecasting of the balancing market and to single out the contribution of various actors into the formation of the price. Our model is data-driven, since information on the day-ahead market transactions is used to tune the agent-based simulation of the market behaviour. In our model we take as static constraints the grid topology, the type of production per node and the transmission rules. Our dynamical constraints are the maximum and minimum generation from power stations and their ramp variation (i.e. how fast can be changed the amount of generated energy); such constraints influence factors like the short term availability of an energy source. The input of our model are typical consumer requests and the forecasted geo-referred wind and solar energy generation. We model the balancing market by introducing agents aiming to maximise their profits; such agents mimic the market operators of conventional generators [22]. Agents' behaviour is modelled by a probability distribution for the possible sell/buy actions; such distribution is obtained by a training process on synthetic data. In each simulation, agents place bids on the balancing market based on the energy requests fixed by the ODA market. In order to ensure the system security, the Transmission System Operators (TSO) selects the bids to guarantee energy balancing in real time. We model the TSO behaviour by choosing bids combinations according to the TSO's technical requirements and the economic merit order. Our model allows not only to forecast the statistics of the fluctuations in power offer/demand – related to energy security – but also the behaviour of the balancing market on a detail basis and to infer the market share of the various energy sources (e.g. oil, carbon etc.); hence, it has important practical implications, since it can be used as a tool and a benchmark for agencies and operators in the distribution markets. Moreover, our modelling allows to understand the changes in the market equilibria and behaviour due to the increasingly penetration of distributed generation and to address the question of economic sustainability of given power plants. As a case study, we present a detailed one-day analysis of the Italian electricity market.

4.2 Results

RES impact fundamentally the functioning of electricity market due to the technical constraints of the power system that requires an instantaneous balance between the power production and demand. In fact, the electricity market is structured to guarantee the matching among the offers from generators and the bids from consumers at each node of the power network according to an economic merit order [8]. To perform this task, the exchanges starts one day ahead on the basis of a daily energy demand forecasting and then successive market sections refine the offers at the aim of both satisfying the balancing condition and of preserving the power quality and the security of energy supply.

The most extensively studied market sector is the day-ahead market, which has been modelled both in terms of statistical analysis of historical data [30], game theory for the market phase [85] and stochastic modelling of the market operators behaviour [69].

On the other hand, few models have been proposed for the last market section [8, 17, 38, 61], devoted to assure the *real-time power reserve*. In fact, ASR allows to compensate the unpredictable events and/or the forecasting errors that can occur on the whole power system. In particular, the Balancing Market (BM) has a fundamental role in guaranteeing the reliability of the power system in presence of the deregulated electricity market.

The most important studies in ASR modelling aim to provide methods that allows the forecasting the amount of power needed for network stabilization purposes [8, 38, 61], whereas only few research activities deal with the energy price forecast [69]. With respect to the state of the art, we present in this paper an alternative model for daily BM time evolution. In particular, we reproduce the operator market strategies by means of an agent based approach, where agents represent typical market operators.

Our model is characterised by three phases: sampling of the perturbations, training of the agents and forecast of the balancing market.

In the first phase we use the information about the ODA and ID market to infer realistic power flow configurations by taking into account the physical constraints of the electric grid. We then introduce stochastic variations related to the geographically distribution of power consumption and RES generation; in such a way, we generate a statistical sample of configurations representing realistic and geo-referenced time patterns of energy requests/productions to be balanced. The difference at each time between the total actual power requests and the volume of the ODA+ID market is the size of the balancing market. The result of this phase samples the statistics of fluctuations induced by renewable sources; hence, it has important applications respect to energy security (forecasting energy congestions and/or outages) and to maintaining quality of service. We show in Figure 4.1 the setup of the system for the first phase; in particular, panel (a) shows the topology of the electricity transmission network in Italy, panel (b) shows the Italian market zone splitting and panel (c) shows a typical daily time evolution of ODA+ID outcomes with the detailed contribution of each primary energy source. Notice that market zones are used for managing eventual congestions occurring in the Italian electricity market.

In the second phase we use such balancing requests together with the static and the dynamic constraints of conventional power plant to train the agents of the balancing market by optimising their bidding behaviour (see sec.4.4). Notice that in the balancing market generators are only conventional; hence, optimising the usage and implementation of renewable resources to diminish short time market fluctuations is crucial to augment the sustainability of power production.

In the third phase we use the balancing market size and the trained agents' biddings to evaluate market price evolution by performing a statistically significant number of simulations. In such simulations, each agent can place bids, both for positive (upward market) or negative (downward market) balancing needs. This data is produced along the day at fixed intervals on a geo-referenced grid; for the Italian balancing market bids are accepted each 15 minutes. Typical simulations outputs in the upward and the downward electricity balancing market are:

- The time evolution of the balancing market size.
- The time evolution of the electricity prices
- The market share for each technology type

In figure 4.2 we compare the results of the model with real data of the actual upward and downward balancing market obtained from the Italian market operator web site [1]; notice that the data reported in [1] are aggregated for each hour. We take as a reference period the 2011-2012 winter season. In the upper panels of figure 4.2 we show that the predicted sizes of the downward and upward markets – expressed in term of energy reductions/increases for balancing requirement – agree with the historical data of the reference period. In the lower panels of figure 4.2 we show that the predicted prices in the downward and upward markets also agree with the historical data of the reference period. We notice that price and size have a similar shape, highlighting the expected correlation among sizes and prices. To the best of our knowledge, this is the first time that is possible to forecast the behaviour of the balancing market without using historical time series analysis but using informations coming out from the one-day ahead power system.

An interesting output of our approach is the forecast of the detailed contribution of each primary energy source to the downward and upward electricity balancing market. In figure 4.3 we show that conventional energy sources contribute in a different manner to the upward and downward market. As an example, due to dynamical constraints, carbon power plants contribution is negligible (due to the limits in the minimum operative power generation, mostly in the upward market) even if their energy cost is the lowest. This result highlights that market shares do not depend only on energy costs but stems from an equilibrium among dynamic response, energy cost, geographical positions and interactions among the different energy sources.

4.3 Discussion

The use of renewable energy sources is creating a new energy market where it is of the utmost importance to be in a condition to anticipate trends and needs from users and producers to reduce inefficiencies in energy management and optimize the production. The future transformation of the traditional passive distribution network in a pro-active is requiring the implementation of energy system where production and request fluctuations can be efficiently managed. In particular, fluctuations have the strongest impact on markets and energy continuity at short-time scales.

Previous research on short time energy forecasting concentrates on next-day electricity prices showing that the analysis of time series yields accurate and efficient price forecasting tools when using dynamic regression and transfer function models [69] or ARIMA methodology [30]. Systematic methods to calculate transition probabilities and rewards have also been developed to optimize market cleaning strategies [86]; to improve market clearing price prediction, it is possible to employ neural networks [60]. A further step toward and integrated model of (day ahead) market and energy flows has been taken in [17], where authors propose a market-clearing formulation with stochastic security assessed under various conditions on line flow limits, availability of spinning reserve and generator ramping limits. However, one-day ahead markets and balancing markets are fundamentally different and need separate formulations [8].

Since wind power is possibly the most erratic renewable source, it has been the focus of most investigations on short-time fluctuations. The analysis of possible evolutions in optimal short-term wind energy balancing highlights the needs of managing reserves through changes in market scheduling (more regular and higher) and in introducing stochastic planning method as opposed to deterministic one [53]. In [95], together with a probabilistic framework for secure day-ahead dispatch of wind power, a real-time reserve strategy is proposed as a corrective control action. On the operator side, the question regarding the virtual power plant (i.e. a set of energy sources aggregated and managed by a single operator as a coherent single source) participation to energy and spinning reserve markets with a bidding strategies that takes into account distributed resources and network constraints has been developed in [61] resorting to heavy computational solutions like nonlinear mixed-integer programming with inter-temporal constraints solved by genetic algorithms.

In this paper we model both the electric energy flows and the very short time market size taking into account the variability of renewable generation and customer demands via a stochastic approach. Network and ramping constraints are explicitly taken into account via the AC power flow model while market price prediction is modelled through an agent based simulation of energy operators. The input of the model are the day-ahead prices and sizes, quantities that is possible to successfully predict [30, 69]. Our approach falls in the class of models of inter-dependent critical infrastructures. We validate our model in the case of the Italian power grid and balancing market; we find that even a simplified stochastic model of production and demand based on uncorrelated Gaussian fluctuations allows to predict the statistics of energy unbalances and market prices. Our model complements the virtual-plant approaches that concentrate on the marketing strategies of single operators managing several sources. To the best of our knowledge, the explicit mechanism through which fluctuations enter into the price determination has never been considered explicitly before our investigation.

In the actual phase of transition from a centralised to a distributed generation system, our approach allows to address the complex task of estimating the additional cost associated to the balancing of renewable energy sources. Such evaluation would allow to better understand the real impact of green sources in diminishing the carbon footprint, since balancing – in absence of a well developed technology of energy storage – still relies heavily on conventional generators. Moreover, by comparing the current situations with novel scenarios where new generators (nodes in the model) are introduced, our approach allows for a detailed geo-localised what-if analysis of the energy planning. An important direction to develop for our model would be a deeper understanding and modelling of fluctuations. In fact, the probability distribution of fluctuations in energy production has different statistics according to the renewable type. Moreover, both spatial and temporal correlations should be taken into account: as an example, weather influenced sources – like wind and solar generators – display naturally a cross correlation among nearby located sources, and a temporal correlations due to the non-instantaneous character of weather variations. Though our analysis stems from a theoretical approach to understanding the effect of stochastic components in an interconnected system, it has immediate practical implications since the computational burden of our method is compatible with the scheduling time of the balancing market permitting the potential use of this software for on-the-fly decision support.

An important development of our model would be to address what-if analysis aimed to understand how the introduction of new rules and policies affects the market. In fact, it has been shown that regulatory intervention affect – via cash out arrangement – not only spot price dynamics, but also price volatility (i.e. fluctuations). Moreover, by predicting power unbalances, our approach allows for a better understanding of the energy security risks induced by renewable sources. In fact, the introduction of the stochastic components is crucial for the management of electrical energy system, for which the deterministic approach has historically allowed a proper functioning of the electric energy system, by virtue of (i) an accurate profile for the management of generation and (ii) a high degree of accuracy in loads prediction, i.e. conditions that are nowadays deeply changed.

4.4 Methods

The development of models that allow the evaluation of ancillary service cost in an electricity system during a RES-based transition phase, has practical implications particularly important in the energy system planning. Moreover, the associated tools can be useful implemented by the TSOs and the market operators to forecast in real time both the expected amount of energy required for balancing purposes and their price evolution.

In previous studies [30, 69], market sizes and the electricity price forecasts have been evaluated by statistical analysis of historical time series. Despite of the good accuracy of these methods, their formulations do not allow the forecasting of the possible changes in markets caused by a transformation of the system involving market rules and/or infrastructure evolution (different power grids topology, transmission codes, new or different management of power plants). Here we propose a methodology that is able to take into account any upgrade since it models the behaviour of the market operators subject to a realistic set of perturbations of the actual system. The reference configuration of the power system is obtained starting from two datasets. The first dataset is related to the characteristics of the power system (from the TERNA website [92]) and includes: the geo-referenced position of every 220 and 380 KV substations together with their electrical characteristics, the geo-referenced position of conventional generators together with their power rates and power ramp limits and the electrical characteristics of the power network. The second dataset (from the GME website [1]) reports the detailed time evolution of production/consumption for each 15 minutes of a reference day in the winter period 2011-2012.

Since we aim to describe the entire electricity balancing market session, we perform a complete simulation for each of the market subsections. For each interval of 15 minutes, the simulation is characterised by three phases: sampling of the perturbations, training of the agents and forecast of the balancing market.

In the first phase, the electric state of power grid is initially perturbed stochastically, in order to reproduce both the power production variability of RES generators and the fluctuation in the electricity demand. As output, a realistic set of perturbed physical states of electricity network, at each of which correspond an unbalance power condition, is given. This phase allows the statistical forecasting of the size of the balancing market.

In the second phase, the forecast sizes of the balancing market are used to train the agents tuning their offer propensities, i.e. their willingness to offer a certain amount of energy at a certain price. These propensities are, in the real case, due to an expertise of the operators in understanding market fluctuations and placing the bid that ensures them to reach the maximum profit.

In the third phase, trained agents place bids on a set of realistic perturbations representing the possible balancing requirements; price is formed according to TSO's merit order.

The implementation of the proposed methodology requires a detailed description and analysis of the power system from a technical and economical point of view. In particular, the evaluation of the perturbed states in a medium-size national power transmission grid is a complex task; in our Italian case-study, it involves around a thousand of interconnected nodes dispatching power, around a hundred of conventional generators, around a thousand of RES generators, and around thousands of loads. Each node is subject to complex physical constraints which have to be modelled adequately in order to ensure a correct description of the system. In addition, global system constraints must be considered in order to ensure the correct behaviour of the system in term of the quality of the supply. Moreover, the distributed RES generators and loads which are aggregated at the corresponding transmission nodes, assume values of power that fluctuate in time and space. We model their power production or consumption in a statistical way, assuming Gaussian-like forecast errors with standard deviations σ_i, which represent the expected power variations at each single node i of the power grid in a given time. The application of AC power flow algorithm [100] allows the validation of the dynamic and static physical constraint giving the possible states of the power system. The considered variables associated to them are:

- Load power demand D_l and the corresponding σ_l;
- Wind power production G_w and the corresponding σ_w;
- Photovoltaic power production G_{PV} and the corresponding σ_{PV}.

The system variability is tackled via a statistical mechanics approach; the set of possible states of the system at a defined time is numerically sampled by adding to the expected power production and consumption at every node i and RES generator of the grid a random value extracted from a Gaussian distribution with zero mean and variance σ_i. Each perturbed state is characterised by a different total power production G^{tot} and demand D^{tot}, and their difference $S = G^{tot} - D^{tot}$ is the required balancing power; hence, S is a random variable that represents the market size; to sample the statistics of the market behaviour, we need a significant number of possible balancing requirements. To such an aim, we generate 6000 statistically independent perturbed states for each time interval.

In order to model the balancing market, the specific rules on which it is based on should be described. In general, a market session is an auction, in which the bids placed by market operators are accepted by the TSO according to a cost minimization method. The operative rules of the Italian balancing market are briefly described in supplementary informations section. For each perturbed state, an auction will be made with a corresponding sampled value S of the market size. Since S can be either positive or negative we can have respectively a so-called upward market or a downward market session.

In a market session, each agent (market operator) k represents a conventional power plant and can place a bid (p_k, g_k) on the auction, in which it specifies the amount of energy g_k that the corresponding power plant can provide to the system, and its price p_k. Once the bids have been placed, the TSO accepts all the viable offers until the total energy needed for balancing is reached, according to the price and complaining with the actual power flow constraints.

Since the bid values are obtained according to the agent k propensities described by a specific probability distribution M_k, agents must be trained to estimate their propensities. To such an aim, we start from an initial guess $M_k = M^0$ and perform several market sessions in which each agent updates its propensities in order to maximise a profit function as described in detail in the supplementary informations section.

Once the agents have been trained, we can forecast the behaviour of the balancing market by performing market sessions on the sampled perturbed states. In addition to the market size S, we can calculate the global price per kilowatt $P = \sum p_k/S$ from the set of accepted offers. Notice that P is a random variable associating a market price to each perturbed state of the system.

The outputs of the simulations are the sampled distributions $\mathbf{P}^{up}$, $\mathbf{P}^{down}$, $\mathbf{S}^{up}$ and $\mathbf{S}^{down}$ of sizes and prices of the upward and downward market. In order to describe the system evolution during time, this distributions have been obtained for each time interval t, obtaining a dynamical distribution of market size and energy price. In order to validate the outcomes of our simulations with the available balancing market outcomes [1], results has been aggregated for each hour of the day.

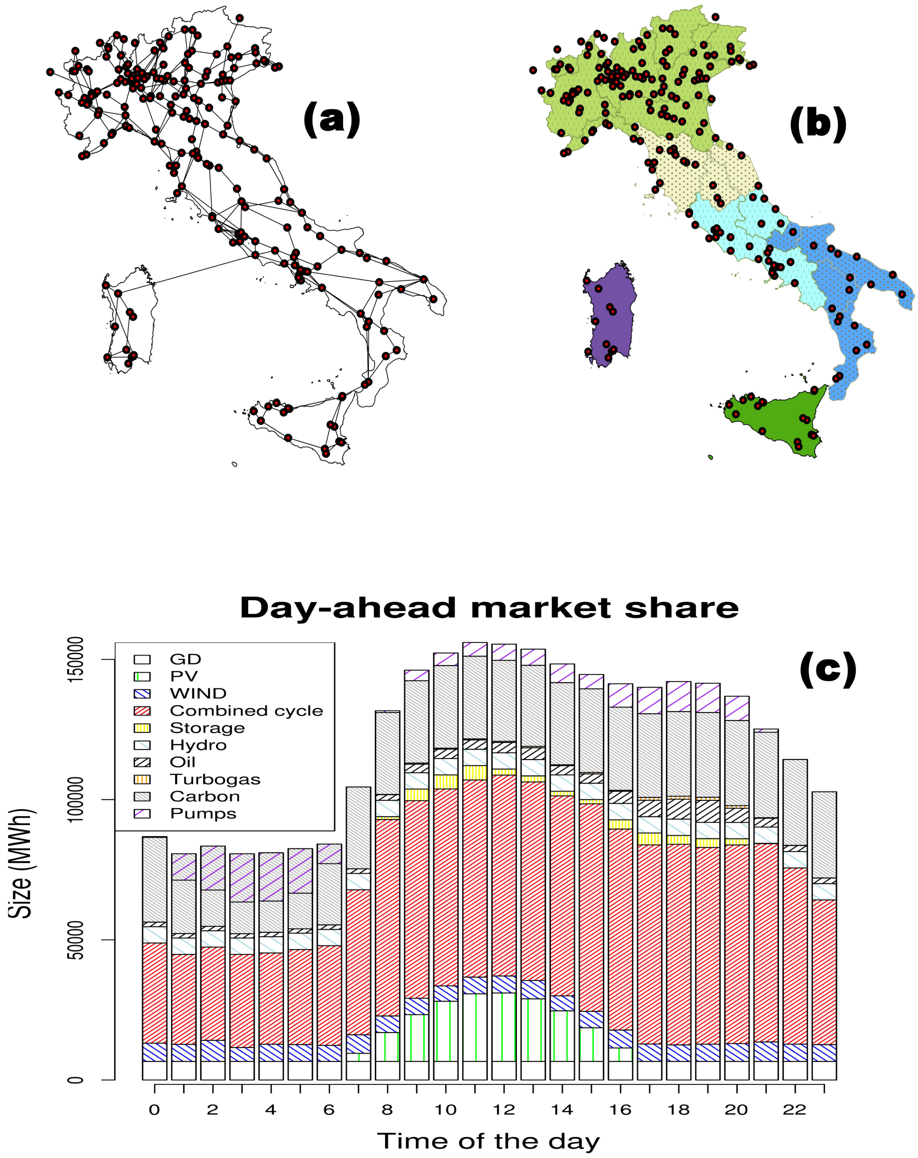

Figure 4.1: Input elements for evaluating the size of the balancing market (i.e. the short time fluctuations in power generation/demand). In panel (a) we show the electric transmission network in Italy; the topology and the physical characteristics of lines and generators are the constraints that influence the power flow. In panel (b) we show the market zone splitting used for managing the congestions of the entire Italian network. In panel (c) we show a typical ODA+ID market final output with the detailed contribution of each primary energy source; hence, it represent the day ahead energy needs as foreseen from energy operators. The balancing market takes care of short time fluctuations that occur during the day respect the scheduled ODA+ID output.

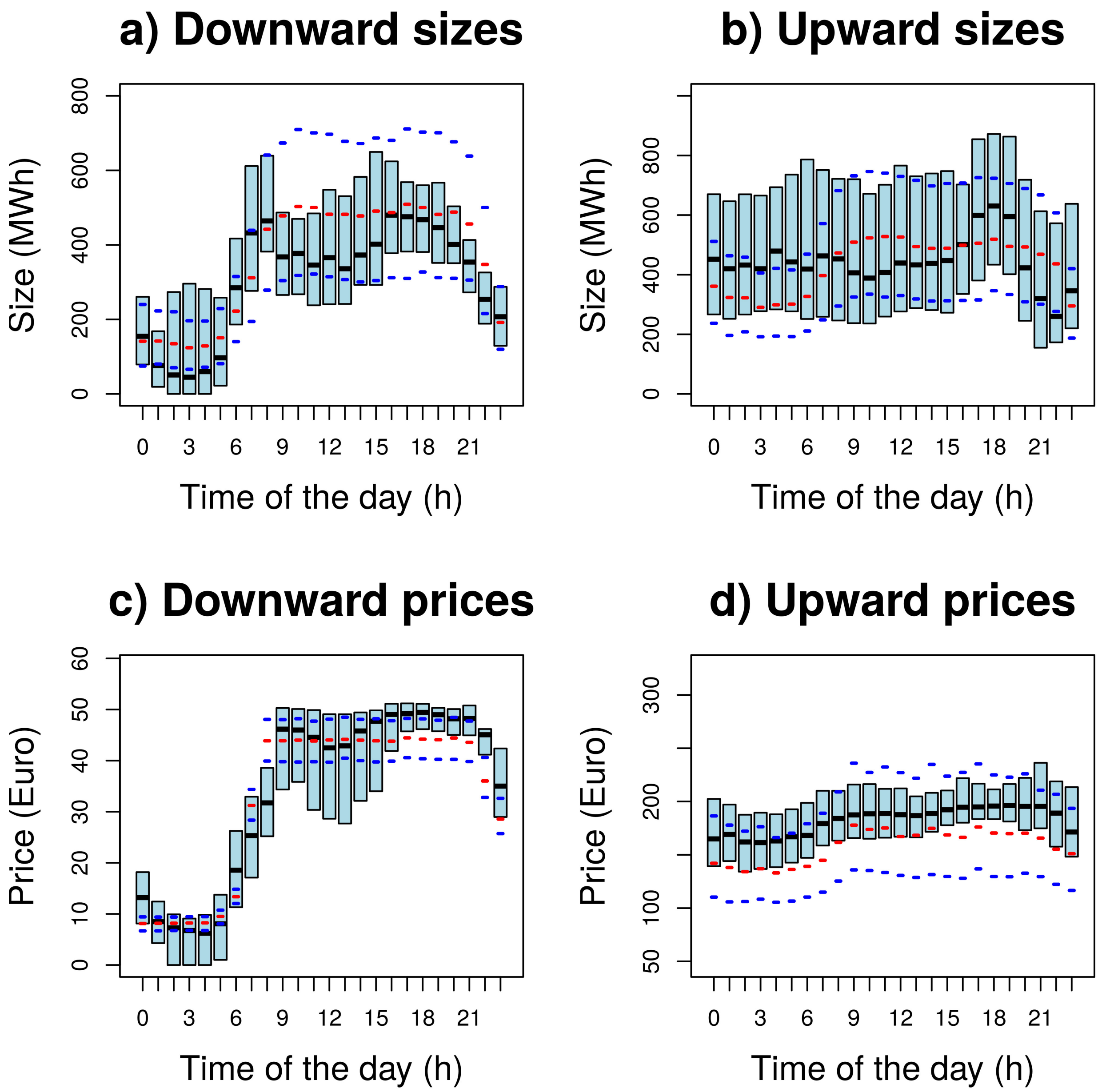

Figure 4.2: Comparison among the results of our model and the real balancing market. Notice that unbalanced power can either lead to (i) the necessity of producing *less* power than what foreseen (left panels, downward markets) or to (ii) the need of more power than what foreseen (right panels, upward markets). Full rectangles represent the $1^{st} - 3^{rd}$ quartile range (i.e. data is inside such range with 50% probability) of the real data; the black segment in the full rectangles is the median of the real data. Red segments correspond to the median and blue segments define the range from the 1^{st} to the 3^{rd} quartile of the data synthetically generated from our models. In the upper panels we show the comparisons among real data and the predicted size of upward and downward markets, i.e. the difference among the foreseen energy production and the actual request. In the lower panels we show the comparison among real market prices and the ones predicted from our agent based model.

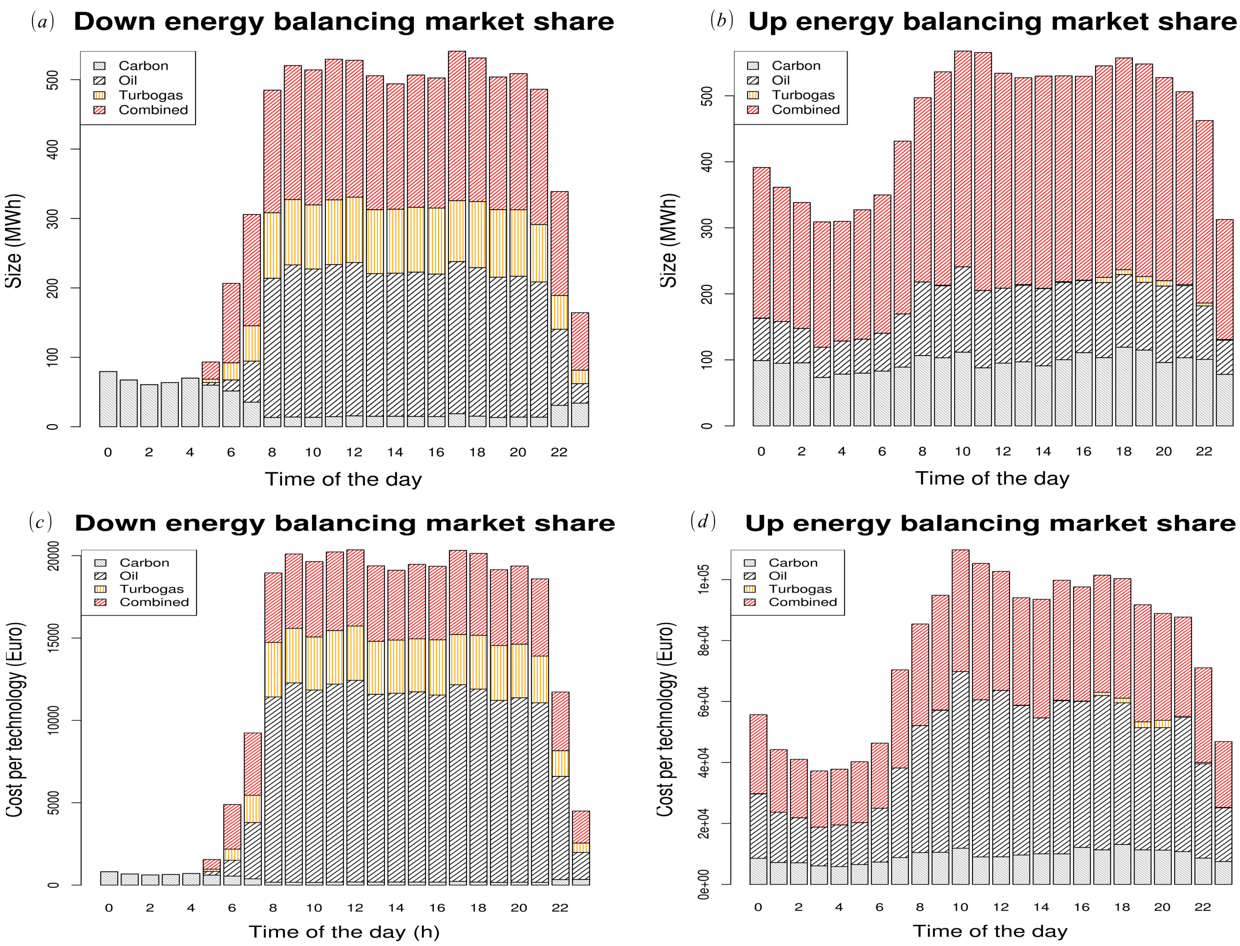

Figure 4.3: Estimated total energy (a-b panels, downward and upward market respectively) and total cost (c-d panels, downward and upward market respectively) in the balancing market; notice that our model is able to detail the contribution of each conventional power plant technology. As expected, due to low ramping (i.e. slowness in changing operational conditions), carbon sources have a very low impact on the balancing market even if they have often the lowest costs.

Supplementary Information to:

Green power grids: how energy from renewable sources affects network and markets

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4.5 The Italian balancing market

Due to the difficulty in storing electrical energy, the equilibrium of supply and demand is a key aspect of electricity transmission and distribution, as it has to be maintained dynamically at every instant. The aim of electricity market is to provide a optimal framework able to ensure real time equilibrium, guaranteeing at the same time realistic energy prices. In the following, an overview of electricity markets is presented, starting from the definition of the market operators and ending with a description of the various market phases.

Electricity market as a balancing feature on power systems The power system is mainly composed by a power network, whose goal is to transfer the energy produced by the power system supply side towards the system demand side. The network operations are usually entrusted to a single entity, the so-called transmission system operator (TSO). The main responsibility of the TSO is to guarantee the correct functioning of the transmission network and to provide an high quality energy to the demand side. Usually, there is a small number of TSOs in each power system (in Italy, there is only one).

The aim of the entire power system is to provide high quality energy to consumers, by ensuring highly controlled voltage and frequency output. Such consumers are usually supplied by long-term contracts, so the supply-side of the market has to account for all the flexibility to keep the electricity system in a power balanced state. In addition, power production goal is to supply to the system all the needed power in a way that allows the TSO to transmit this power to the demand side. The main power production side actors are the system power plants. Power plants are able to produce power and to supply it to the network. Generally, these power generators size range from an order of KW to hundred of MW, and their ability to dispatch power is usually slitted into two different sub-classes: programmable or non programmable sources. The so-called programmable ones are those whose production is controllable during time, like big conventional power plants; the non-programmable ones are those whose production is dependant from various factors as wind or sun level, like RES. The first ones provide flexibility to the market, given by their ability to change power production as needed; the second ones are hard to control, and add variability to power demand that increases with the increasing of fraction of power provided by them. For this reason, an increase in the amount of power produced by non-programmable sources will likely cause instabilities on the power system.

Electricity demand has a cyclical behaviour with a time-scale that varies from day-time and night-time differences, to weekly and seasonal differences. In order to reach power equilibrium, energy production must be guided in an efficient way, able at the same time to guarantee both power balance and economic equity. The best way to obtain this equilibrium has been identified as a set of electricity market phases, in which electricity demand and production sides interact seeking economical rules, trying to reach an economically optimized system response to power production and consumption variations. The main goal of this set of phases, also called electricity market, is to guarantee the instantaneous equilibrium of supply and demand.

Reserve markets Achieving equilibrium between power supply and demand is not easy, and therefore three different control levels have been implemented in order to control every aspect of it. The main difference between them is the time responsiveness and the cost. They are called the Primary, Secondary and Tertiary Reserve:

- Primary reserve: Primary reserve is an automated process that forces power plants to adjust their production in order to react to sudden changes in total load. All the generators that are expected to provide this service are made working away from their operational margins, in order to guarantee the availability of power when and if is needed. Primary reserve is limited and expensive, has a typical reaction time of the order of minutes, and it is used only for small adjustments in power production, compared to the total system operative powers.

- Secondary reserve: Generation facilities involved in secondary reserve are directly called by the TSO when medium changes in loads or production happens into the system. A typical secondary reserve scheme is a failure of a small power plant or a great increase (or decrease) in production of renewable generators, due to unexpected meteorological conditions. Typically, secondary reserve players are asked to adjust their power production directly by the TSO when some power related problem occurs, and have to react in a time frame of 10- 15 minutes. Due to this restricted time frame, there is not sufficient time to shut down or start up generators. For this reason, only already running generators can participate to secondary reserve by varying their production.

- Tertiary reserve: basically, it works like the secondary reserve, but on larger time steps. A typical scheme is the failure of a great power plant on the system. In fact, one or more power plants are asked to provide the missing energy to the system, by varying their production or, in case of needing, by an emergency starting procedure.

Energy market phases Power balancing on the power system is achieved by different market steps, performed over time scales that span from months to minutes. In the following, an overview of the various phases is given.

- Long-time market, or Futures market (LTM): During this market phase, that lasts from a year to a week before the effective power delivery, market operators sell futures regarding the amount of power that is planned to be produced. In relation to their great capacity but little ability to change power output in time, the main actors in this step are great power generators.

- Day-ahead market (ODA): one day before the effective power dispatch, more detailed forecasts on power demand and RES generation are available. By using this datasets, an improved market phase is performed, in which the LTM offers can be reconsidered by the market operators. By doing so, the effective power produced by each generator is adjusted to match the energy needs of the entire system. Usually, this phase energy prices are taken as a reference.

- Intra-day market (ID): After the day-ahead market is closed, some changing can occur in both demand and supply side of the market. In order to balance the effect of such oscillations, market operators are allowed to vary their production accordingly to the network needs. Usually, the amount of energy exchanged in this session is smaller then the one exchanged in day-ahead.

- Ancillary services market: takes care of the grid deviations from power balance. ODA and IM outcomes are based on one-day ahead forecast of load power consumption and RES power production, and these forecasts carry an intrinsic variability that will likely cause real time systemic deviations from equilibrium. For these reasons, a real time power balancing method is needed in order to ensure the correct functioning of the system. This power balancing is made by means of the so-called ancillary services markets. In Italy, it starts right after IM clearing with the MSD ex-ante phase, where market reserve is created. After such phase Balancing Market (BM) is performed: here, the abilited market operators offer to change their power supply for a certain cost. In order to limit the network fluctuations, the TSO accepts or not these offers ordering them to change the power supply of the generators under their control. Due to the small time frame of these processes, the BM energy sell price will be higher than the previous phases one.

4.6 Agent based simulation of electricity balancing market

We base our agent model on the Roth-Erev algorithm [75]; such kind of algorithms have already been applied for simulating the Italian ODA electricity market [78]. In such kind of models, agents learn how to place optimal bids in competitive auctions with the aim of buying (or selling) in the most convenient way.

The behaviour of real operators is related to their market knowledge, often obtained by a learning process performed during time. Roth-Erev algorithms simulate this learning process by adjusting propensities using a self-consistent methodology whose goal is to maximize profits. In this paper we apply a modified version of Roth-Erev algorithm as introduced by Nicolaisen et al [68]. Since we don't have the information on the exact relationships among market operators and brokers, we consider every conventional power plant generator as a single agent.

We describe operator propensities using a statistical description of the possible bidding strategies. The bidding strategies of the operator k are described by a finite discrete set $\mathbf{S_k} = \{(m_k^i, s_k^i)\}$. Here $0 < i < N$ is the strategy index, N is the number of possible strategies, s^i is the operator propensity to offer at a given markup value m_k^i ($1 \leq m_k^i \leq 10$ for upward bids, $0 \leq m_k^i \leq 1$ for downward bids); in our simulations $N = 50$. The mark-up value allows to calculate the bidding price as $p_{off} = C_{prod} \cdot m^i$, where C_{prod} is the production cost (per MWh) of each generator, given by his technology type. The behaviour of the operators is modelled by a stochastic process in which the probability of placing a bid at a given price $p_{off} = C_{prod} \cdot m^i$ is the normalised propensity $q^i = s^i / \sum_i s^i$.

An agent k can offer an amount of power g_{off}^k that must meet the following constraints:

- $G_{min}^k \leq G_{given}^k + g_{off}^k \leq G_{max}^k$: every generator has a minimum G_{min}^k and a maximum G_{max}^k of allowed power supply; G_{given}^k is the actual power production of the generator.

- $-G_{ramp}^k \leq g_{off}^k \leq G_{ramp}^k$: due to construction and technological limits, each generator has ramping constraints that limits in time their maximum change in power production G_{ramp}.

To optimise the propensities of the agents, we apply an iterative algorithm. At the beginning of the learning algorithm, all propensities s_n have the same value $s_n = 1$. The iterations of the algorithm are divided in three phases:

1. Bid presentation: Every agent presents a bid (g_{off}, p_{off}), both for upward and downward market. This bid is given by a feasible quantity of offered energy g_{off} (i.e. satisfying the physical constraints) and by a price p_{off} that will be drawn from agents' propensities.

2. Market session: Given the knowledge of the balancing needs of the system, the TSO accepts all the bids needed to ensure that energy while seeking economic profit, verifying that the physical constraints of the system are met.

3. Agent update: Market outcomes are communicated to each agent, that updates his propensities in relation to the profit made in the session. Agents propensities at iteration t are updated as follows:

$$s_i(t) = (1 - r) \cdot s_i(t - 1) + E_i(t) \tag{4.1}$$

where $r \in [0, 1]$ is a memory parameter and $E_i(t)$ is obtained from the relation:

$$E_i(t) = \begin{cases} (p_{off} - C_{prod}) \cdot g_{off} & \text{if bid has been accepted at time } t \\ e \cdot m_i(t - 1)/\,(N - 1) & \text{otherwhise} \end{cases} \tag{4.2}$$

where $e \in [0, 1]$ is an experimental parameter that assign a different weight to played and non-played actions.

To the best of our knowledge, Roth-Erev algorithms have been always applied by training agents over historical data. In this paper we overcome the need of historical data by training the agents on realistic system states that are synthetically generated.

Part III

Traffic analysis as a method for the evaluation of Electric Vehicles impact

Overview

About 15% of the total CO_2 emissions is ascribable to mobility. For this reason, a crucial point in the limitation of global CO_2 emissions is the migration from a fossil fueled towards a more clean and green EV mobility. Despite the increasing efforts made in technological research related to the improving of electric vehicles performances, EV mobility necessarily needs an ad-hoc infrastructure perfectly integrated with cities and local electrical power systems. This integration fits perfectly in a **smart city** vision, in which the different systems forming a city must be integrated and interconnected. Aim of this vision is to improve the smart city technical, social and economical performances and to make the entire system sustainable: for such purpose, new studies related to infrastructure planning and analysis are needed.

In this thesis, two different approaches are proposed. In **Community core detection in transportation networks**, a topological study on the Sardinian mobility network is performed. In such paper, an improvement to Louvain community detection method is proposed, able to identify the most important and central nodes in each of the obtained communities. As application of the method, analysis of the city of Atlanta traffic and of Sardinian commuting network are performed. For each of them, has been possible to identify the communities in which these systems are split, and the most central nodes among them. In the second one, **An Agent Based Approach for the Development of EV fleet Charging Strategies in Smart Cities** a novel agent based traffic model is presented, able to estimate the charging needs of an EV fleet in a medium size city. This model, an extension to the queue model [26], allows to obtain, by georeferenced way, the time evolution of power needed by the analysed EV fleet for charging purposes.

By using this information, has been possible to propose and test an infrastructure planning procedure that can be used for the implementation of such charging infrastructure into the studied city. Moreover, has been possible to test different charging strategies that can be performed by the infrastructure management company, and their possible impact over the power system in terms of charging power requirements.

Chapter 5

Community core detection in transportation networks

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Published on Phys. Rev. E 88, 042810 DOI 10.1103/PhysRevE.88.042810

5.1 Abstract

This work analyzes methods for the identification and the stability under perturbation of a territorial community structure with specific reference to transportation networks. We considered networks of commuters for a city and an insular region. In both cases, we have studied the distribution of commuters' trips (*i.e.*, home-to-work trips and viceversa). The identification and stability of the communities' cores are linked to the land-use distribution within the zone system, and therefore their proper definition may be a useful approach in transport infrastructure planning. In particular, the identification of community cores can be used to improve the transport infrastructure quality, helping to identify the optimal positioning of traffic related services, like parking lots and EV charging stations, enhancing the transition of private and public mobility towards green, zero emission technologies.

5.2 Introduction

Many Complex Systems can be modeled as networks, in which vertices are the entities of interest in the system under investigation and edges are the relations between couple of vertices/entities. For example in the World Wide Web the vertices are the web pages and the edges are the hyperlinks (in this case the network is directed and we have arcs instead of simple edges). Intuitively, not all vertices and edges have equal roles within a large-scale network; some vertices may be of some importance for the distribution of traffic in the network, and the edges that carry most of the traffic do so because they connect "groups" of vertices that are particularly important within the network. The scope of this paper is to understand the nature of these "groups", their "community structure" or "clustering", and find ways to determine the importance of vertices inside each community, revealing its inner hierarchy. The community structure of a network is a topic that has been comprehensively treated in [42].

The first problem of graph clustering is one of definition. Although the concept is intuitive, it is not defined in a rigorous way, as there is no definition of community boundary, or a unique way of determining whether a particular edge is part of a community and not of another. Therefore, as pointed out in [42], communities are algorithmically defined, *i.e.*, they are the final product of the algorithm, without a precise *a priori* definition.

As an application, this paper analyses methods for the identification and the stability of a community structure using two transportation networks.

The two analysed networks are: a regionwide network of commuting trips in the insular region of Sardinia, in Italy, and a network of daily commuting trips in the metropolitan area of Atlanta, USA. In both cases, we have studied the distribution of commuting trips, *i.e.*, home-to-work trips and viceversa. The choice was determined by the fact that trips of these types are clearly defined to planners, because their correlation to the land-use is well understood, necessarly tied to the population of the origin zone and the employment of the destination zone.

The field of transportation is a natural choice for the definition of a community structure, though the field itself has some inherent limitations. One of the main challenges that the world will face in the next 20 years is given by the transition of private and public mobility towards less greenhouse emissions technologies. Despite the great technological advances in electrical engines technologies, electric vehicles (EV) are still uncommon. In order to successfully implement EV as main mobility vectors, new models able to describe and identify the optimal support infrastructure are needed. An important approach able to describe such systems is given by complex networks theory and in particular by the studies related to spatial networks. The identification of the most relevant vertices from the point of view of the internal stability of a community and the overall partition structure could help to improve transportation infrastructure description, being a powerful method in the identification of a correct investment plan. On a practical matter, the measurement of important traffic variables is lengthy and expensive. For once, different methods to count traffic volumes return different answers, especially in the identification of commercial vehicles [4]. Additionally, the development of a regionwide origin-destination (OD) matrix at the zone level is a long and costly procedure; in particular the matrix of the metropolitan area used in this study has been derived after a year-long survey process, and the final OD matrix is assembled by weighting a matrix of survey responses according to the population of the areas where the partecipants live. A second calibration stage is generally done to test whether the OD matrix obtained assignes traffic compatibly with the traffic on the major highways of the study area; as a result of this process, the trip distribution and assignment may work well *globally*, but larger discrepancies may persist *locally*. Finally, during the time occurred to carry out this process, conditions on the ground may have already changed, since the land-use of an area is constantly changing, therefore creating discrepancies in the final OD matrix.

Notwithstanding these inherent difficulties, the identification of communities within a metropolitan area network still holds great importance. First, the formation of communities in a network is a byproduct of land-use development. Land-use development occurs for a number of reasons (service maximization, profit, etc), and the location for development is chosen according to the optimization in terms of different variables, like price of land, proximity to transit, regulation, that are however variables related to each zone/vertex of the system. For example, demand for transport between two vertices may lead to the opening of a new edge (*e.g.*, a new bus route, a new road), which in turn may lead to more demand for transport (in the form of "induced demand", [62, 73]). The community structure is not solely a function of the attributes of each zone/vertex, but also of the network arrangement, hence it forms a more comprehensive measure of the importance of a group of zones as a subsection of the zone system.

It is important to know which vertices are the most relevant from the point of view of the internal stability of a community and the overall partition structure. We will see in the next section that this idea is at the cornerstone of the community stability. In other fields the problem has been studied in terms of network breakdown, which has found applications in the accessibility of a transportation network for flood damage. Knowledge of community structure can serve planners in the situation of natural disasters to predict the onset of network breakdown, as studied in [83]. In other fields, it has been applied to the identification of crucial edges in a web network under cybernetic attack [7, 81, 84].

5.3 Materials and Methods

5.3.1 Community detection and modularity

There are now many community detection methods [42] and the most popular is the modularity optimization introduced by Newman and Girvan [66]. This method has various drawbacks, the most important of which is the existence of a resolution limit [43] which prevent it to detect smaller modules, but has also the advantage of being easy to implement. The modularity function that needs to be optimized is defined as [67]:

$$Q = \frac{1}{2m} \sum_{ij} (A_{ij} - P_{ij})\, \delta(C_i, C_j) \tag{5.1}$$

where the sum is over all the node pairs, A is the adjacency matrix, m is the total number of edges and P_{ij} is the expected number of edges between the vertices i and j for a given null model. The function will result in a null contribution for couples of vertices not belonging to the same community ($C_i \neq C_j$). For an unweighted network, the choice $P_{ij} = k_i k_j / 2m$ equates to taking as a null model a random network with the same degree sequence as the original network.

To optimize the modularity we used the Louvain algorithm [14] based on two steps that are repeated iteratively until a global maximum is reached. In the first step we create a network partition where the number of communities is equal to the nodes number. Then, the algorithm iterates over all nodes and computes for each node the modularity gain within the communities of its neighbors; a node movement is maintained if it leads to a positive variation in modularity. The iteration is repeated until a local maximum is reached, that is until there is not any other move that lead to an increase in modularity.

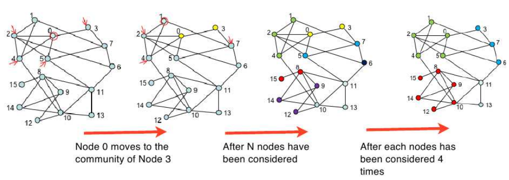

Figure 5.1: (Color online) This figure shows an example of the first step execution over a network with 15 nodes: at the beginning all nodes are isolated (left), then the algorithm start to merge several nodes together (center) until the local maximum is reached (right) (after Blondel et al. [14])

In the second step the algorithm creates a new network whose nodes are the communities; the total weight of the links between communities is the total weight of the links between the nodes of these communities. Typically the nodes number diminishes drastically at this step and this ensures the rapid convergence of the algorithm for large networks.

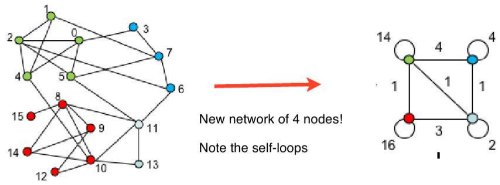

Figure 5.2: (Color online) This figure shows an example of the second step where it is possible to note the creation of self links associated to the communities internal connections(after Blondel et al. [14]).

The main problems of all algorithms for community detection is the fact that the community definition does not provide any information about the importance of a node inside its own community. Nodes of a community do not have all the same importance for the community stability: the removal of a node in the "core" of a network affects the partition much more than the deletion of a node that stays on the edge of the community (*i.e.* a node connected in the same way with nodes internal and external to its community). The purpose of the following section is to develop a novel way for detecting cores inside communities by using the properties the of modularity function.

5.3.2 dQ analysis for cores detection in a partition

By definition, if the modularity associated to a network has been optimized, every perturbation in the partition leads to a negative variation in the modularity (dQ). If we move a node from a partition we have $M-1$ possible choices (with M the number of communities) as possible targets for the new host communty of this node. We decided to define the dQ associated to each node as the smallest variation in absolute value (or the closest to 0 since dQ is always a negative number) for all the possible choices and this is in our view a measure of how that node is internal in its community.

Fig. 5.3 shows the typical dQ frequency distribution of nodes inside a community; the data points were fitted using a decaying exponential form $\exp(-x/\ell)$ with typical length ℓ. The typical lenght ℓ and defines a starting point to discriminate the core nodes. For practical purposes, the threshold value $d_{thr} = 2\ell$, is an appropriate boundary value to differentiate between core nodes (the ones below the threshold) and the border nodes (the peripheral nodes).

Fig. 5.4 shows the cores detected for the city of Atlanta, GA, using the method described above.

5.4 Datasets

5.4.1 Sardinian Inter-municipal Commuting Network

Sardinia is the second largest Mediterranean island with an area of approximately 24,000 square kilometers and 1,600,000 inhabitants. At the date of 1991, the island was partitioned in 375 municipalities, the second simplest body in the Italian public administration, each one of those generally corresponding to a major urban centre (in Figure 5.5 we report the geographical distribution of the municipalities). For the whole set of municipalities the Italian National

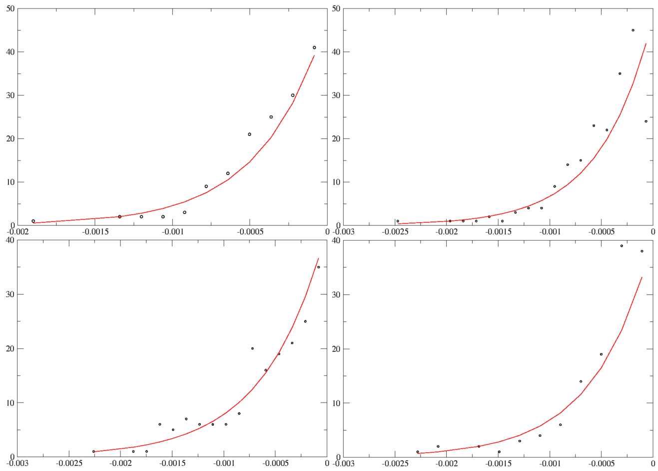

Figure 5.3: (Color online) dQ frequency plots relative to 4 communities detected for the city of Atlanta, GA. The correlation coefficients of the exponential fits are (from top right to bottom left, respectively) 0.956, 0.946, 0.937 and 0.933. In general, these distributions are the tipical dQ frequency distribution inside a community (provided there are enough nodes to perform an exponential fit).

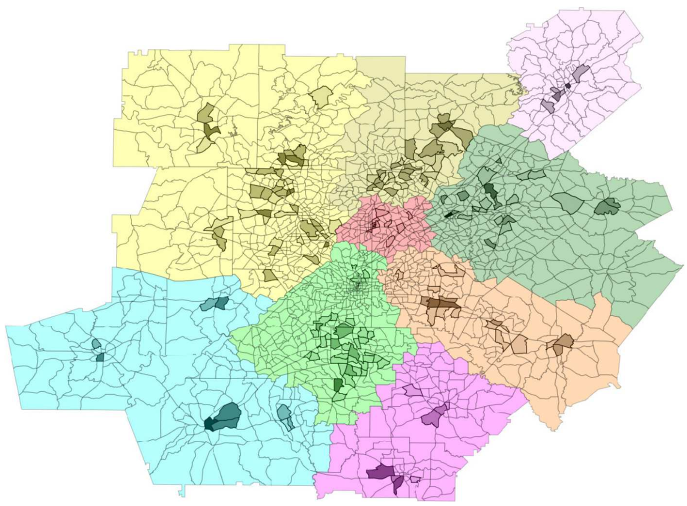

Figure 5.4: (Color online) Cores detected for the city of Atlanta, GA, using a threshold equal to double the typical length of the exponential distribution of the dQ frequencies.

Institute of Statistics [48] has issued the origin-destination table (OD) corresponding to the commuting traffic at the inter-city level. The OD is constructed on the output of a survey about commuting behaviors of Sardinian citizens. This survey refers to the daily movement from the habitual residence (the origin) to the most frequent place of employment (the destination): the data comprise both the transportation means used and the time usually spent for displacement. Hence, OD data give access to the flows of people regularly commuting among the Sardinian municipalities. In particular we have considered the external flows $i \to j$ which measure the movements from any municipality i to the municipality j and we will focus on the flows of individuals (workers and students) commuting throughout the set of Sardinian municipalities by all means of transportation. This data source allows the construction of the Sardinian inter-municipal commuting network (SMCN) in which each node corresponds to a given municipality and the links represent the presence of a non-zero flow of commuters among the corresponding municipalities.

The standard mathematical representation of the resulting network is provided by the adja-

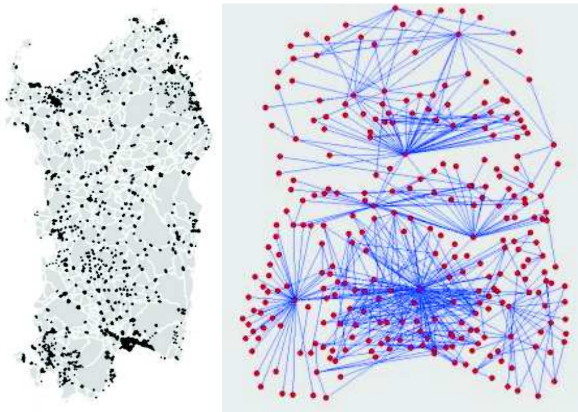

Figure 5.5: (Color online) Geographical versus topologic representation of the the Sardinian inter-municipal commuting network (SMCN): the nodes (red points) correspond to the towns, while the links to a flow value larger than 50 commuters between two towns.

cency matrix A of elements (a_{ij}). The elements on the principal diagonal (a_{ii}) are set equal to zero, since intra-municipal commuting movements are not considered here. Off-diagonal terms a_{ij} are equal to 1 in the presence of any non-zero flow between i and j ($i \rightarrow j$ or $j \rightarrow i$) and are equal to 0 otherwise. The adjacency matrix is then symmetric and describes regular bi-directional displacements among the municipalities. The adjacency matrix contains all the topological information about the network but the dataset also provides the number of commuters attached to each link. It is therefore possible to go beyond the mere topological representation and to construct a weighted graph where the nodes still represent the municipal centres but where the links are valued according to the actual number of commuters. Analogously to the adjacency matrix A, we thus construct the symmetric weighted adjacency matrix W in which the elements w_{ij} are computed as the sum of the $i \rightarrow j$ and $j \rightarrow i$ flows between the corresponding municipalities (per day). The elements w_{ij} are null in the case of municipalities i and j which do not exchange commuting traffic and by definition the diagonal elements are set to zero . According to the assumption of regular bi-directional movements along the links, the weight matrix is symmetric and the network is described as an undirected weighted graph. The weighted graph provides a richer description since it considers the topology along with the quantitative information on the dynamics occurring in the whole network.

5.4.2 ARC Network

The Atlanta Regional Commission (ARC) maintains a network model for land use purposes of the metropolitan area of the city of Atlanta, in the State of Georgia, USA. The ARC travel demand model is designed to represent the state of the practice in travel demand modeling and to meet all modeling requirements in the US EPA Transportation Conformity Rule. Further details on the arrangement of zones are reported in [3].

The main data source for the calibration of the travel demand models was a household travel survey of eight thousand households conducted for the ARC from April 2001 through April 2002. The household survey data was the main source of data for developing the trip generation and distribution model. The trip generation model is a fairly unique trip based model in that it estimated the frequency a person will make trips, by the purpose of the trip, and then applies this frequency to individual persons to determine the total amount of travel made by the residents of the region. Therefore, as in the case of the SMNC network, the trips reported in the ARC model are produced by a trip generation model, which is calibrated according to the result of a survey. The calibration is achieved by matching the trip length, frequency and by evaluating geographic area biases (*e.g.*, natural features, political or service delivery boundaries, etc).

The work presented in this paper is centered on the activity of commuters, which in the ARC model are described as Home Based Work (HBW) trips. It is commonplace to describe such trips as trips made for the purpose of work and which either begin or end at the traveler's home. This is a typical trip purpose that is related to the employment at the destination zone and population/household income of the traveler or the household at the origin zone. Mode details on the nature and calibration of the HBW demand and distribution model can be found in [3] for this specific model. The nature of the relationship between demand for travel and land-use are further explored in the modeling review works by Wilson [5] and Batty [12].

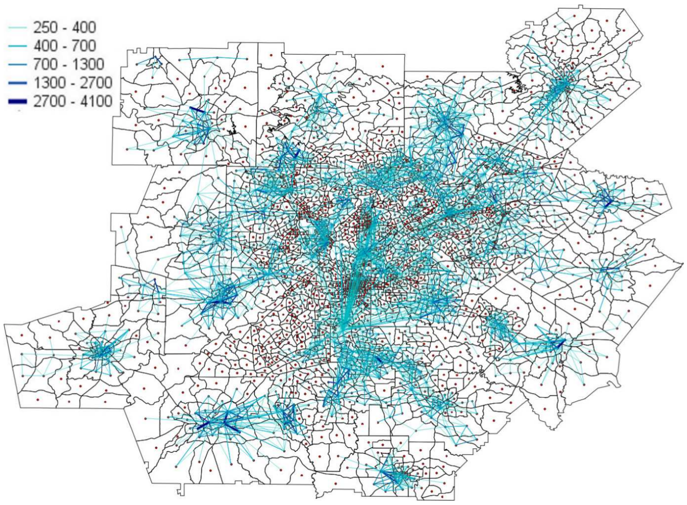

Figure 5.6: (Color online) Extension of the zone system in the ARC model. Only the links with a weight greater than 250 have been shown. Each point is a centroid of a TAZ.

A number of socioeconomic variables are recorded in the ARC model, which are of importance for planning purpose and as inputs to the trip generation and demand growth algorithms. The figures below show, in order, the gradient plots of population and employment per zone, as recorded in the nationwide Census 2010. Darker zones indicate higher value for the corresponding variable.

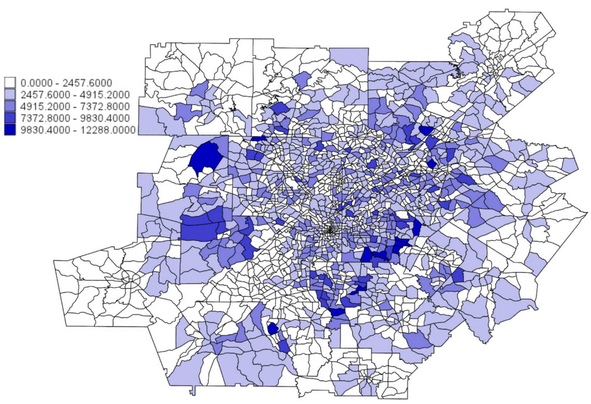

Figure 5.7: (Color online) Gradient plot for Population in the ARC model.

Figure 5.7 shows the gradient plot of the zone population. Population is seen in this figure as being scattered around the center that forms the core of the downtown area.

Figure 5.8 shows the gradient plot for the zone employment, measured as the number of jobs located in the zone the variable refers to. Employment is seen in this figure as primarily

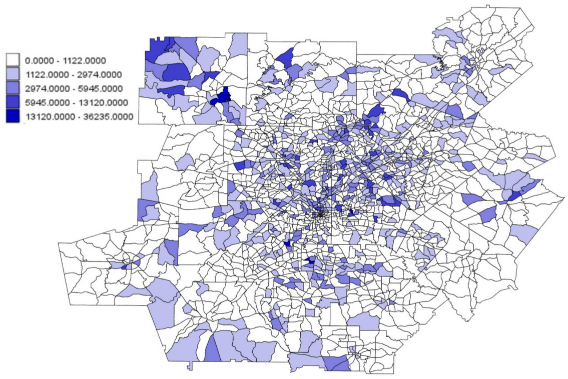

Figure 5.8: (Color online) Gradient plot for Employment in the ARC model.

in-strength	Correlation
Employment	0.984
Academic	0.977
Both	0.984

Table 5.1: Results of correlation analysis between dQ and the in-strength related to particular segments of the traveling population in the SMCN network.

located in the downtown zones (which are quite small in size) plus other job centers in the suburban metropolitan areas.

5.5 Results

The sequence of charts that follow describes the correlation of the quantity dQ and the various socioeconomic variables that are available for analysis.

The table below shows the result of correlation analysis between the computed dQ and the in-strength of the various zones in the SMCN network. For the sake of clarity, the Sardinian and ARC networks are in principle directed, as previously described in 5.4, and the in-strength has been computed starting from these original networks. On the contrary, the community detection has been performed using undirected networks obtained from the directed ones by summing up the weigths of incoming and outgoing links. The correlation results shown in the table 5.1 only give a overall picture of the quality of correlation between traffic and community structure. Figures 5.9-5.10 show the geographic distribution of the gradients of dQ values across the zone system. Figure 5.9 shows the values of dQ arranged by color (darker color indicates higher value). Higher dQ indicates that the zone under investigation is more to the center of a community than the zones with lighter color. The data in Figure 5.9 shows that the two likeliest centers of a community (the two darkest zones in the figure) are not both centers of population and/or employment, nor are all large centers of population and/or employment necessarily key zones to the definition (and for its definition, stability) of a community. In other words, community and socioeconomic activity are not on a one-to-one relationship, and it is not always possible to imply a ranking of one of these quantities with respect to the other and viceversa.

Figure 5.10 (right) below shows what the communities identified look like with respect to the political subdivisions of the island of Sardinia, the provinces that corresponds to the NUT3 regions in the international classifications (left). To put this result in context, it is important

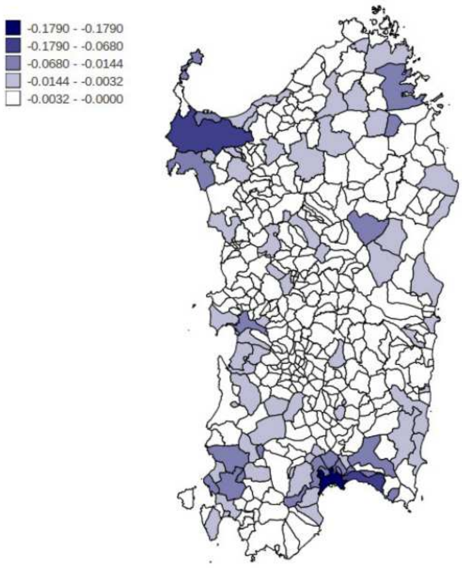

Figure 5.9: (Color online) dQ plot for the network related to Employment in the SMCN network.

to note that the present political subdivision in eight provinces took effect in 2005 after a law passed in 2001 raised the number of provinces from the original number of four. Therefore, at the time the ISTAT data was collected (2001), Sardinia was subdivided politically in four provinces, hence the results of the modularity analysis showed that at least seven communities existed, subdivided geographically roughly along the lines of the boundary of the new (and present time) provinces. The two subdivisions, "topological" the first, political the second, are remarkably alike, suggesting that either the political subdivision was designed to accomodate the arrangement of commuting movements, or the topological subdivision is a result of ease of movement within a (not yet established) political subdivision.

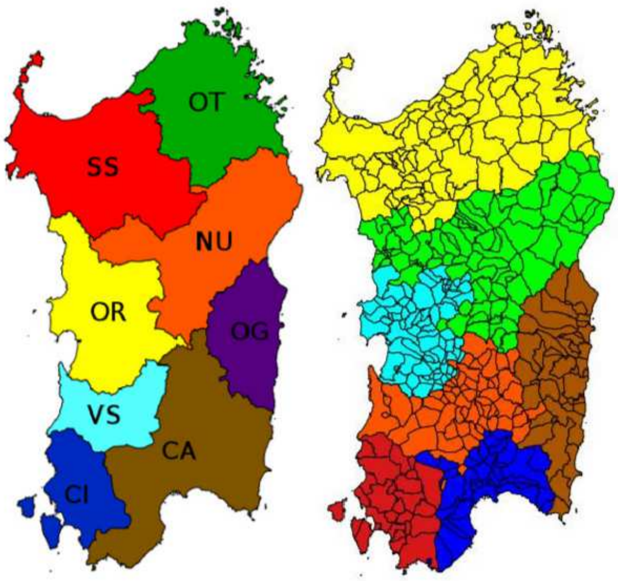

Figure 5.10: (Color online) A comparison between the current provincial division (CA = Cagliari, CI = Carbonia-Iglesias, VS = Medio Campidano, OR = Oristano, OG = Ogliastra, NU = Nuoro, SS = Sassari and OT = Olbia-Tempio) of the Sardinia region, Italy, and the result of the community detection.

Finally, it is worth noting that, according to the results of a regional referendum in May 2012, the four new provinces established in according to the 2001 law will be abolished starting March 2013.

Table 5.2 shows the result of the correlation between in-strength, dQ and employment for the ARC network. Correlation with employment is quite poor while, as in the case of the SMCN network, correlation with the in-strength is quite good. It is instructive then to see the geographic arrangement of the communities and other features of the network. Figure 5.11

Variable	Correlation
in-strength	0.782
Employment	0.052

Table 5.2: Results of correlation analysis between dQ and various variables in the ARC network.

shows the dQ distribution for the ARC network. Darker zones indicate zones with higher dQ, and the darkest zones can be considered as the center of a community. Figure 5.12 show (color-coded) the community boudaries. The correlation between dQ and in-strength is explored

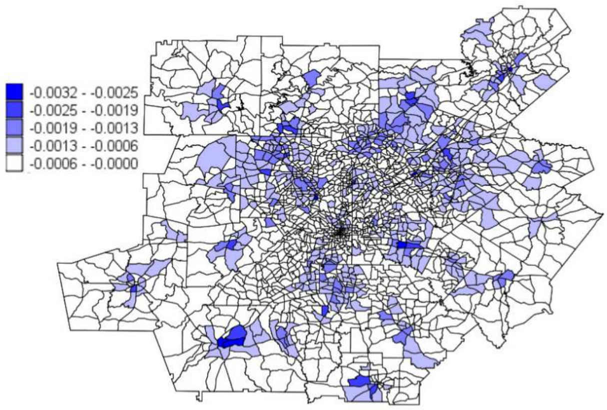

Figure 5.11: (Color online) dQ plot for the ARC network.

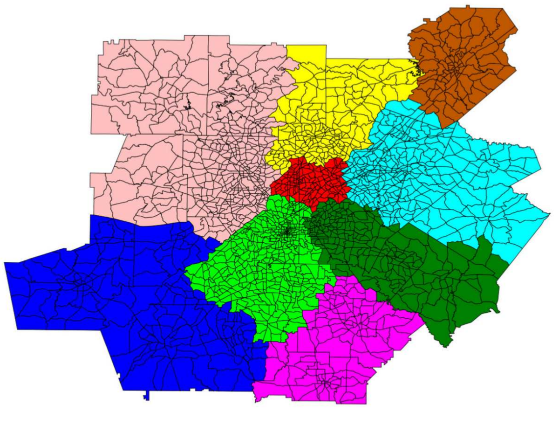

Figure 5.12: (Color online) dQ and community boundary plot for the ARC network

by means of the Figure 5.13, which shows a correlation of almost 0.8. As per the case of the SMCN network, community and socioeconomic activity are not on a one-to-one relationship, and it is not always possible to imply a ranking of one of these quantities with respect to the other and viceversa.

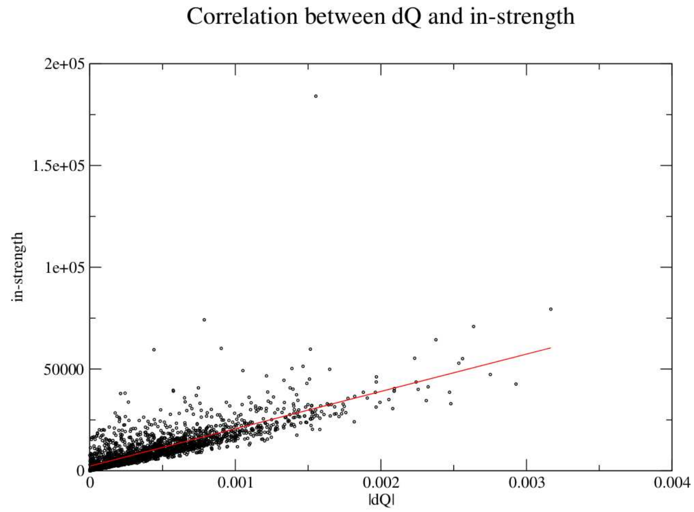

Figure 5.13: (Color online) The correlation between dQ and in-strength is equal to 0.78.

5.6 Discussion

The two case studies that have been the subject of this analysis showed that community structure coming from the networks analysis with its cores definitions, and socioeconomic activity are not on a one-to-one relationship, and it is not always possible to imply a ranking of one of these quantities with respect to the other and viceversa. Hence, the "community" is a distinct mathematical object with its own land-use meaning that contains some valuable infromation to be exploited. Correlation between the community stability (expressed in dQ value) and socioeconomic variables only tells part of story, while the remaining contribution to the community stability is to be found in the topological property of the networks. Our application to transportation networks has been a kind of territorial benchmark for this novel approach, but the proposed method for detecting cores in communities through the optimization of the modularity function is quite general and can be applied to other networked systems.

Chapter 6

An Agent Based Approach for the Development of EV fleet Charging Strategies in Smart Cities

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Published on Proceedings of Electric Vehicle Conference (IEVC), 2014, IEEE International DOI 10.1109/IEVC.2014.7056178

6.1 Abstract

In the present paper an agent based approach, addressed to simulate the behaviour of a Plug-in Electric Vehicles (PEV) fleet into a Smart City, is presented. Considering the traffic data-set available from mobility plans, a spatial and time model, representing the evolution of travel patterns, can be developed considering each vehicle as an agent. The following statistical analysis in space and time of the agent behaviours is used to plan the PEV charging infrastructure of municipalities. The proposed planning methodology has been tested on an European city in order to evaluate the effectiveness of the proposed procedure. Such charging infrastructure, defined according to the mobility needs, has been tested and used to evaluate the customer satisfaction of PEV users in term of charging demand. The proposed charging system has been implemented to estimate the average daily energy profiles for charging the smart city PEV fleet during a typical workday. This has been finally used as one day ahead energy reference profile to develop a market-oriented EV charging strategies. The performance of the proposed smart charging strategies has been finally simulated and compared.

6.2 Introduction

Thanks to the increasing environmental awareness and to the will to reduce both the dependence on fossil sources and the emissions of greenhouse gases, the energy policy of many governments around the world is oriented to strongly support the exploitation of renewable energy sources (RES). In particular, the European Union (EU), through its Energy and Climate Policy, has set two ambitious targets by 2020: providing 20% of gross energy consumption from RES and reducing by 20% the greenhouse gases respect the values registered in 1990 [93]. In addition, the EU, considering the huge impact of the mobility sector by the energy point of view, has imposed, as a mandatory constraint, that 10% of the overall energy consumption in the land transport will have to be supported by RES. This could be achieved by means of bio-fuels and electric vehicles (EVs). Although the first solution seems to be more rapidly viable, the second one provides many more opportunities from the technical, economical and social points of view. In this framework, the urban mobility and its integration with the power system represent promising opportunities toward the application of the smart grid paradigm to small-medium size cities with the aim of introducing a novel city concept, known as *"smart city"*. The smart city basic idea is to manage complex systems (like cities) in a novel manner. This new concept is based on an integrated vision of the different systems forming a city in order to improve its technical, social and economical performances making the entire system sustainable. Energy is one of the main topics involved in the development of a *"smart city"* and contemplates (by means of a wide use of communication devices) the integration and synergic management of distributed generators, controllable loads and energy storage systems. The main goal is to improve the overall city energy performance, reducing at the same time the CO_2 emissions [94]. In this context, the urban mobility has a fundamental role because its transformation towards sustainable technologies could support both the reduction of energy consumption and the implementation of diffused, controllable loads and energy storage systems suitable for the development of smart grids [76]. In particular, the use of EV batteries according to the Grid to Vehicle (G2V) [77] or Vehicle to Grid (V2G) concepts [52] allows their use as distributed controllable loads or energy storage systems. In fact, if the charging process is appropriately managed by an aggregator, the cluster of the plugged EV batteries can be considered as a controllable load (when only the G2V is applied) or a controllable distributed energy storage system, in accordance with the V2G paradigm [33]. Moreover, storage devices allow to mitigate the intermittence of non-dispatchable or stochastic generators, e.g. wind turbines and PV plants, especially in weak networks [59]. In these applications, according to the V2G concept, EVs could be seen both as electricity consumers and as electricity suppliers, offering an integrative solution for the implementation of distributed energy storage. Several studies have analyzed V2G as a promising option for providing ancillary services [57] [87]. Most studies identify economic benefits for electric vehicles owners and great technical advantages for network operators when EVs provide extra power supply, peak load shaving, load shifting, spinning reserve and frequency regulation services [33]. Different methodologies have been developed taking into account the mobility needs of EVs owners. Although the reference studies on V2G considered only average mobility behaviours [52], the impact of driving habits on the V2G capability has been recently investigated and evaluated by means stochastic models [31]. Nevertheless, besides the mobility requirement of an EV user, the availability of charging infrastructures plays an important role in defining the EVs battery capacity available for V2G services.

In the present paper an agent based model (ABM) has been developed to simulate the behaviour of a EV fleet into the municipalities and subsequently to estimate the time evolution and spatial distribution of EVs charging stations in a smart city. The definition of the correct sizing, in terms of number and rated power of charging stations, has been developed by means of a planning procedure based on a georeferenced estimation of power requirements referred to a defined dimension of EV fleet. Defined the charging infrastructure that optimizes the requirements of EVs, appropriate charging strategies are finally proposed in order to firstly satisfy the customer demand and then to forecast, manage, and optimize the charging station electricity supply.

6.3 Mobility Model

The knowledge of mobility requirements is considered the starting point in approaching both the EV mobility planning and the definition of smart charging strategies. For these reasons, the mobility modeling is a key topic for the development of energy management algorithms in mobility systems. In the present paper, a traffic model, based on the so-called *queue* model, has been applied [26]. This method is suitable for medium size cities characterized by the movement of several thousand of vehicles both for commuting and other duties needs. This approach considers vehicles as agents that operate in an infrastructure network represented by means of a weighted directed graph whose topology is deduced from the city road map.
The graph is obtained considering as nodes the intersections of city roads and as edges the city roads, weighted in order to take into account the crossing time of the vehicles. Each node is georeferenced in order to relate its position into the graph to city road map. The agents develop their travel respecting the graph topological constraints and choosing a route that minimizes the travel time. Given the informations about commuting, number of employees for each zone, and population density, a number of agents and their destination can be generated. On the basis of these hypotheses, the effect of those trips on the entire mobility network can be simulated in a day-time window.

6.3.1 The agent based approach

According to the proposed approach, each vehicle in the city is described as an agent, which can be classified referring to the type of mobility habits (commuter and free flowing) and to the power-train characteristics of the car – conventional vehicle (CV) or EV. Each agent is characterized by an energy state and a mobility state. The energy state is connected to the available energy for travelling purposes, whereas the mobility state is associated to moving or parking condition.
In particular, the parking time represents an important information for mobility modeling. Hence it has been statistically represented considering Poisson distributions used as follows. If the agent is a commuter, his parking time, expressed in seconds, is modeled by means of two distributions, equally distributed among the agents, with $\lambda = 21600$ (6 hours) or $\lambda = 28800$ (8 hours), otherwise the agent is a free flowing, and his parking time is modeled considering just a distribution with $\lambda = 3600$ (1 hour).
The Poisson probability distribution used for the above mentioned purposes is defined as follows:

$$\gamma(k) = \frac{\lambda^k \cdot e^{-\lambda}}{k!}, \quad k \in N \tag{6.1}$$

Considering the average distance travelled by the vehicles in the city, the mobility energy constraints of CV can be neglected. This hypothesis cannot be extended to EVs due to their limited autonomy which depend on the energy that can be stored in their battery-packs; to take into account the EV energy constraints, the following parameters have been introduced in order to evaluate the EV agent autonomy:

- EV battery capacity, E_{EV}^{max};
- EV stored energy at the time t, $E_{EV}(t)$;
- EV state of charge at time t, $SOC(t)$;
- EV energy consumption during the travel pattern.

Table 6.1: Electric power required by EV vs. average speed

v(km/h)	P(W)
10	1000
20	2010
30	3415
40	5040
50	7070
60	4816
70	6410
80	8370
90	10730
100	13575
110	16940

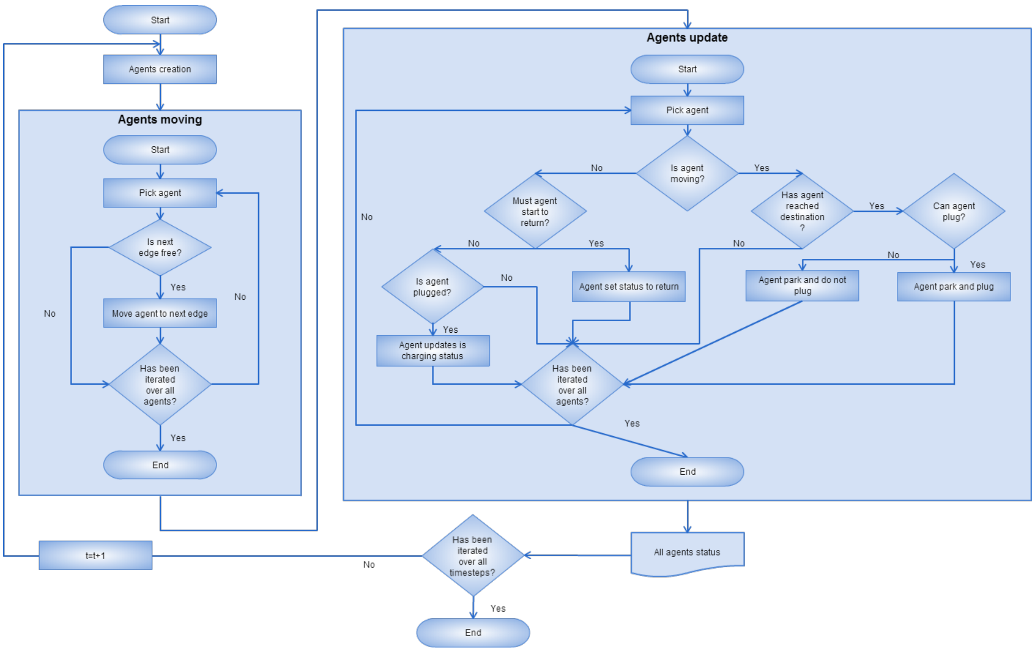

Figure 6.1: Schematic description of the proposed Agent Based mobility model. In the Flowchart is highlighted the three main phases referred to a time step: generation of agents, agents movement evaluation, and agents update.

In the latter case, the consumption is estimated referring to a typical EV city car and taking into account the different energy consumption between city/non-city environment. The EV electricity consumption is evaluated referring to a simple function of electric power vs. EV average speed, as reported in Table 6.1.

Moreover, the EV mobility status is characterized by an additional condition when it is parked. It can be plugged to the charging station, or no-plugged. All these conditions must be opportunely modeled. Once the agents properties have been defined, it is necessary to describe the agents interactions in order to represent the urban traffic condition. For these purposes, the following modeling has been proposed, considering in each time-step, three phases:

1. In the first phase, new agents are generated;

2. In the second phase, each single agent position is updated, using the *queue* model;

3. In a third phase, agent energy and mobility states are updated.

In the following, each phase is described in detail. The entire method is also schematically depicted in the flowchart reported in Fig.6.1

Generation of Agents

The generation of agents is modeled resorting to the database of the urban and mobility plans, from which the following main informations must be extracted:

- the number of incoming vehicles that move from each municipality k towards the smart city $C_{in}^k(t)$, is used to determine the normalized distribution reported in (6.2);
- the number of vehicles that move from the smart city to each municipality l, $C_{out}^l(t)$ is used to determine the normalized distribution reported in (6.3);
- the normalized population density distribution a_i, in a generic zone i, in which the smart city is divided, is defined as reported in (6.4), where A_i^{ab} is the given number of inhabitants per i-th zone;
- the normalized 2D spatial distribution of employees determined as reported in (6.5), where W_i, is the 2D spatial distribution of employees in i-th zone;
- the normalized 2D spatial distribution of the number of commercial activities s_i.

$$c_{in}^k(t) = \frac{C_{in}^k(t)}{\sum_k C_{in}^k(t)} \tag{6.2}$$

$$c_{out}^l(t)^* = \frac{C_{out}^l(t)}{\sum_l C_{out}^l(t)} \tag{6.3}$$

$$a_i = \frac{A_i^{ab}}{\sum_i A_i^{ab}} \tag{6.4}$$

$$w_i = \frac{W_i}{\sum_i W_i} \tag{6.5}$$

Considering these parameters, the rules that govern the agent generations are reported in the following. In particular, the previously described distributions are used to statistically generate origin and destination points of each agent. The process starts with the random extraction of the origin and destination zone i of each agent referring to its mobility classification as reported in the following:

- *"Incoming commuters"* – the origin is extracted from distribution $c_{in}^k(t)$ and destination from w_i;
- *"Outcoming commuters"* – the origin is extracted from distribution a_i and destination from $c_{out}^k(t)$;
- *"Intra-city free flowing agents"* – the origin is extracted from distribution a_i and destination from s_i;
- *"Inter-city free flowing agents"* – the origin point is extracted from the k municipalities and the destination from distribution s_i;

Once origin and destination of each agent are generated, the algorithm calculates the shortest path which connects those two nodes. If the agent is an EV user, due to the fact that his autonomy must be sufficient to reach his destination, the extracted length route must comply this constraint otherwise the path is assigned to a CV. At the end of this check-process the assigned shortest path is the effective agent route.

The queue model

The *queue* model is used for the estimation of time effects of urban traffic on agent movement. The model determines iteratively, for each time-step Δt, the novel position of each agent on a graph. This iterative process computes the new position of each agent at the time t starting from the positions at time $t - \Delta t$ of all agents operating in the graph. Then, knowing, for each city road, the free flow maximum speed v_0, the road length L, the integer flow capacity C, and the street lines n, the crossing time T_0 of each road can easily be computed by $T_0 = \frac{L}{v_0}$. This information together with the number of agents travelling at time $t - \Delta t$ in each edge, allows the estimation of the time evolution of the agent movement taking into account the effects of traffic. As a consequence the agents position is changed iteratively for each time-step, following the rule that each agent can move to the subsequent element of his path if the following conditions are fulfilled. The agent crosses the link in a time $t_{cross} > T_0$ if $N - 1 < C$, where N is the number of vehicles that already crossed the link and if the next link of agent path is not already full. If one of these condition is not satisfied, then the agent remains in his actual link and updates his crossing time t_{cross}. Iterating this simple rules-check over each agent, the system status is updated and the movement of each single agent can be represented.

Agents update

In this phase, performed at the end of each time-step, the agents mobility and energy states are updated. Each agent can assume at the time t, according to his position in the graph at the time $t - \Delta t$, the following mobility state:

- *In movement* to destination – if the agent has not reached the end of his route at the time t;
- *In movement* from destination – if the agent is coming back home and he has not completed his route at the time t;
- *Parked* – if the agent has reached his destination at the time t;

If the agent is an EV user, there is also an update in the energy state, which depends on the agent mobility state at the time $t - \Delta t$. In particular, if the agent is *in movement*, then the energy state E_j^{EV}, is updated as reported in (6.6).

$$E_j^{EV}(t) = E_j^{EV}(t - \Delta t) - P_j(v_0) \cdot T_0 \cdot B_{cross}, \tag{6.6}$$

Where $P(v)$ is the electric power supplied to the vehicle for travelling speed v, and B_{cross} is a logic variable that assumes the value of 1/0 if the vehicle, according to *queue* model, has/has not crossed a link. If the agent is *parked & plugged* to charging station the EV updates his energy state according to (6.7).

$$E_j^{EV}(t) = E_j^{EV}(t - \Delta t) + P_j^{charge} \cdot \Delta t, \tag{6.7}$$

Where P_j^{charge} is the power provided to the agent's EV by the charging station. If the agent is *parked & no-plugged* the energy state is not updated and $E_j^{EV}(t) = E_j^{EV}(t - \Delta t)$.

6.3.2 Model outputs

For each time-step, the model outputs are: the agents position, the EVs charging state, and the total number of active agents $N(t)$. Moreover, the power provided at each plugged EV can be monitored and recorded. These output data can be aggregated in order to determine the entire charging profiles and the customer satisfaction indexes. In particular, the j-th agent satisfaction index has been defined as the daily energy supplied to the EV, E_j^{sup}, respect to the energy required, E_j^{req}.

$$S_j = \frac{E_j^{sup}}{E_j^{req}} \tag{6.8}$$

In the following the parameters introduced to analyse and to evaluate the performance of the mobility system are reported:

- j-th agent customer satisfaction index defined according to (6.8);
- the traffic situation in the city at each time-step;
- the number of EVs *in movement* ;
- the number of vehicles in each edge of the graph;
- the electric power required by each plugged EV in the city;
- the electric power required at each charging station;
- the number of free and used plugs in each charging station.

In order to limit statistical fluctuations, the entire simulation has been iterated a significant number of times, so that the outputs can be considered representative. The results associated to the city are handled in order to represent them by means of distribution for each time of the day. Furthermore, the time evolution of the following outputs, representing globally the EV mobility in the city is obtained. The total electric power supplied by the charging stations $P^{tot}(t)$ has been used to evaluate in the period of time $t_b - t_a$ the energy provided to supply the EV fleet of the city E_{prov}.

$$E_{prov}(t_a; t_b) = \int_{t_a}^{t_b} P^{tot}(t)dt; \tag{6.9}$$

The average customer satisfaction index of the EV users related to proposed charging strategy is evaluated by means (6.10) where AB is the total number EVs enabled to charge, and N_{AB} is the total number of those vehicles.The average state of charge state of the cluster of EV at the time t is defined according to (6.11)

$$\overline{S} = \frac{\sum_{j \in AB} S_j}{N_{AB}}, \tag{6.10}$$

$$\overline{SOC}(t) = \frac{\sum_j SOC_j(t)}{N_{EV}(t)}. \tag{6.11}$$

Finally, global variables E_{prov}^{tot}, $\overline{S^{tot}}$ and $\overline{SOC^{tot}}$ are obtained, as the temporal means of the previous defined values over the entire day.

6.4 EV Charging Infrastructure Planning

The proposed mobility model has been firstly used to develop a methodology able to determine, on the basis of EV user request, the correct localization in a municipality of the EV charging station and the relative power size and plugs number. In order to achieve this goal a planning procedure has been proposed. The basic idea is to consider an *"ideal case"* in which no constraints in space, time and power occur at EV charge. At the aim of geographically identifying the energy demand, the city has been divided in zone each characterised by an *"ideal aggregator"* able to satisfy all EV plug-in. Under this hypothesis, the EV users are free to move and to park because they are sure to be plugged-in. This condition represents the optimal situation, in terms of charging customer satisfaction. Hence, to develop the planning process the dimension of the EV fleet to be served by the proposed infrastructure is firstly defined. Then, in order to evaluate the power needed by the system at each time-step, it has been supposed that the j-th vehicle is supplied with a constant power $P_j(t)$ able to fully charge the battery-pack during the estimated parking time t_j^{leave}

$$P_j(t) = \frac{E_j^{max} - E_j^{EV}(t)}{t_j^{leave} - t} \tag{6.12}$$

This approach joint to the mobility model previously described allows the estimation of the number of vehicles plugged and of the total charging power profile $P_i(t)$ for each time step Δt and for each i-th zone. The statistical analysis of the obtained data per *"ideal aggregator"* allows the identification of the zones characterised by the maximum average number of potential connections and the average power profile required. Sorting the obtained results, it is possible to determine, by means of a Pareto analysis, the trade-off between the number of served city areas and the number of served agents. Subsequently, considering the power profile of each optimal *"ideal aggregator"* and defined the service time $[T_1 \div T_2]$, the optimal power P_i^{opt} and the number of plugs N_i^{opt} can be is estimated by :

$$P_i^{opt} = \frac{\int_{T_1}^{T_2} P_i(t)dt}{T_2 - T_1}; \tag{6.13}$$

$$N_i^{opt} = \frac{\int_t N_i^{plugged}(t)dt}{T_2 - T_1}. \tag{6.14}$$

Finally, considering the parking area and the power grid constraint into the i-th area, it is possible to plan the distribution of the charging stations in terms of rating power and numbers of plugs.

6.5 Charging Strategies

Considering the proposed mobility model and defined a suitable spatial distribution of charging stations for a planned EV fleet, the development of charging strategies in a smart city has been fulfilled. The methodology followed to define them is based on the criteria of maximising the EV user satisfaction index, implementing at the same time a city charging profile that minimizes the global electricity cost.

In order to achieve this purpose a distributed approach has been implemented considering for each i-th area a local aggregator that is able to manage and control the power delivered by each plug of charging station. Obviously, the rated power of the charging station and the constraints of the power system impose a maximum power profile for each i-th area $P_i^{max}(t)$ evaluated referring to the most severe condition. Under this hypothesis, for each time-step Δt, the charging stations of the i-th area cannot provide more power than that expected, evaluated as average by the mobility model in the most severe condition. Using this assumption, two supply profile schemes have been used. The first one is the so-called *"flat profile"*, in which $P_i^{max}(t) = P_i^{opt}$. This profile ensures the maximum customer satisfaction, because allows the supplying of the entire energy required in the *"ideal"* maximum case determined in planning study. In fact the modulation of charging power of each plug-in vehicle allows globally a

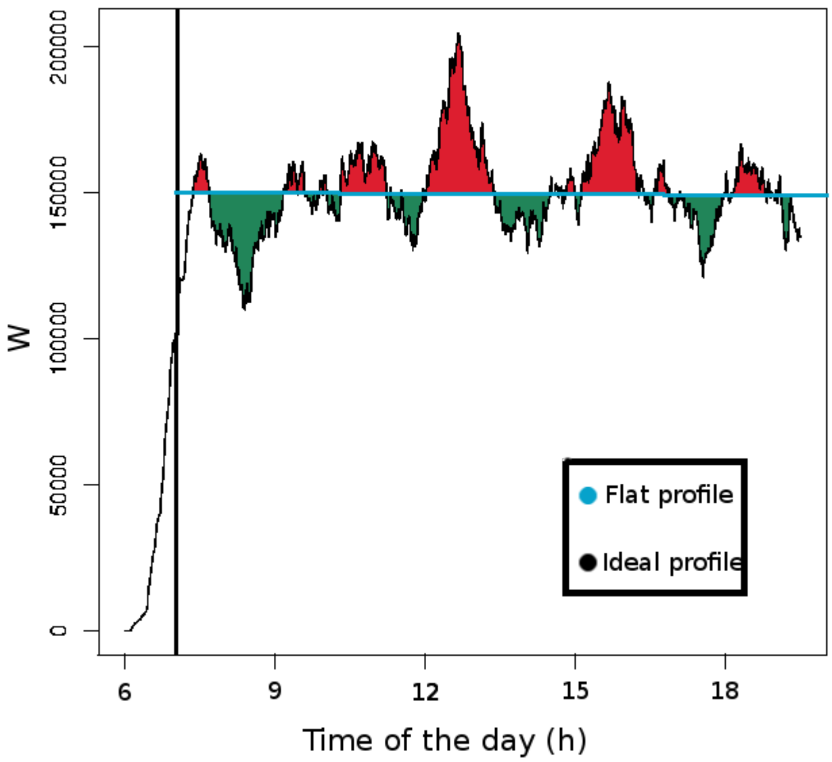

Figure 6.2: Comparison between the *"ideal"* charging profile determined in planning procedure and *"flat"* charging profile with proposed charging strategy in a generic i-th area.

peak shaving and valley filling of the *"ideal"* power $P_i(t)$ required in the i-th zone. In Fig.6.2 is reported the strategy used that is able to *"modulate"* the charging process of each EV so that the power profile in the i-th zone assumes a flat profile, assuring that the energy equivalence between the two profiles. The second one is called *"price-related"* profile. It satisfies the constraint that in each time-step the provided energy must have the same cost E_{cost}. Considering the day-ahead market prices $\alpha(t)$ in each hour of the day, the reference charging profile can be obtained by (6.15).

$$P_i^{max}(t) = \frac{E_{cost}}{\alpha(t)\Delta t} \tag{6.15}$$

In order to define a reference value for energy cost E_{cost}, the minimum value of flat profile cost $min(E_{cost}^{flat}(t))$ has been used. A comparison among the three different profiles is shown in Fig.6.3. The picture highlights a difference in energy supply which causes a reduction in the customer satisfaction index. However, the *"ideal"* charging is generally oversized respect to the average demand. On the basis of this consideration, the proposed smart charging has been developed. In particular, a power modulation of charging process of the single plugged EV is developed, imposing a limitation to the charging station access oriented to maximize the energy service and based on the EV charge conditions. To develop such charging strategy, it is necessary to have in real-time for each charging station the information about the number of EVs plugged and the SOC_j of each plugged-EV in i-th zone and the total amount of power that can be provided globally in the i-th area $P_i^{max}(t)$ and specifically to each j-th plugged EV P_j^{plug}. Using these informations, the j-th charging plug uses a prioritized smart charging strategy based on the assumption that for each time-step the maximum power must be supplied to the plugged vehicles, hence the supply has to be developed according to priority list. The EV priority is obtained as follows:

1. During the plug-in process, each agent decides a priority class between a value of 1, 2 or 3 at which is associated a E_{frac} parameter;
2. At each time-step, the local aggregator sorts the j-th plugged vehicle by a value PI_j defined in (6.16)
3. Following this order, the aggregator starts to provide to each plug a power P_j^{plug} until it reaches his limit power $P_i^{max}(t)$.

$$PI_j = (1 + E_{frac}) \cdot SOC_j; \tag{6.16}$$

The presence of different priority classes gives to each user the possibility to choose the charging service quality. This strategy has the great advantage to avoid the use of forecasted external information, referring only to parameters under his direct control, like the SOC of his plugged vehicles or the total power provided. This ensures a great flexibility.

6.6 Case study

In order to validate the proposed methodology, the mobility model and the EV charging infrastructure planning procedures have been tested in an European city. The municipality chosen

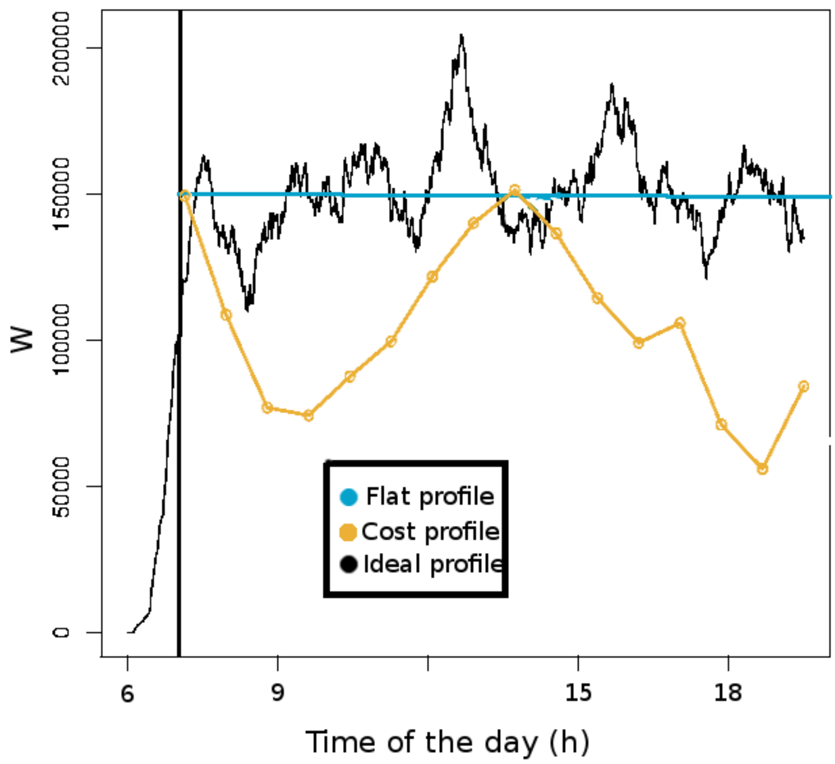

Figure 6.3: A comparison between different profiles: in black the ideal one, in blue the flat one, and in yellow the price-related one. E_{cost} is assumed to be equal to 100% of the minimum flat profile cost.

Figure 6.4: Geographical dataset of Cagliari used to develop the mobility model: the census zones are reported in black and the mobility infrastructure in red). Sub-plot a) shows the entire metropolitan area. Subplot b), c) and d) shows details of suburbs of Cagliari.

as case study is Cagliari, the chief town of Sardinia Region in Italy. It is medium-size city that represents the main attractor of the metropolitan area characterised by 11 neighbour municipalities and by a population of about one half million of habitants. The mobility infrastructure of this metropolitan area is reported in Fig.6.4. The open-street map datasets has allowed the definition of a detailed graph representation of the mobility system. Vehicle behaviours and all the information required for the development of the proposed algorithms are deducted by 2001 Italian census and Cagliari's Urban Mobility Plan (UMP) [29, 48]. The dimension of the municipality daily car flow is reported in Table 6.2. Considering that the number of commuters moving to, from, and into the city at each hour of the day is referred to the census zone of the city, the spatial distribution of Cagliari census zones has been used to geographically split up the municipality, as highlighted in Fig.6.4. Moreover, the UMP provides detailed information about the measured daily average number of vehicles that moves into the municipality at each hour, that can be used for the validation of the mobility model simulation results.

This data-set allows the application of the mobility model and the planning process de-

Table 6.2: Daily Number of cars moving to, from and into the city of Cagliari

	Incoming	Outgoing	Internal
Commuters	2976	11452	29865
Free-flowing	8274	25597	86852

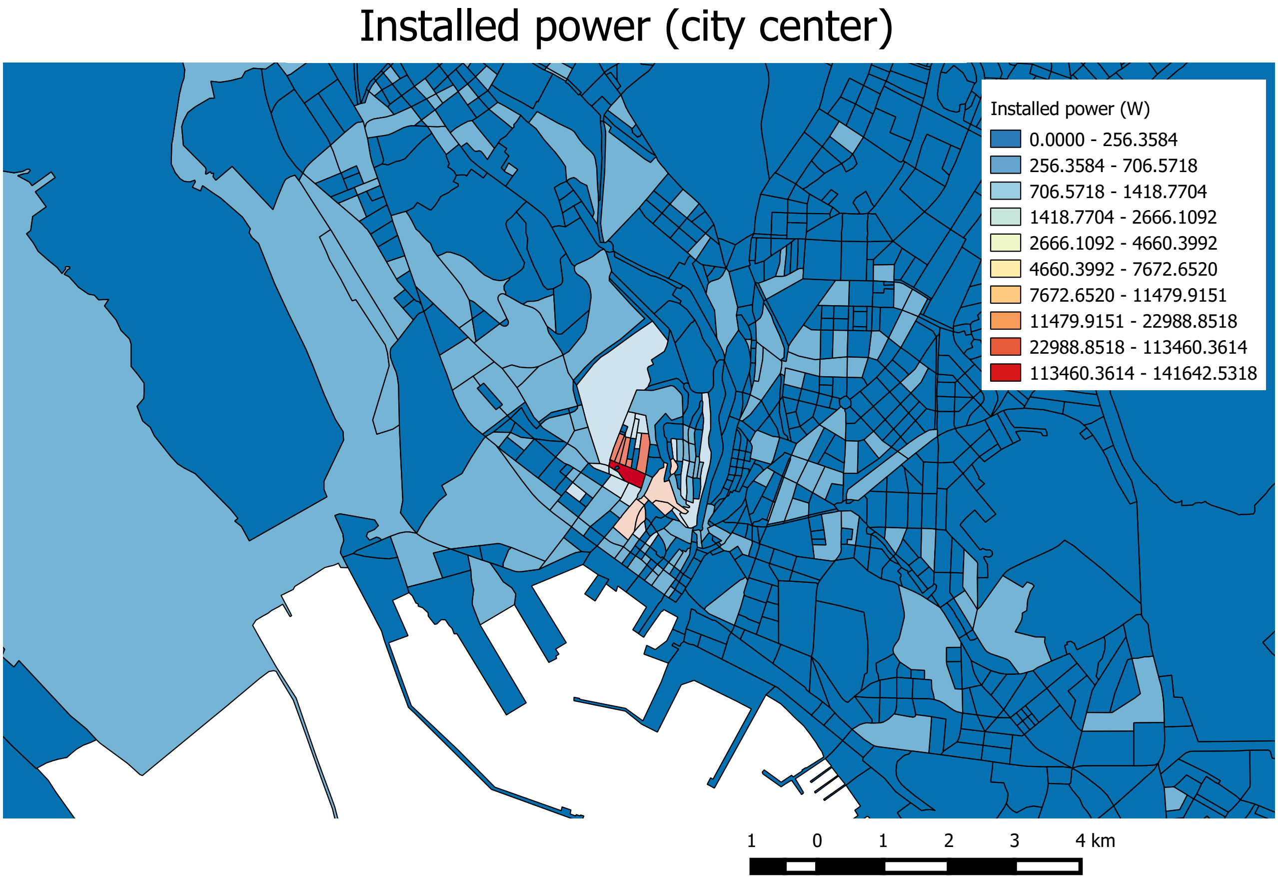

Figure 6.5: The georeferenced distribution of *"ideal"* charging power in the case of study, used for planning procedure in the case of an EV fleet representing the 10% of entire vehicle fleet.

scribed in sections 6.3 and 6.4 respectively. The validation of the mobility model is the first step for the following development of charging infrastructure planning and charging strategy tests. The simulation results of the proposed mobility model are compared with the UMP confirming the worth of the proposed methodology. Subsequently, to develop the EV infrastructure planning a reference dimension of the future city EV fleet has been set. In particular, in the proposed case study, it is defined equal to 10% of entire vehicle fleet of Cagliari. Referring to the planning procedure described in section 6.4, the estimation of the *"ideal"* power and number of plugs of each zone of the city has been computed. Under this hypothesis the simulation outputs highlights that the daily mean value of electric power required by *"ideal"* EV charging infrastructure is equal to $\overline{P} = 1,26MW$, and the mean number of connected EV is $\overline{N} = 1358$. The georeferenced distribution of *"ideal"* charging power, referred to each area of Cagliari, is showed in Fig.6.5. The analysis of the geographic distribution of power, needed to recharge EVs, shows the presence of a limited number of zones characterised by high values of power demand. In particular, the Pareto analysis shows that the 20% of the census zones provides the 81,5% of the total recharging demand.

On the basis of this result the final charging infrastructure has been defined distributing the charging stations just in these areas. The charging infrastructure is defined referring to the commercial rating power available. The stations have been distributed in order to provide *"fast charge"* (rating power 12 kW) and *"slow charge"* (rating power 3 kW) in the proportion, respect to the plugs available, of 10 % 90%, respectively. The number of charging stations are 27 and the number of plugs are 807. The charging system is able to modulate the charging

power in order to perform smart charging strategy.
Defined the charging infrastructure, the entire mobility system of Cagliari, considering an EV fleet representing the 10% of vehicle fleet, has been again simulated with the aim of verifying the effect of the proposed stations distribution on EV demand. In particular, the *"flat profile"* charging strategy without any limitation to the access at the charging infrastructure is considered. The results, reported in Fig.6.6, highlight that the installed power is oversized and the analysis of the customer satisfaction index, reported in the first row of Table 6.3, highlights that the 97% of the EV charging demand has been satisfied and no-stops in the EV, due to the unavailability of charging structure, occurs.

6.6.1 Smart Charging Strategies

The charging strategy proposed in section 6.5 has been tested considering the charging infrastructure previously described. In particular, after the statistical analysis of the mobility results, a reference profile for the city aggregator has been defined for the *"flat"* profile and for the *"price-related"* profile. The charging reference profile is evaluated referring to the rated power *"flat"* profile by means of the introduction of a scaling factor parameter C_{frac} defined as follows:

$$C_{frac} = \frac{E_{cost}}{min(E_{cost}^{flat}(t))} \tag{6.17}$$

In order to manage the access to the charging station avoiding the connection of charged EV, a limit of the state of charge SOC^{lim} is imposed. The results of the proposed charging strategies for one of the possible case of mobility pattens extracted according to the statistical model, reported in section 6.3, are shown in Fig.s 6.7 and 6.8. The global index of performance are reported in Table 6.3. In particular, an utilization energy factor defined as the fraction of energy delivered by the system respect to the forecast one E_{frac} has been introduced. Considering the uncertainty of the EV agent evolution and of the consequent EV electricity demands, it can be stated that in both cases the time evolution of required power is able to well track the reference profile determined one day-ahead by the statistical analysis. The daily error is well synthesised by global parameter E_{frac}. The results reported in Table 6.3 highlight, as expected, that considering *"price-related"* profile the global satisfaction index of EV agents is lower respect to the other profile but the global error in the energy profile definition one-day ahead is very small and the total cost, determined referring to the spot price in the Italian electricity market, is significantly lower than the *"flat"* profile. This makes the *"price-related"* profile a suitable reference in order to develop novel smart charging oriented to maximise the satisfaction index.

6.7 Conclusion

In the present paper an agent based approach, addressed to simulate the behaviour of a Battery Electric Vehicles fleet into a Smart City, is presented. The proposed model is used to plan the charging infrastructure and subsequently to forecast the daily time evolution of EV charging requirements. In order to keep the one day-ahead consumption profile into defined boundaries, a smart charging is proposed and tested on the municipalities of Cagliari in Italy. The simulation

Table 6.3: Comparative Analysis of the charging strategy Results

Profile	$SOC^{lim}(\%)$	$C_{frac}(\%)$	E_{frac}	$\overline{S^{tot}}$	$C((Euro)$
Flat	100	100	81	97	767
Flat	95	80	88	86	613
Cost	95	80	93	68	458

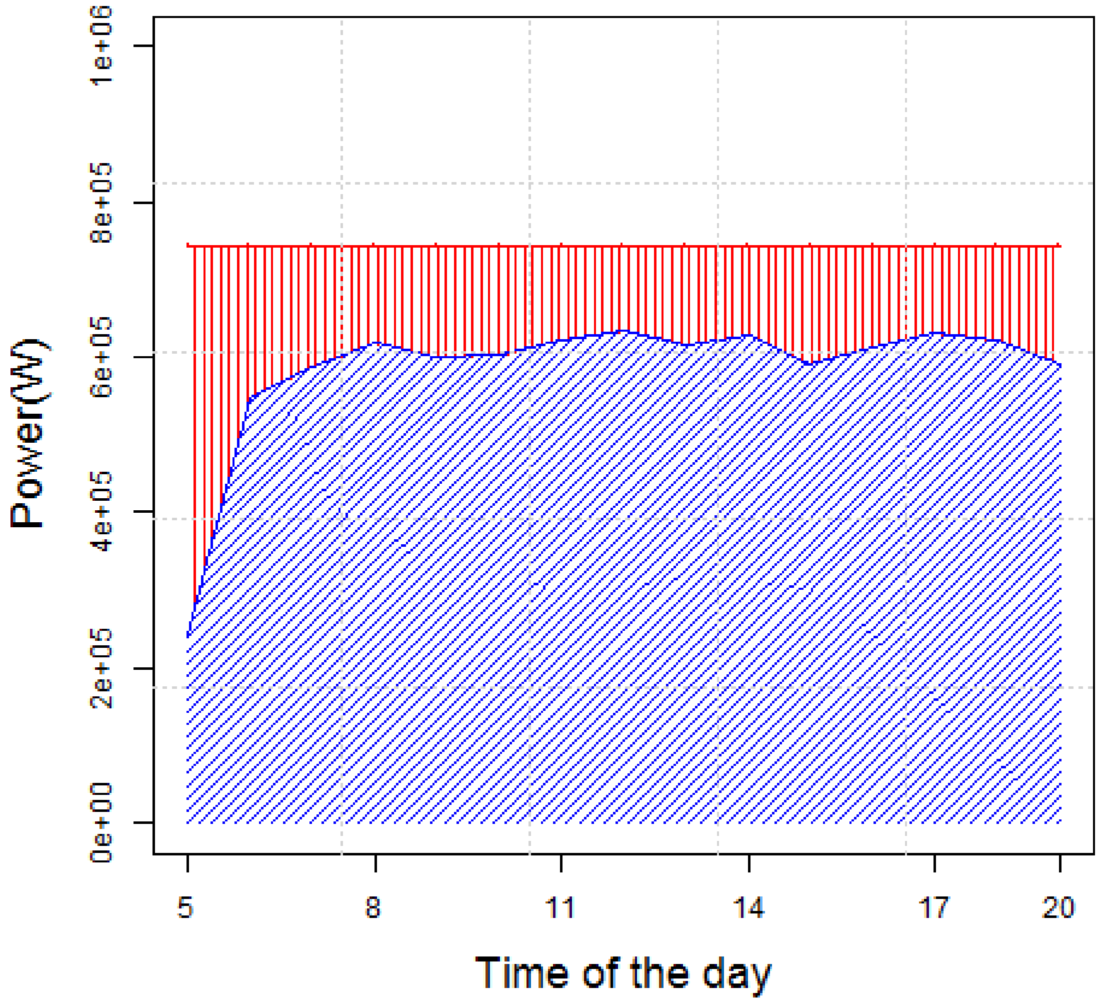

Figure 6.6: Planning validation – comparison between the power available at the charging station and power supplied to EV fleet by the charging stations using the flat profile strategy in one of the mobility condition simulated.

of the proposed methodology has allowed to verify the different behaviour of the same charging infrastructure when different charging strategies are implemented and when the uncertainty of EV mobility behaviour occurs, highlighting the worth and the potentiality of the proposed methodology.

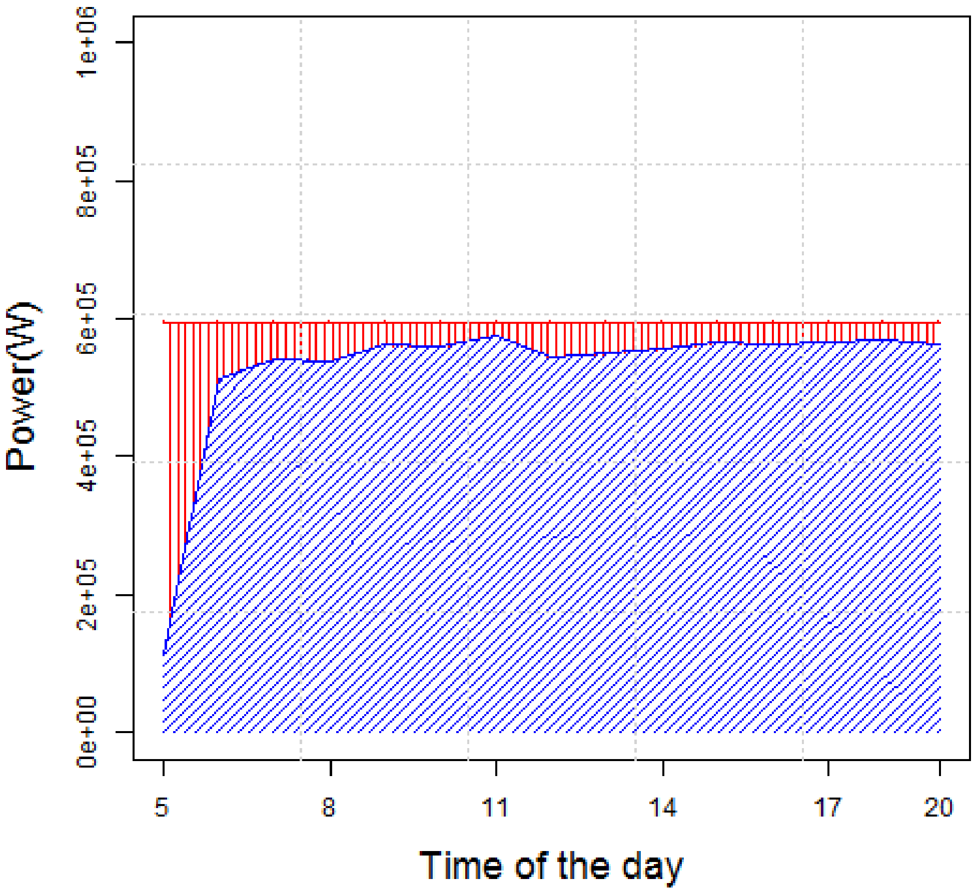

Figure 6.7: Comparison between the flat power reference profile and the provided one by EV charging infrastructure considering of C_{frac} 80%.

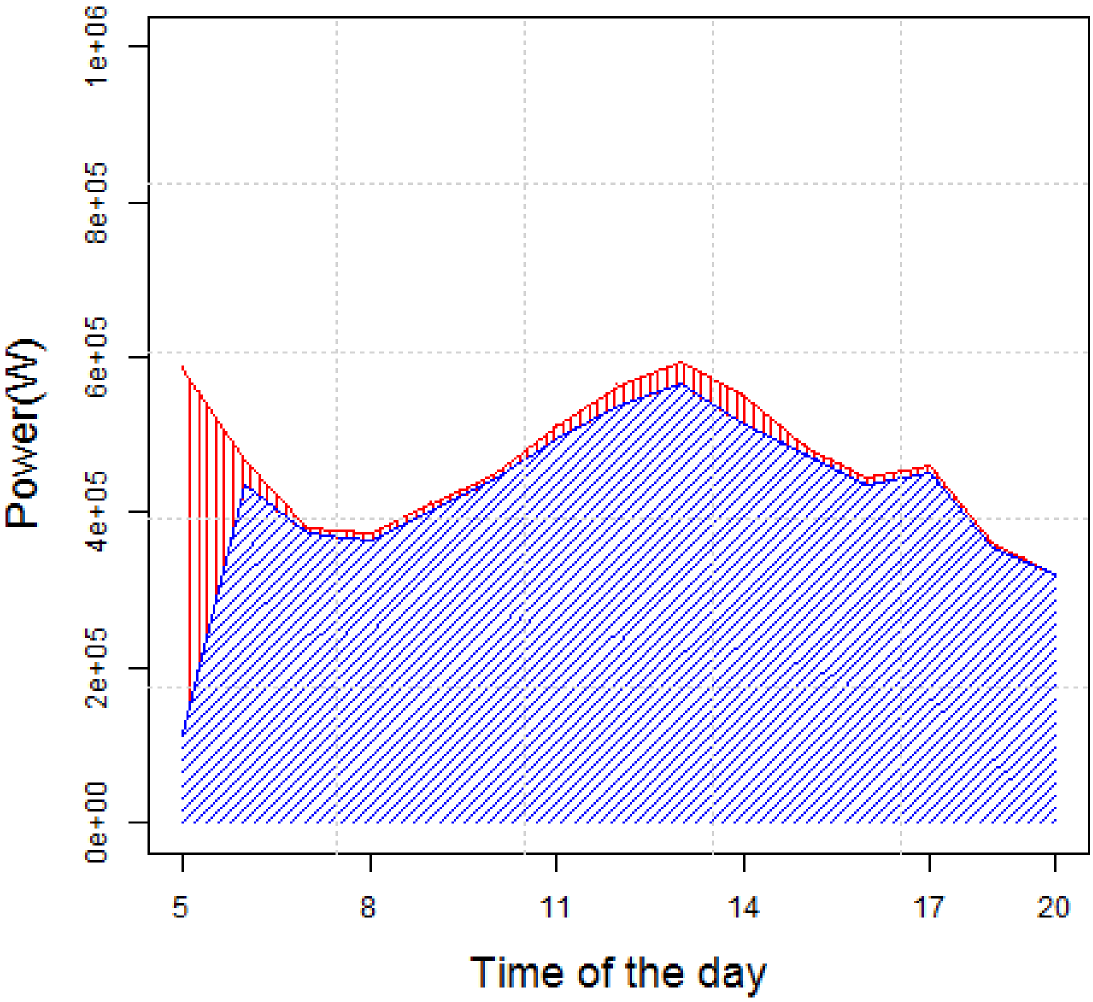

Figure 6.8: Comparison between the *"price-related"* power reference profile and the provided one by EV charging infrastructure considering of C_{frac} 80%.

Conclusions

The great impact of mobility and electricity generation on global CO_2 emission, perceived as the main cause of global warming, is pointing out the need to switch towards more clean and emission-free energy sources. Such issue, together with the increasing efforts required for fossil fuels harvesting and the negative public opinion view towards nuclear power production, has lead to the exploitation of wind and photovoltaic power generation systems as cleaner, easier and reliable energy sources. An increase in energy production by such generation technologies, and in general of all the so-called renewable energy sources (RES) is viewed as a crucial achievement in most industrialized countries.

Despite the great advantages associated to such energy sources, their intrinsic variability in power production badly fits with the highly hierarchical structure and the strictly dispatch rules of actual power systems. For such reason, the actual power transmission and supply infrastructures are not able to properly manage a large-scale integration of RES power generation, and new physical, economic, and engineering models are needed in order to implement features able to manage the impact of such sources on the system.

In this thesis, a new approach based on statistical mechanics methods has been introduced, able to model the effects of RES generation on both physical and economic aspects of power systems infrastructures. Such approach is based on the assumption that systems with high intrinsic variability can not be easily described in a deterministic way. For this reason, three different RES power production fluctuations effects have been evaluated over a numerical sampling of possible states in which the system could evolve: the number of voltage critical nodes on the Polish power grid, the power unbalances in the Italian power system, and the cost associated to their balancing procedure. Such methods and their results are described in two papers, reported in part II. In the first one, **Distributed generation and Resilience in Power Grids** [80], the voltage stability of Polish power system in relation to the amount of installed RES distributed generation is studied. In particular, it has been found that small RES generation facilities distributed all over the system can limit the number of critical effects over the nodes. On the other hand, an increase in the size and number of such generators can produce a great unstability over the entire system. Application of the method has also shown how the use of centrality measures as index for the preferential positioning of such generators can limit their impact on system stability. In the second paper, **Green power grids: how energy from renewable sources affects networks and markets** [64], the global system approach previously described is used for the determination of power unbalances in the Italian power system due to the presence of RES generation. Furthermore, the cost associated to the management of such unbalances has been calculated by means of an agent based modeling of the electricity balancing market, and validated with the real data obtained from the network authority archive.

In addition, in part III the papers **Community core detection in transportation networks** [35] and **An Agent Based Approach for the Development of EV fleet Charging Strategies in Smart Cities** [65] are reported. In such papers, two different mobility infrastructure studies are presented: in the first one, an improvement of Louvain community detection method is used for the identification of mobility infrastructures critical nodes; in the second one, an agent based approach is used to model EV mobility in the metropolitan area of a medium sized city, in order to find the time and spatial evolution of an EV fleet charging needs. Such information has been used to implement and test a planning procedure able to identify the optimal space distribution of charging stations over the system. A successive test phase of such planning procedure has shown a great reliability in the identification of high charging power needs zones. The further development of such methods could lead to a model able to represent the possible interactions among the mobility and the power system infrastructures. One of the most interesting extensions is related to the modelization of the impact of EV charging on the power system; through the analysis of stability effects induced by such distributed power consumption, could be possible to identify critical issues associated to such practice and to propose and test related solutions. Furthermore, the impact of Vehicle to Grid approach (V2G) [32] on power grids stability can be tested. By this approach, charging EVs can be used as distributed storage system over the entire power system, serving as a buffer able to limit the fluctuations in RES power production.

All the proposed studies are based on the simulation and observation of the system from a global point of view, and do not rely on historical data analysis. For such reason, the proposed models can be used for infrastructure planning, allowing to test possible system expansions and regulation changes, in order to understand their possible effects in both physical and economic perspective. Despite the excellent results obtained by such method, is important to point out the limitations introduced by the global statistical description of the system. A common remark associated to such vision is her faultiness in the detailed space and time description of localized phenomena. Such representation is common in stochastic systems; the variability associated to a large number of elements make a detailed description of the system evolution impossible. On the other hand, such approach allows to identify, from a statistical perspective, a vast number of features and phenomena proper of the system, allowing to quantify their impact from a physical and economic point of view. For this reason, the proposed methods can be widely used by both infrastructure management authorities and private companies interested in providing services related to the infrastructure well-behaviour. Moreover, such methodologies can be used for the estimation of possible future scenarios outcomes, improving our knowledge of interacting infrastructures global behaviour, and enhancing the possibilities to switch towards more clean and emission free energy generation in the nearest future.

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