Green Power Grids: How Energy from Renewable Sources Affects Networks and Markets

Mario Mureddu[1,2,3], Guido Caldarelli[2,4,5,6], Alessandro Chessa[2,6], Antonio Scala[4,2,5], Alfonso Damiano[2,7] *

1 Dipartimento di Fisica, Università di Cagliari, Cagliari, Italy, 2 IMT Institute for Advanced Studies, Lucca, Italy, 3 Department of Physics and Earth Sciences, Jacobs University, Bremen, Germany, 4 Istituto dei Sistemi Complessi (ISC), Roma, Italy, 5 London Institute for Mathematical Sciences, London, United Kingdom, 6 Linkalab, Cagliari, Italy, 7 Dipartimento di Ingegneria Elettrica ed Elettronica, Università di Cagliari, Italy

* alfio@diee.unica.it

Abstract

The increasing attention to environmental issues is forcing the implementation of novel energy models based on renewable sources. This is fundamentally changing the configuration of energy management and is introducing new problems that are only partly understood. In particular, renewable energies introduce fluctuations which cause an increased request for *conventional* energy sources to balance energy requests at short notice. 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 for the forecast of short time fluctuations related to renewable sources in order to estimate their effects on the electricity market. To account for the inter-dependencies in the energy market and the physical power dispatch network, we use a statistical mechanics approach to sample stochastic perturbations in the power system and an agent based approach for the prediction of the market players' behavior. Our model is data-driven; it builds on one-day-ahead real market transactions in order to train agents' behaviour and allows us to deduce the market share of different energy sources. We benchmarked 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 [1, 2]. This new awareness is contributing to the development of a novel approach in energy planning, based on the rational use of local resources [3]. 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 [4]. Moreover, the recent emphasis on sustainability, also related to climate-change policies, requires a fast development in the use of renewable

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resources in local energy systems. This determines a fast growth of distributed generation and co-generation, there has not been a corresponding fast upgrade of the electricity infrastructure. This inhomogeneous evolution of the different components of power systems is the consequence of the present structure of the electricity network, which, being characterised by strict dispatching and planning rules, hardly fits with the increasing demand for flexibility connected to the distributed generation [5].

Such a 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) [6–8]. In fact, due to their non-programmable characteristics and widespread geographic distribution, the development of RES-based distributed generation is undermining the technical and economic models on which the electricity system are currently based. 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 example of such problems comes from the analysis of the effects of policy of the subsidies 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 amplification 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 [9], it constitutes a crucial advantage in emissions trading. Generators based on renewable sources have an intrinsic high level of 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 such as difficulties in voltage controlling [10] or unforeseen blackouts [11] and eventually causes a significant error in the power flow forecasting, which can give rise to extreme results in the energy market, such as very high prices or null/negative selling price. 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.

Current 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) [12]. Almost all the simulation approaches for the electricity market are either based on stochastic [13, 14] or on game theoretical [15] studies based on past data-series, while few models focus on market equilibrium as obtained from production and transmission constraints [16]. To the best of our knowledge, nobody has 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 us both the forecasting of the balancing market and the singling out of 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: (i) the grid topology; (ii) the type of production per node and (iii) the transmission rules. Our dynamical constraints are the maximum and minimum generation from power stations and their ramp variation

(i.e. how fast the amount of generated energy can be changed); such constraints influence factors like the short term availability of an energy source. The inputs of our model are typical consumer requests and the forecast of geo-related 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 [17]. The agents' behaviour is modelled by a probability distribution for the possible sell/buy actions; such distribution is obtained by a training process using 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 system-security, the Transmission System Operator (TSO) selects the bids to guarantee energy balancing in real time. We model the TSO behaviour by choosing bid combinations according to the TSO's technical requirements and the economic merit order. Our model allows us 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 detailed infrastructure knowledge and to deduce 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 us to understand changes in the market equilibria and behaviour due to the increasing penetration of distributed generation and also to address the question of economic sustainability of specific power plants. As a case study, we present a detailed one-day analysis of the Italian electricity market.

Results

RESs have a fundamental impact on the functioning of the electricity market due to the technical constraints of power systems, which require an instantaneous balance between power production and demand. In fact, the electricity market is structured to guarantee matching between the offers from generators and the bids from consumers at each node of the power network according to an economic merit order [1]. To perform this task, the exchanges starts one day ahead on the basis of daily energy demand forecasting and then successive market sections refine the offers with the aim of both satisfying the balancing conditions 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 [18], game theory for the market phase [15] and stochastic modelling of the market operators' behaviour [13].

On the other hand, few models have been proposed for the last market section [1, 19–21], devoted to assuring the *real-time power reserve*. In fact, ASR allows us to compensate for the unpredictable events and/or the forecasting errors that can occur to 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 of the amount of power needed for network stabilization purposes [1, 19–21], whereas only a few research activities deal with the energy price forecast [13]. 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 forecasting of the balancing market.

In the first phase we use the information about the ODA and ID market to deduce realistic power flow configurations by taking into account the physical constraints of the electricity

grid. We then introduce stochastic variations related to the geographic distribution of power consumption and RES generation; in such a way, we generate a statistical sample of configurations representing realistic and geo-related time patterns of the energy requests/productions to be balanced. In this paper we will consider only the simples stochastic model of variations, i.e. uncorrelated Gaussian fluctuations with zero mean and variances from historical data. 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 for energy security (forecasting energy congestions and/or outages) and for maintaining quality of service. We show in Fig 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 division of the Italian market and panel (c) shows a typical daily time evolution of ODA+ID outcomes with the detailed contribution of each primary energy source. The market zones are used for managing possible congestions occurring in the Italian electricity market.

In the second phase we use such balancing requirements together with the static and the dynamic constraints of conventional power plants to train the agents of the balancing market by optimising their bidding behaviour (see sec.2).

Here 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 these simulations, each agent can place bids, both for positive (upward market) or negative (downward market) balancing needs. This data is produced throughout the day at fixed intervals on a geo-referenced grid; for the Italian balancing market, the bids are accepted each 15 minutes. Typical simulation 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 Fig 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 [22]; the data reported in [22] are averaged for each hour. We have taken the 2011–2012 winter season as a reference period. In the upper panels of Fig 2 we show that the predicted sizes of the downward and upward markets—expressed in term of energy reductions/increases for balancing requirement—match with the time-data series of the reference period. In the lower panels of Fig 2 we show that the predicted prices in the downward and upward markets also match with the time-data series 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 has been possible to forecast the behaviour of the balancing market without using a historical time series analysis but using information coming out from the one-day ahead power system.

A significant result of our approach is the forecast of the detailed contribution of each primary energy source to the downward and upward electricity balancing market. In Fig 3 we show that conventional energy sources contribute in a different manner to the upward and downward market. For example, due to dynamic constraints, carbon power plants' contribution is negligible (due to the limits in the minimum operative power generation, mostly in the
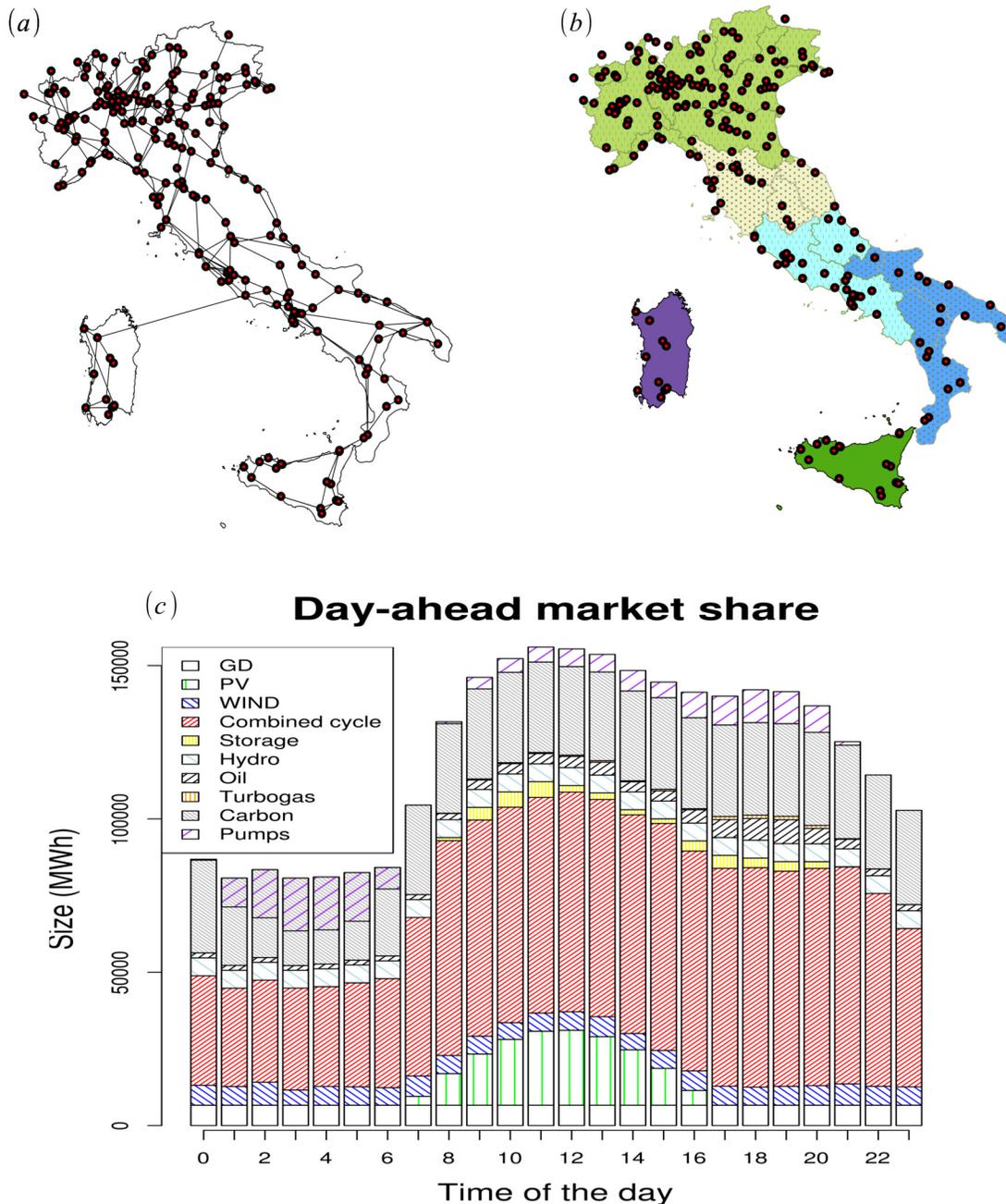
Fig 1. Input elements for evaluating the size of the balancing market (i.e. the short time fluctuations in power generation/demand). In panel (a) we show the electric transmission network in Italy; the topology and the physical characteristics of lines and generators are the constraints that influence 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 (One-Day-Ahead Market + Intraday 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.

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upward market) even if their energy production costs are the lowest. This result highlights the fact that market shares in the balancing market do not depend only on energy costs but stem from an equilibrium between dynamic response, energy costs, geographical position and interactions among the different energy sources.

a) Downward sizes

b) Upward sizes

c) Downward prices

d) Upward prices
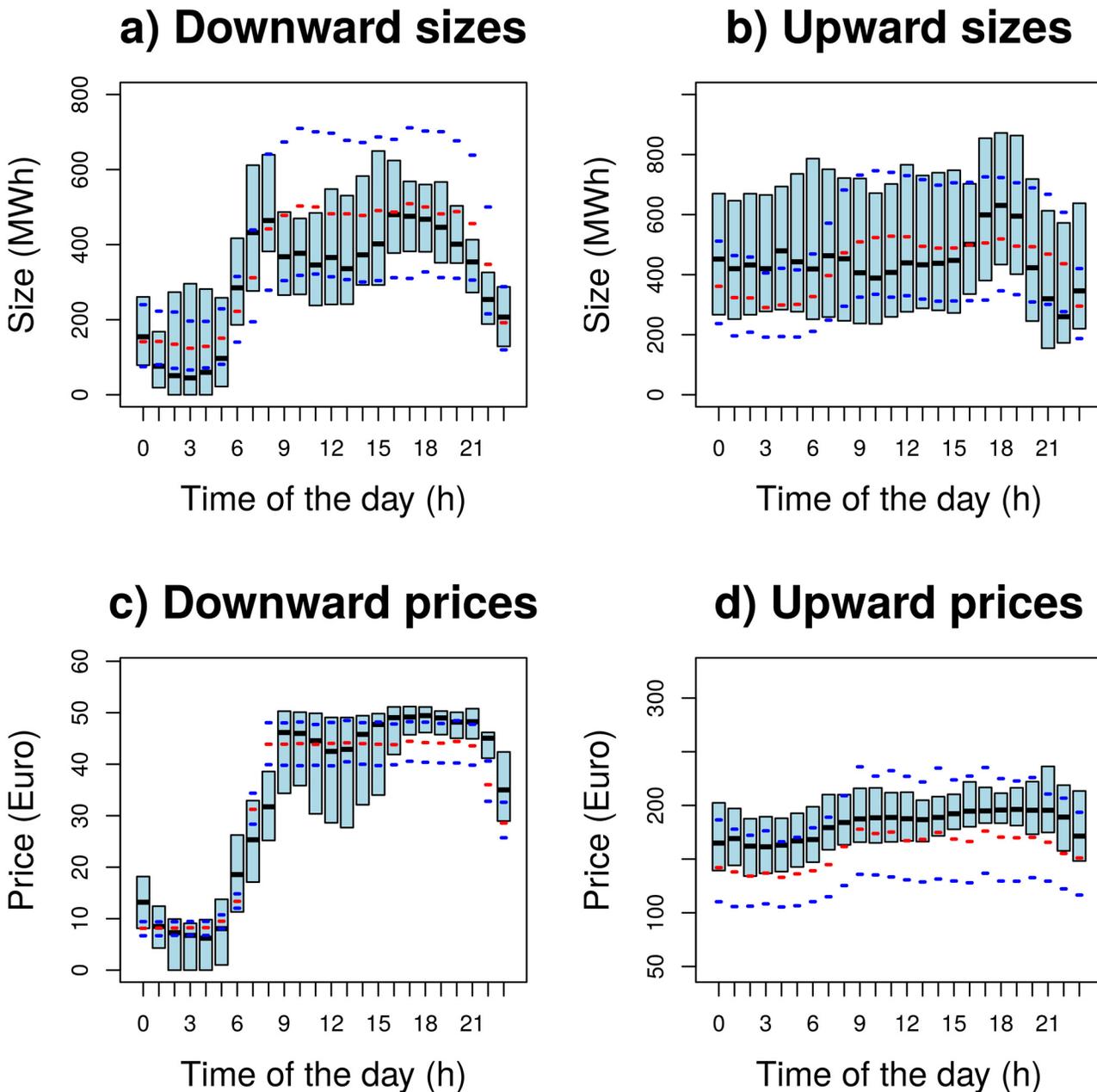
Fig 2. Comparison among the results of our model and the real balancing market. Upper left panel (a): Sizes of the downward market. Upper right panel (b): Sizes in the upwnward market. Bottom left panel (c): Prices of the downward market. Bottom right panel (d): Prices in the upwnward market. Notice 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 1st – 3rd 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 1st to the 3rd 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.

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1 Conclusions

The use of renewable energy sources is creating a new energy market where it is of the utmost importance to be in condition to anticipate trends and needs from users and producers to
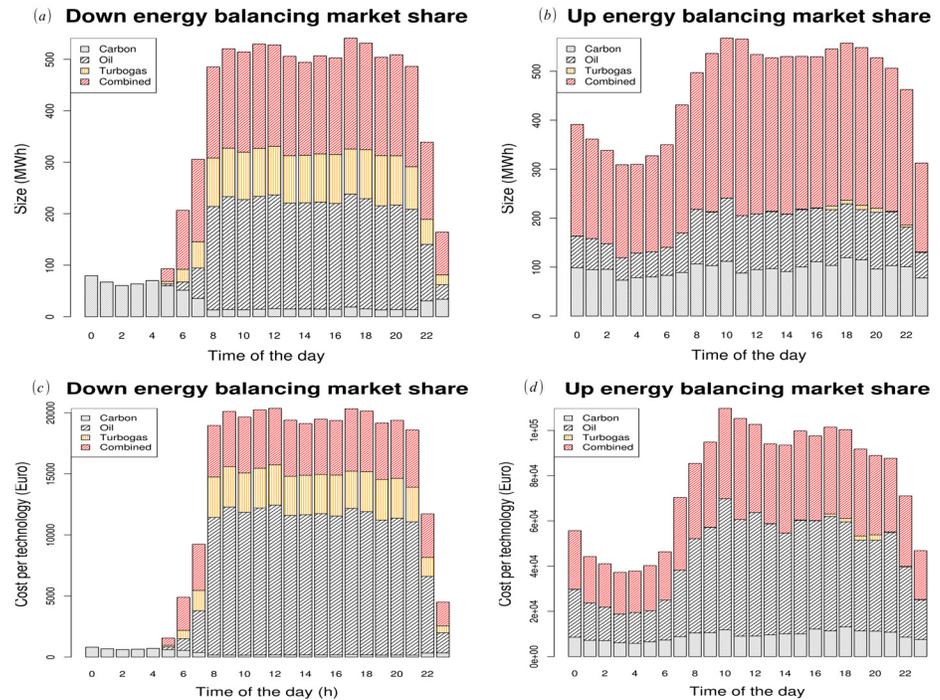
Fig 3. Estimated total energy (upper left panel (a) downward market, upper right panel (b) upward market) and total cost (bottom left panel (c) downward market, bottom right panel (d) upward market) in the balancing market. notice that our model is able to detail the contribution of each conventional 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.

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reduce inefficiencies in energy management and optimize production. The future transformation of the traditional passive distribution network into a pro-active one is requiring the implementation of an energy system where production and power fluctuations can be efficiently managed. In particular, power fluctuations have the strongest impact on markets and on short-time energy-continuity requirements.

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 [13] or ARIMA methodology [18]. Systematic methods to calculate transition probabilities and rewards have also been developed to optimize market clearing strategies [3]; to improve market clearing price prediction, it is possible to employ neural networks [14]. A further step toward and integrated model of (day ahead) market and energy flows has been taken in [20], 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 [1].

Since wind power is possibly the most erratic renewable source, it has been the focus of most investigations into short-time fluctuations. The analysis of possible evolutions in optimal short-term wind energy balancing highlights the needs for managing reserves through changes in market scheduling (higher and more regular) and in introducing stochastic planning methods as opposed to deterministic ones [6]. In [23], 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's 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 in energy and spinning reserve markets with bidding strategies that take into account distributed resources and network constraints have been developed in [21] utilizing complex 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-term market size taking into account the variability of renewable energy generation and customer demands through a stochastic approach. Network and ramping constraints are explicitly taken into account through the AC power-flow model while market price prediction is modelled through an agent-based simulation of energy operators. The inputs of the model are the day-ahead prices and sizes, quantities that are possible to successfully predict [13, 18]. Our approach falls into the class of models of inter-dependent critical infrastructures [24]. We validate our model in the case of the Italian power grid and balancing market; we found that even a simplified stochastic model of production and demand based on uncorrelated Gaussian fluctuations allows us 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 the price determination had never been considered explicitly before our investigation.

In the current phase of transition from a centralised to a distributed generation system, our approach allows us to address the complex task of estimating the additional cost associated with the balancing of renewable energy sources. This evaluation allows us 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 for our model to develop would be a deeper understanding and modelling of fluctuations. In fact, the probability-distribution of fluctuations in energy production has different statistics depending on the renewable type. Moreover, both spatial and temporal correlations among the fluctuations should be taken into account: as an example, weather-influenced fluctuations—like the ones from wind and solar generators—display naturally a cross correlation among nearby located sources; on the same pacing, the non-instantaneous character of weather variations also induces temporal correlations. 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 for our model would be to address "*what-if*" analysis aimed at understanding how the introduction of new rules and policies affects the market. In fact, it has been shown that regulatory intervention affects—using cash-out arrangements—not only spot price dynamics, but also price volatility (i.e. fluctuations) [25]. Moreover, by predicting power umbalances, 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 systems, for which the deterministic approach has allowed a detailed description of the functioning of the electrical energy system, by virtue of (i) an accurate profile for the management of generation and (ii) a high degree of accuracy in load-prediction, i.e. conditions that are nowadays significantly changed.

2 Methods

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

In previous studies [13, 18], market sizes and the electricity price forecasts have been evaluated by statistical analysis of time-data series. Despite the accuracy of these methods, their formulations did not allow the forecasting of the possible changes in markets caused by a transformation of the system involving market rules and/or infrastructure evolutions (different power grids topology, transmission codes, new or different management of power plants). 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 current 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 [26]) and includes the geo-referenced position of every 220 and 380 kV substations with their electrical characteristics, the geo-referenced position of conventional generators with their power rates and power ramp limits and the electrical characteristics of the power network. The second dataset (from the GME website [22]) reports the detailed time evolution of production/consumption for each 15 minutes of a reference day in the winter period 2011–2012.

Since we aimed to describe the entire electricity balancing market session, we performed 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 forecasting of the balancing market.

In the first phase, the electric state of the power grid is initially perturbed stochastically by adding uncorrelated zero-mean Gaussian fluctuations in order to mimic the variability both in the power production and in the demand. In particular, we employ realistic values of the variances of RES generators and of electricity demand to obtain a realistic set of perturbed physical states of electricity network. To each of these perturbed states, it corresponds an unbalanced power condition. The first phase allows for the statistical forecasting of the size of the balancing market.

In the second phase, the forecast sizes of the balancing market are used in order to train the agents to tune their offer propensities, i.e. their willingness to offer a certain amount of energy at a certain price. These propensities are, in practice, due to the expertise of the operators in understanding market fluctuations and placing bids that enable them to reach the maximum profit. To a further details on the operators' behaviour model, please refer to the supplementary informations.

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 involved around a thousand interconnected nodes dispatching power, around a hundred conventional generators, around a thousand RES generators, and thousands of loads. Each node was subjected to complex physical constraints which had to be modelled adequately in order to ensure a correct description of the system. In addition, global system constraints had to be considered in order to ensure the correct behaviour of the system in terms of the quality of the supply. Moreover, the distributed RES generators and loads which

were aggregated at the corresponding transmission nodes, assumed values of power that fluctuated in time and space. We modelled their power production or consumption in a statistical way, assuming Gaussian-like forecast errors with standard deviations σ_i, which represented the expected power variations at each single node i of the power grid in a given time. The application of an AC power-flow algorithm [27] allowed for the validation of the dynamic and static physical constraints, giving the possible states of the power system. The considered variables associated with 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 was tackled though a statistical mechanics approach; the set of possible states of the system at a defined time was numerically sampled by adding a random value extracted from a Gaussian distribution with zero mean and variance σ_i to the expected power production and consumption at every node i and RES generator of the grid. Each perturbed state was characterised by a different total power production G^{tot} and demand D^{tot}, and their difference $S = G^{tot} - D^{tot}$ was the required balancing power; hence, S was a random variable that represented the market size. To sample the statistics of the market behaviour, we needed a significant number of possible balancing requirements. With this aim, we generated 6000 statistically independent perturbed states for each time interval since such number of sampling is enough to get a sufficient accuracy in our statistics.

In order to model the balancing market, the specific rules on which it is based 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 the supplementary information section. For each perturbed state, an auction is 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) at 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.

Since the bid values are obtained related to the agent k propensities described by a specific probability distribution M_k, agents must be trained to estimate their propensities. To this end, we started from an initial guess $M_k = M^0$ and performed several market sessions in which each agent updated its propensities in order to maximise a profit function as described in detail in the supplementary information 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 markets. Fig 4 shows a flow-chart of the whole simulation procedure. In order to describe the system evolution over time, these distributions have been obtained for each time interval t, obtaining a dynamic distribution of market size and energy price. In order to validate the outcomes of our simulations with the available balancing market outcomes [22], results have been aggregated for each hour of the day.
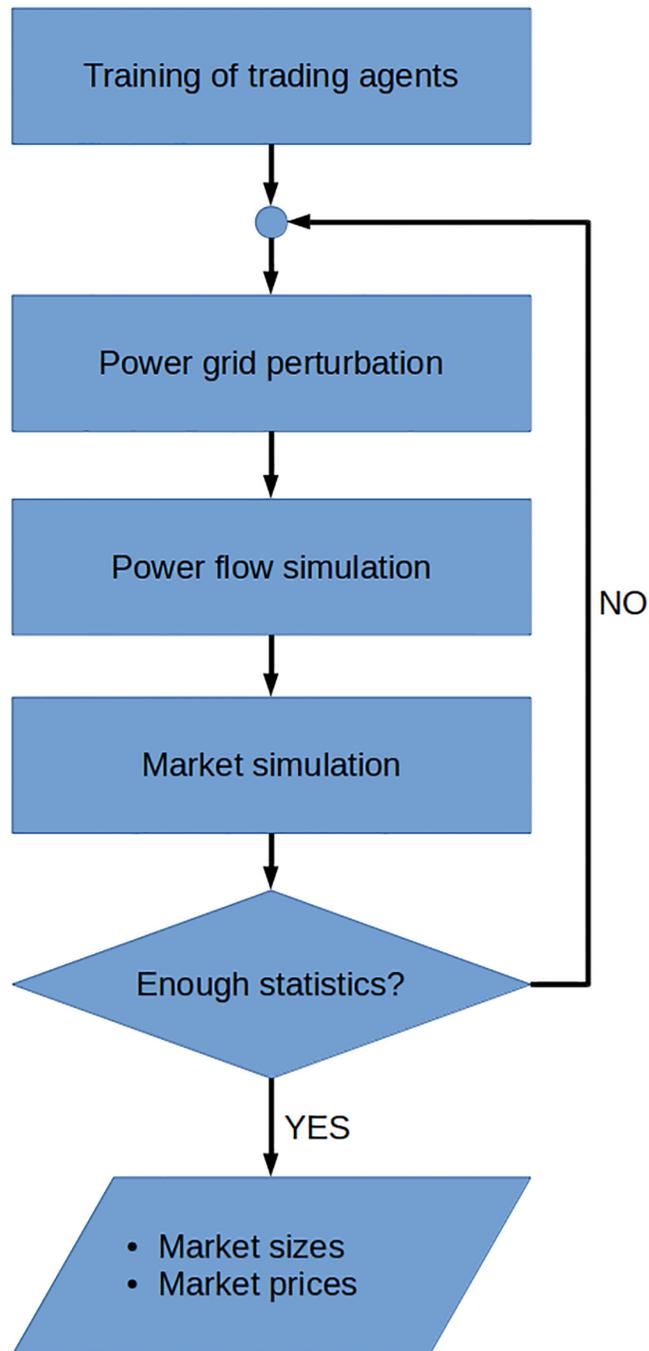
Fig 4. Coarse-grained flow-chart of the simulation procedure for the coupled electric network—electricity market model.

Appendix

The Italian balancing market

The Italian electricity balancing market is a pay-as-bid like market. In such markets, the goods are payed for the amount of money agreed in the placed bid. The BM stage follows the one

day-ahead market (ODA) and intra-day market (IM). In ODA and IM the Market Authority (GME, Electrical Market Authority) decides the amount of energy that each generator must provide to the network, given economic and physical constraints and the forecast power production and consumption of loads and RES generators.

Since there is an the uncertainty associated to power production and consumption, after the ODA and IM market stages there will be a real time market stage, the balancing market (BM), whose target is to balance unpredicted changes in production (or load) that can occur respect to power production and consumption forecasts. In the BM stage, the transmission system operators (TSO) interacts with authorized market operators, i.e. electrical operators (or group of them) that can offer or buy energy. These operators are often represented by a broker, whose job is to submit a bid on the market, specifying the quantity and the price of the energy that the operator plans to sell (or buy) on the BM at each time of the day. After the bidding stage, the TSO communicates to the brokers if their offers are accepted and how much power must be supplied to the system. Normally, there are various market sessions every day (in Italy there are 5 sessions per day, each related to offers spaced by 15 minutes intervals). Power balancing is carried out on a zonal basis. There are 6 zones defined on a geographical basis, as shown on Fig 1(b).

The Italian electricity balancing market is organized in 2 phases:

1. Auction: each broker places an upward and a downward bid for every time interval t_n related to the auction. Every bid is a couple of real numbers (p_{off}, g_{off}), in which the broker specifies the amount of energy g_{off} that the corresponding operator can supply to the system and the associated price p_{off}. When a bid is accepted in the upward market, the operator agrees to provide the energy g_{off} to the system by increasing his production by the same amount; on the downward market, the operator will instead reduce his production by the agreed amount g_{off}.

2. Market: Given the balancing power needs for every time interval t_n, the TSO accepts offers until the system power balance is reached, seeking economic advantage and with the condition that electrical constraints are met.

In S1 Fig we show the time series for the aggregated Italian market sizes and prices.

Agent based simulation of electricity balancing market

We base our agent model on the Roth-Erev algorithm [28]; such kind of algorithms have already been applied for simulating the Italian ODA electricity market [29]. 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 [30]. 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 $q^i = s^i / \Sigma_i s^i$.

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:

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

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

$$E_i(t) = \begin{cases} (p_{off} - C_{prod}) \cdot g_{off} & \text{if bid has been accepted at time } t \\ e \cdot m_i(t-1)/(N-1) & \text{otherwise} \end{cases} \tag{2}$$

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

S2 Fig shows a flow-chart of the market model implementation.

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.

Supporting Information

S1 Fig. Daily values of aggregated market sizes and prices for the reference months.
(TIF)

S2 Fig. Coarse-grained flow-chart of the simulation procedure for the market phase. Notice that the couplings among the electric network and the electricity market must be taken into account during the simulation.
(TIF)

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Author Contributions

Conceived and designed the experiments: AD AS GC. Performed the experiments: MM AC. Analyzed the data: MM. Wrote the paper: AD AS GC MM. Designed the software used in analysis: MM. Retrieved the data: MM.

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