Using Nightlight Remote Sensing Imagery and Twitter Data to Study Power Outages

Gabriella Ferruzzi*
Geoinformatics and Earth Observation Laboratory
Department of Geography and Institute for CyberScience
The Pennsylvania State University
ferruzzi@psu.edu

Guido Cervone
Geoinformatics and Earth Observation Laboratory
Department of Geography and Institute for CyberScience
The Pennsylvania State University
cervone@psu.edu

ABSTRACT

A risk bidding methodology is proposed to help prosumers formulating optimal quantity-price bids for the day-ahead energy market. A prosumer is the manager of a Low Voltage (LV) Micro-Grid (MG), connected to the main electric grid, where generators are paired with renewable energy sources (RES). To present the optimal bidding in the wholesale electricity market, the prosumers need to resolve a short-term management problem and need to identify all influencing variables (i.e. energy exchange, internal production, level of storage, Photovoltaic power plants (PV)). They also have to take into account the uncertainty in RES energy production to evaluate different risks associated with their tolerance preferences. A heterogenous MG which pairs traditional thermal and electrical generators with a PV power production is simulated. An economic model based on genetic algorithms is proposed to formulate the optimal bidding. Although in literature it is possible to find similar decision support models, one of the main original contributions of this work is to estimate the RES input of the proposed model with Analogs Ensemble (AnEn) approach, which is used here to provide day-ahead PV energy forecasting. The results of the model are analyzed evaluating the risk associated with the different prosumer's choices by the expected utility theory. The analyzed case study uses on residential MG and different prosumer risk tolerances (adverse, neutral and incline). Results are shown to demonstrate the effectiveness of the proposed methodology.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Database Applications—*data mining, spatial databases and GIS.*

*Corresponding Author

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General Terms

Management, Human Factors, Verification.

Keywords

Micro-Grids, Forecasting, Energy Market, Optimization Model, Risk Management, Analogs Ensemble.

1. INTRODUCTION

Recently power systems have been undergoing radical changes to satisfy an increasing energy demand. The Micro-Grids (MGs) concept is one of the proposed solutions to cope with these new challenges. It is based on a cluster of time-varying loads and Distributed Energy Sources (DERs), a portion of which includes renewable energy sources (RES). MGs operate as single controllable system that provide power, and optionally heat, allowing bidirectional power flow to and from the main Medium Voltage (MV) power grid [37, 36, 20, 28, 11, 5].

Several investigators have analyzed the role played by these new power systems into the deregulated electricity market, their contribution to energy price reduction and increase reliability of the system, an their impact on the best strategy devising to minimize operating cost [31, 15, 39]. A prosumer is the manager of a Low Voltage (LV) Micro-Grid (MG), connected to the main electric grid, where generators are paired with renewable energy sources (RES).This study presents [38, 41].

One of the main innovations of this work is the use of an Analog Ensemble (AnEn) approach to quantify the uncertainty associated with the electricity production from RES [7, 2]. AnEn uses a single deterministic meteorological forecast, and a historical series of past forecasts and associated energy production, to generate PV power probabilistic predictions. It selects the historical forecasts most similar to the current prediction, and generates probabilistic forecasts of power produced by aggregating the observed historical energy productions associated with the selected historical forecasts. The main advantages of the AnEn method are its ability to provide reliable and bias-calibrated forecasts, and its computationally scalable algorithm that is well suited for parallel processing.

While it is possible to generate a justifiable measure of uncertainty through various methods, using it to make decisions and participate in a deregulated energy market is an open area of research [1]. Basing decisions on a reliable quantification of uncertainty can lead to energy bids that can maximize profits and minimize losses. Moreover, the prosumer can play a crucial role to adjust the elastic demand of consumers that are not able to adjust their demand to varying energy prices.In this work only the uncertainty associated with the RES power generation is considered.

After a description of the methodology applied (Section 2), in which the current deregulated electricity market system and its rules are mentioned, the paper is articulated as follow. In Section 3 the optimal bidding model is shown and discussed; in Section 4 a case study is implemented. In it, the operation of a MG consisting in a PV system and six different power plants, is analyzed. It is assumed that the MG works in grid-connected mode and that the electrical loads and prices are known. The proposed methodology is implemented in MATLAB, and numerical results show the feasibility and the effectiveness of the proposed approach.

2. METHODOLOGY

A classic scheduling problem can be divided it into three sequential, interrelated sub-problems: Economic Dispatch (ED), Unit Commitment (UC) [42, 30, 33], and Optimal Power Flow (OPF) [24, 4, 10]. The proposed methodology focuses on solving the first sub-problem (ED) and it consists in the development of a bidding algorithm for MGs (Figure 1).

To determine the bidding, the first sub-problem is solved for a set of price profiles, ranging between a minimum and a maximum. Assuming price and load demands are known using historical data, the prosumer defines the optimal hourly bidding strategy, the interchange with the LV distribution network, the production of each DER unit, and the amount of energy charged/discharged from the storage units, when present [40, 35, 29, 17, 6].

The proposed approach is organized in the following steps. First the uncertainty of PV energy production is estimated being the main limiting factor for the participation of a MG in the day-ahead market [3]. The AnEn methodology is used to estimate this uncertainty. Ensemble prediction systems in general represent discrete samples of a finite number of the forecast probability density function (pdf). Probability forecasts may be generated by assuming the distribution of ensemble members predicting an event as an estimate of the probability of that event occurring. The risk associated with the uncertainty of variable power production is then analyzed to understand the potential impact of different sub-optimal choices. There are different ways to evaluate the risk associated with a decision [21]. In this work expected utility theory is used [18, 27]. This theory evaluates the choices privileging outcomes with the highest expected utility rather than with the highest expected value.

The expected utility theory takes into account the attitude of individuals with regard to risk (aversion, neutrality or propensity to the risk) to make decisions that minimize negative returns [22]. According to this approach, for each possible outcome x a certain value is assigned on the basis of the individual's utility function $u(x)$. The expected utility is obtained as the average weighted utilities associated with each possible outcome, where each weight is determined by the respective outcome probability. The final step is to use the results from the previous two steps to determine the optimal bids to present in the day-ahead market [25, 32, 16, 26, 23]. Depending on the rules of the market, each offer may consist of a generic curve or of a price-quantity pair [12].

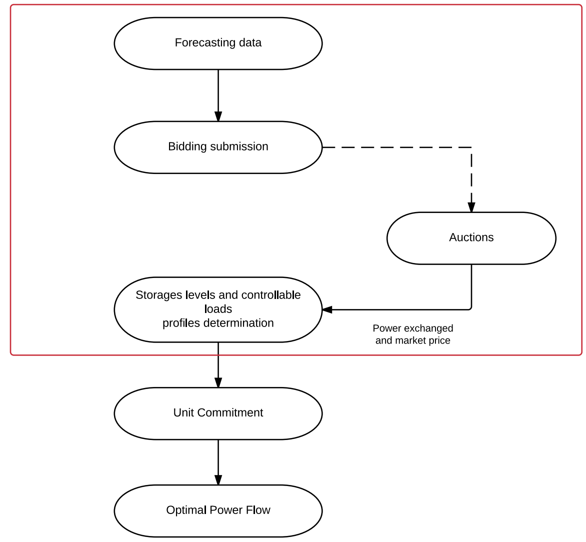

Figure 1: Temporal sequence of the short-term determinations

It is worth noting that the bids may be unique (only a certain quantity at a certain price) or multiple (more price-quantity pairs). Therefore, multiple bids are characterized by a series of steps that identify a bidding curve that is piecewise constant, monotonically non-decreasing or non-increasing, depending on whether they are offers to buy or to sell, respectively (Figure 2). The maximum number of price-quantity offers is defined by the rules of the market. For example, in Spain, 25 pairs can be offered, whereas only four can be offered in Italy.

3. THE OPTIMAL BIDDING MODEL

Let Ω_C be the set of CHP plants, Ω_B be the set of heat production plants, and Ω_G be the set of power plants that only produce electricity, and $\Omega_{D_{th}}$ and Ω_{D_e} be the sets of total thermal and electrical loads, respectively. $P_{Ce_{t,j}}$ indicates the power of the j^{th} unit of CHP generation production at the t^{th} hour; $P_{G_{t,j}}$ is the power of the j^{th} unit of only electricity production at the t^{th} hour and $P_{B_{t,j}}$ is the thermal power of the j^{th} heat production at the t^{th} hour; P_{grid_t} is the power interchange with the MV distribution network at the t^{th} hour. The latter is assumed positive if is bought from the utility grid and negative if is sold to the utility grid. Finally, ${\rho_t}^e$ is the energy price at the t^{th} hour, which is assumed equal for both buying and selling. Then, the optimization problem consists of minimizing the

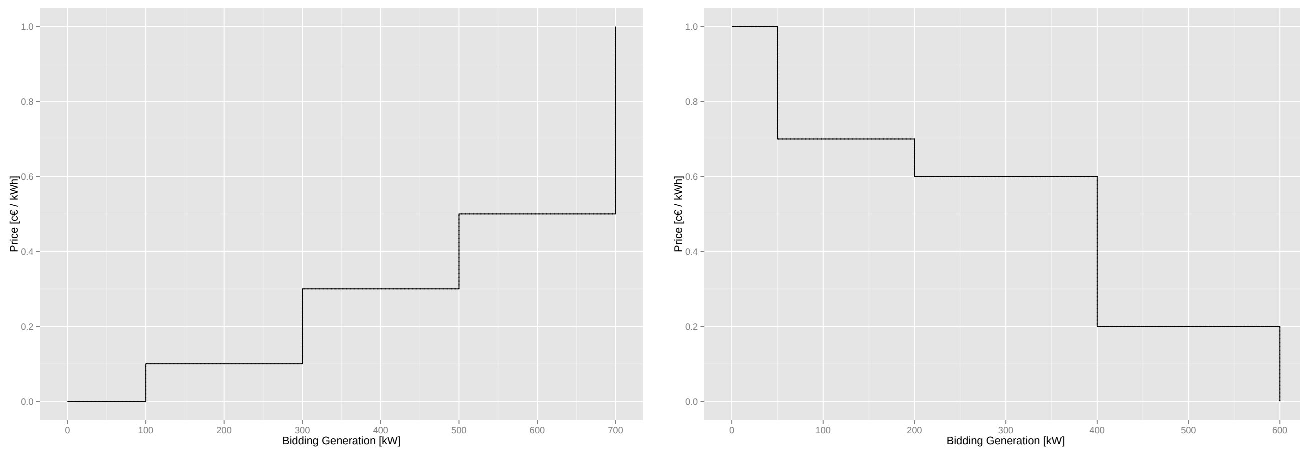

Figure 2: Multiple quantity-price bidding strategy for a MG when selling electricity (left) and when buying electricity (right).

following function under a set of technical and operational constraints:

$$\sum_{t=1}^{24}\left\{\left[\sum_{j\in\Omega_C} C_{C_j}\left(P_{C_{e_{t,j}}}\right)+\sum_{j\in\Omega_B} C_{B_j}\left(P_{B_{t,j}}\right)+\right]\right. \sum_{j\in\Omega_G} C_{G_j}\left(P_{G_{t,j}}\right)+\rho_t^e P_{grid_t}+\left.\sum_{p=1}^{20}\xi\rho_t^e(x_t-\bar{x_t^p})\right\} \qquad (1)$$

where ξ is a weight that takes into account the case in which the difference $(x_t-\bar{x_t^p})$ is positive (over production) or negative (under production), which is only caused by PV systems. The last term of the Equation (1) represents the difference between the expected value of the power produced by PV plants and the probabilistic value of the analogs. The variability, associated with the non deterministic production from PV sources, introduces non-linearities in the model. The optimization problem shown in Equation (1) is solved using an evolutionary algorithm [13].

$$\xi=\begin{cases} g_{up}(x_t-\bar{x_t^p}), & \text{if } x>\bar{x_t^p}. \\ g_{down}(x_t-\bar{x_t^p}), & \text{if } x<\bar{x_t^p}. \end{cases} \qquad (2)$$

The functions g_{up} and g_{down} are built as traditional functions of demand and supply in the market. Lets, moreover, $P_{D_{th_{t,j}}}$ and $P_{D_{e_{t,j}}}$ be the values of j^{th} load, thermal and electric, respectively, at t^{th} hour, having assumed that all of the loads aren not controllable. The energy constraints can thus be expressed as balance constraints:

$$\sum_{j\in\Omega_C}\frac{P_{C_{e_{t,j}}}}{\eta_j}+\sum_{j\in\Omega_B}P_{B_{t,j}}=\sum_{j\in\Omega_{D_{th}}}P_{D_{th_{t,j}}} \qquad t=(1,...,24)$$

$$\sum_{j\in\Omega_C}P_{C_{e_{t,j}}}+\sum_{j\in\Omega_G}P_{G_{t,j}}+P_{grid_t}+PV_t=\sum_{j\in\Omega_{D_e}}P_{D_{e_{t,j}}} \qquad (3)$$

Finally, the following inequality constraints must be considered:

$${P_{C_{e_{t,j}}}}^m\le P_{C_{e_{t,j}}}\le {P_{C_{e_{t,j}}}}^M \qquad (t=1,..,24) \qquad (4)$$

$${P_{B_{t,j}}}^m\le P_{B_{t,j}}\le {P_{B_{t,j}}}^M \qquad (t=1,..,24) \qquad (5)$$

$${P_{G_{t,j}}}^m\le P_{G_{t,j}}\le {P_{G_{t,j}}}^M \qquad (t=1,..,24) \qquad (6)$$

$$-{P_{grid_{t,j}}}^M\le P_{grid_{t,j}}\le {P_{grid_{t,j}}}^M \qquad (t=1,..,24) \qquad (7)$$

4. CASE STUDY

The proposed model is tested on a residential MG [19, 8, 14] with electrical loads characteristic of a summer day (the third Wednesday of June), as shown in Figure 2. The electrical load demand is the aggregate of the loads of six different entities, namely a hotel, a sport center, a hospital, a manufacturing plant, a supermarket, and several offices [43, 44, 34, 9].

To successfully deploy a MG it is necessary to integrate different generation sources. In this simulation there are six thermoelectric units, 2 traditional power plants and 4 cogenerators. There are also a 400-kW PV and an independent boiler for the generation of thermal energy.

Their technical and economic characteristics are reported in Table 1.

Table 1: Technical and economic characteristics of the plants

Power Plant	${P_j}^m$	${P_j}^M$	γ_{G_j}	β_{G_j}	α_{G_j}	
XA: 400 kW	80	400	1054	21.63	0.0005	
XB: 400 kW	80	400	1054	9.87	0.0025	
YA: 60 kW	10	60	800	45.81	0.2222	
YB: 60 kW	10	60	461	51.60	0.1000	
ZA: 180 kW	36	180	892	34.40	0.0021	
ZB: 180 kW	36	180	892	25.78	0.0420	
Boiler	0	4500				63.0

Table 2: Minimum and maximum spot prices and electrical loads averaged over 12 months for a 24 hours period.

Hour	Min Price (€/MWh)	Max Price (€/MWh)	Load (kW)
1	30.7	102.6	440
2	25.7	96.6	440
3	21.4	92.0	440
4	17.3	87.0	440
5	14.9	85.7	440
6	16.6	86.8	740
7	16.1	85.5	1200
8	16.6	145.1	1905
9	26.4	188.8	2345
10	32.7	207.0	2405
11	32.2	207.1	2420
12	29.5	206.5	2440
13	27.2	143.9	2470
14	15.2	121.9	2465
15	12.1	144.5	2450
16	12.8	163.7	2395
17	20.2	186.6	2360
18	36.5	196.6	2335
19	56.9	222.3	1695
20	69.9	211.9	1425
21	64.1	324.2	1295
22	60.0	156.3	955
23	52.0	144.4	530
24	39.1	101.7	425

Spot prices are obtained using historical data for 12 consecutive months of the Italian electricity market [12]. We assume that there are three different prices for each hour (peak, mean and low price). The energy price is one of the input for the simulation, along with the probabilistic forecasts for PV generation. The forecast trends of power generation from the PV system are reported in Figure 3. Each panel shows the boxplots of the forecast for the power generated by the PV system and computed by the AnEn algorithm. It includes three curves resulting from the genetic algorithm optimization, and they quantify the amount of PV electricity included in the price-quantity bidding. The three curves differ depending on the prosumer adversity to risk: solid (high risk), dotted (medium risk) dashed (low risk). The three different risk taking strategies are affected by the energy price.

In Figure 4 the grid exchange (blue curve), the power produced by traditional power plants (green curve),and PV power (red curve) are compared with the electrical load

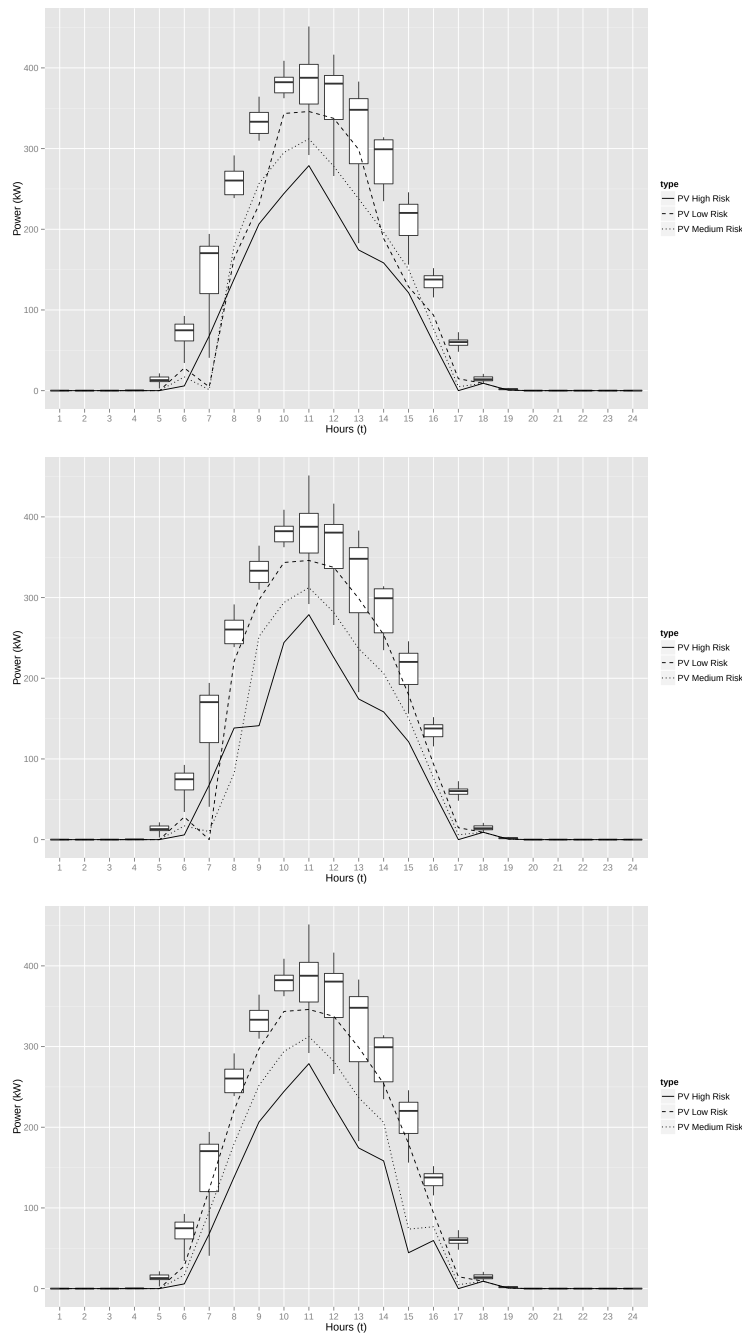

Figure 3: PV power production as a function of risk adversity and price: high (top), medium (center), low (bottom). The boxplots show the AnEn PV power forecasts, and the different curves indicate the quantity of PV electricity included in the bidding depending on the prosumer adversity to risk.

profile (sky blue curve) are reported for difference prices and risk. In fact, the prosumer can change the amount of energy that he needs and the power that he can produce, with the PV system too. The last is function of the risk that he wants to sustain.

Figure **??** shows the total power produced by the different generators in comparison with the load, and that in correspondence of maximum price the traditional power generators work almost always at maximum, while in the case of minimum price, they work at a minimum. In both situations, when the generation exceeds the load, the MG can sell the excess energy to the main electrical grid. On the other hand, if the generation cannot satisfy the load demand, energy is bought from the main electrical grid.

Figure 5 shows that optimal bidding curve at 08h00 for different risk taking strategy of the prosumer. The vertical axis shows the different electricity prices, and the horizontal axis shows the different power produced. Most difference between the three risk taking strategies can be seen for low power values.

The curve of the total optimal production versus the spot price coincides with the curve of the equivalent marginal cost of production. This curve is obtained by summing for the same price the marginal costs of the various units. For each point of the bidding curve, the value of power offered is equal to the difference between the total electrical load requested and the total electrical power produced within the MG. The hourly power offered in the day-ahead energy market coincides with the power exchanged with the LV distribution network, in correspondence to a specific market price. The choice of the offer points must be made in such a way that the hourly power exchanged is derived from the marketâĂŹs outcomes.

The power corresponding to the vertical segment of the bidding curve is the difference between the load and the maximum production of the generating units compatible with the constraints, including the energy produced by the PV system for the specific hour. Usually, there is another vertical segment of the bidding curve that corresponds to the difference between the load and the minimum production of the generating units, including the energy produced by the PV system. This latter vertical segment appears only at low energy prices. In the presented application, this segment corresponds to prices that are outside the range considered and therefore it is not shown in Figure **??**.

5. CONCLUSIONS

In this paper a risk bidding strategy for the day-ahead energy market is proposed to determine optimal economic choices for the management of a MG. It is assumed that the MG pairs a large number of distributed generators with PV renewable energy resources, and that it is controlled by a prosumer who manages distributed energy sources, storage units, ICT elements, and loads involved in the grid. The prosumer participates to the electricity market and needs to determinate the optimal bidding. Results show that PV energy production can be integrated with optimal results in a residential MG if the prosumer strategy takes into account the uncertainty linked to the energy output.

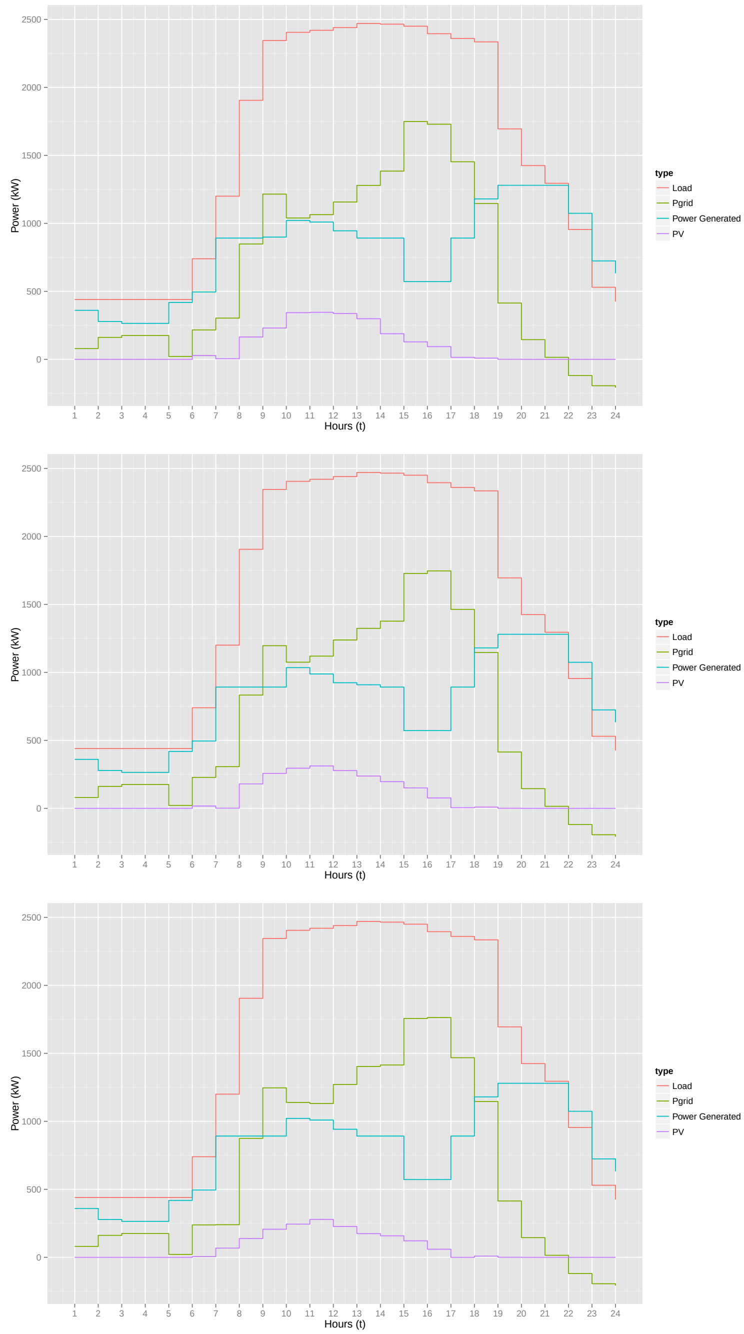

Figure 4: Power production in function of risk adversity and low price: red line (top) is the electricity load, green line (medium) is the power that buy/sell from the MV grid, blue line (bottom) is the power generated. The last line is the total amount of energy produced by PV plants.

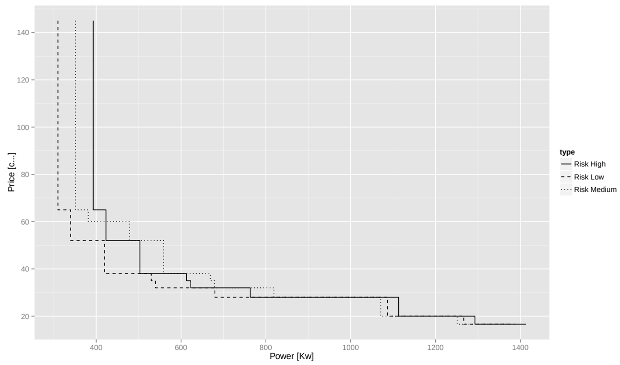

Figure 5: Bidding curve for the 8^{th} hour assuming a prosumer taking high risk (solid), medium risk (dotted), and low risk (dashed).

Furthermore, results show different optimal bids depending on the risk adversity with respect to the uncertainty of PV power production. The proposed methodology shows most improvement during the hours when the price of electricity is high and when the prosumer is inclined to take risks.

The participation of the MG in the ancillary services market was not accounted for because it usually cannot satisfy the requirements of minimum power. This means that, regardless of the market structure, the prosumer must consider the power to be offered in the day-ahead market and the power to offer in the ancillary services market as variables of the problem. However, when there are more microgrid aggregations, and consequently, more prosumer aggregations, the MG participation in this market must be considered.

Further research will focus on the optimal offers to be presented to the ancillary services market, coupled with the energy market issues, since it is clear that the energy market and auxiliary services market cannot be considered separately.

Moreover, the uncertainty of the energy price and electricity load were not objective of this work. Work in progress are focus on the evaluation of the uncertainty related to them.

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