Optimal Scheduling of Virtual Power Plants, a Day Ahead Dispatch Using Stochastic Optimization

Programación óptima de plantas de potencia virtuales, un despacho del día siguiente usando optimización estocástica

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ABSTRACT

This paper presents simple yet accurate stochastic optimization model for day ahead dispatch of theoretical virtual power plants in the context of the Colombian energy market. The resulting mathematical model is convex and hence the global optimum is guaranteed. Performance of the proposed optimization model is tested using real data of solar radiation and spot market prices.

Keywords: Convex optimization, day-ahead, distributed generators, stochastic optimization, Virtual Power Plant.

RESUMEN

Este artículo presenta un modelo de optimización estocástico simple pero preciso para el despacho de plantas de potencia virtuales teóricas en el contexto del mercado energético Colombiano. El modelo matemático resultante es convexo y, por lo tanto, el óptimo global está garantizado. El rendimiento del modelo de optimización propuesto se prueba utilizando datos reales de radiación solar y precios del mercado spot.

Palabras clave: Optimización convexa, Optimización estocástica, planta de potencia virtual, generadores distribuidos.

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I. Introduction

The environmental crisis derived by greenhouse gas emissions and the fuel price volatility have drawn increasing attention over the use of renewable energies [1]. In particular, the energy mix is highly renewable in Colombia [2]. The country relies on large-scale hydro-power complemented by a suitable percentage of thermoelectric which are required to deal with the phenomena of El Niño, a complex weather pattern resulting when temperatures in the Pacific Ocean increases form the norm. Although, it is a natural phenomenon that typically occurs every two to seven years, the 2015-2016 El Niño was particularly intense as consequence of the global warming. The level of the reservoirs decreases to less than 20% and for such reason a diversified energy mix started to be evident [3]. There is a high potential of wind and solar energy in the Country; moreover, this potential increases when El Niño occurs. Hence, wind and solar are complementary to hydroelectricity.

Conventional power systems are characterized by a top-down approach where large and centralized power plants dominate electricity generation [4].

Nowadays, the system is shifting away from this traditional approach in the direction of distributed energy resources which have caught widespread attention because of their renewable, clean, and flexible characteristics to produce environmental friendly energy. It is worthwhile to mention that large photovoltaic power stations could create additional environmental impacts and compromise the use of land in agriculture. Hence, DERs are a preferable technology.

DERs consist on relatively small-size installations with an intermittent power output due to the fact that the primary resource (i.e. solar or wind) is highly variable and uncertain. These features leads a problem at the moment of participating in electricity market for the reason that they should pay a punishment in the case of deviation from their scheduled productions [5]. Additionally the increase share of uncoordinated activity of distributed energy resources over the grid makes some serious problems for system operators in terms of stability, security and reliability [6].

On the other hand all of these working cooperatively are a solution in itself to few problems in the grid, that is the context of the virtual power plant (VPP) which makes possible to integrate renewable energy sources, energy storage systems and controllable loads, into large power systems offering technical and commercial advantages leading to cost reductions and improved controllability.

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A possible solution for these problems is to integrate DERs under the paradigm of Virtual Power Plants (VPPs). In this, a lot of DER owners act as one exchanging power with the electricity grid when the market and environmental conditions are optimal. It is expected that VPPs effectively manage internal DERs and controllable loads to behave like a conventional power plant. Nevertheless, in VPP there are still uncertain factor such as load forecasting error, power fluctuation of renewable energy resources and market prices that make day-ahead dispatch in VPP a complex task.

Different methods have been used in the technical literature to deal with the offering problem of a VPP, on the one hand methods that consider a stochastic programming approach [7] [8] [9] [10], and on the other hand methods that use a robust optimization approach [11] [12]. Reference [7] propose a stochastic bi-level model for a VPP that participates in the day-ahead electricity market, which represents the market-clearing problem and VPP profit. Similarly, in [8] it uses a classical two-stage stochastic programing to tackle the uncertainties and adding the battery degradation costs to the model. Scenario-based stochastic optimization programming is used in [9] [10] which creates a large number of scenarios to model uncertainties. However, the computational load of these methods is significant, especially with high level of uncertainties. Alternatively in [11] uncertainties in market and wind power production of VPP participating in Day-Ahead and real time markets are modeled using confidence bounds through robust optimization approach. Also in [12] is used robust optimization for the formulation of VPP bidding where the uncertain parameters are modeled through uncertainty sets instead the hard to obtain probability distribution on the uncertain data.

In this paper we adopt a stochastic optimization approach for dealing with uncertainties in a day-ahead since these uncertainties are characterized by a distribution that can be sample and due to efficient computational cost of exact solution by convex formulation problem. The main objective of the proposed methodology is to obtain a simple yet suitable model that can be used in a more sophisticated model of VPP that includes operation in real time based on this DER scheduling.

The rest of the paper is organized as follows: In Section **II** a general description of the problem is presented followed by the mathematical model in Section **III**. The case of study is described in Section **IV** as well as numerical simulations. Finally, conclusions and references are shown in Section **V** and section **VI**.

II. Virtual Power Plant Operation

Our VPP is defined as a set of generating units and storage facilities, that are grouped and operated as a single entity with the aim of optimizing the energy resources. Taking into account that distributed energy generators are small and weak in front of market due to capacity and generation fluctuations the VPP proposed in this paper is composed by distributed photovoltaic generator, energy storage devices and diesel power plants as depicted in Figure **1**.

Photovoltaic generators are assumed that they are property of different users but energy storage devices as well as diesel power plants are property by the distribution system operator (DSO) which is in turns the owner of the VPP. The objective is to maximize its profit in day-Ahead deciding when storing, buying or selling energy.

The Colombian electricity market requires an hourly offer of price and capability of generation a day ahead of the operation. As the expected power in the market of the VPP is low (compared to large generators) the final price of the sold energy is given by the spot price (i.e. a stochastic variable). In addition, deviation of the dispatched generation is penalized. Therefore, the VPP operator must take into account this risk in order to avoid penalization or load shedding to its users. In addition, dealing with the offering strategy in the day-ahead market, the VPP has to handle with additional uncertain parameters such as market prices and photovoltaic generation that need to model.

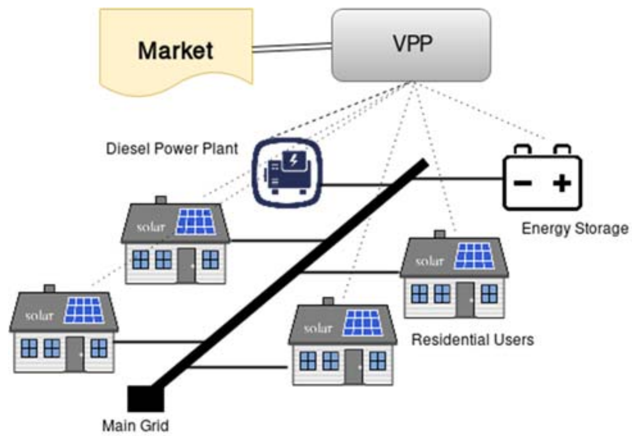

Figure 1. Schematic diagram of a virtual power plant

The behavior of market price variable along time is shown in Figure **2**, from that is possible to assign a normal distribution to market price variable at each hour of day and obtain confidence bounds of variable that is used in the stochastic robust approximation.

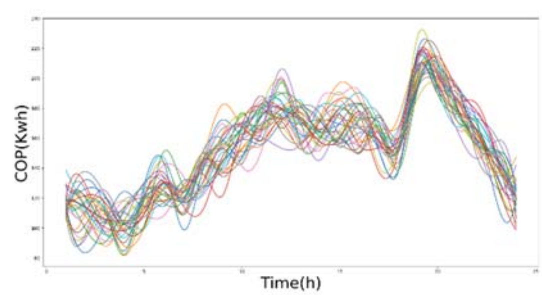

Figure 2. Market prices vs. time for September 2016. Data taken from [13]

Similar to market price variable, the solar radiance parameter used for predict photo-voltaic generation was studied for each hour in Pereira city. Its behavior is depicted in Figure **3** for a particular month, from which is possible assume a normal distribution for photovoltaic generation variable and use it in stochastic approximation.

The convex formulation model of day-ahead through stochastic approximation is a simple and efficient way of solve the dispatch problem and can be easily complemented with a more sophisticated convex formulation model of VPP that includes operation in real time based on this DER scheduling.

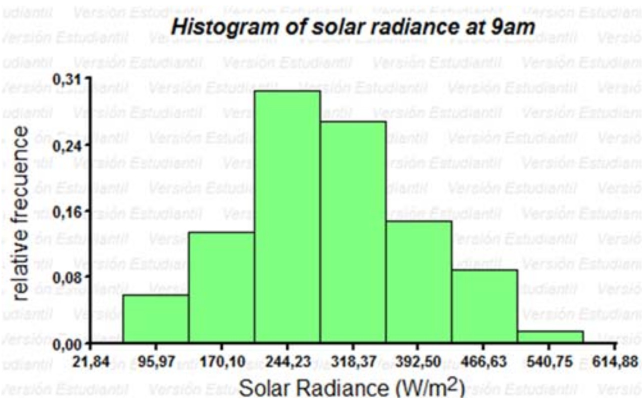

Figure 3. Solar radiation vs. time for September 2016. Data taken from [14]

III. Mathematical Model

In this section, the mathematical notation used are shown first, after that the deterministic model for day-ahead in VPP is described, then the uncertainties treatment through stochastic approximation are explained and finally the stochastic robust approximation mathematical model that include the uncertainties in photovoltaic generation and market prices are defined.

A. Notation

$C_{m(t)}$ Market cost at t time

C_d Diesel costs in litres

C_{dg} Diesel generator cost

Nd Number of diesel power plants

Ns Number of energy storage systems

Npv Number of photovoltaic generators

$P_{vpp(t)}$ Power of VPP at t time

$P_{s(t)}$ Power of storage "s" at t time

$P_{d(t)}$ Power of diesel plant "d" at t time

$P_{pv(t)}$ Power of photovoltaic generator "pv" at t time

Ps_{max} Max power in storage "s"

E_{fixed} Amount of energy fixed at 1 and 24 hour

Pd_{max} Max power of "d" diesel power plant

B. Deterministic model

The problem of determining the optimal offering strategy of virtual power plant in day-ahead market can be modelled as a convex optimization problem as follow:

$$\max_{\theta_t} \sum_{t=1}^{24} \left(C_{m(t)}\, P_{vpp(t)} - C_{dg(t)} \right) \quad (1)$$

Subject to:

$$\sum_{d=1}^{Nd} P_{d(t)} + \sum_{s=1}^{Ns} P_{s(t)} + \sum_{pv=1}^{Npv} P_{pv(t)} = P_{vpp(t)} \quad (2)$$

$$P_{s(t)} = \frac{\Delta E_{s(t)}}{\Delta t} \quad (3)$$

$$\left| P_{s(t)} \right| \leq Ps_{max} \quad (4)$$

$$\Delta E_{s(t)} = E_{s(t-1)} - E_{s(t)} \quad (5)$$

$$E_{s(1)} = E_{s(24)} = E_{fixed} \quad (6)$$

$$0 \leq E_{s(t)} \leq Es_{max} \quad (7)$$

$$0 \leq P_{d(t)} \leq Pd_{max} \quad (8)$$

Where set $\theta_t = \{P_{vpp(t)}, P_{d(t)}, P_{s(t)}, E_{s(t)}, \Delta E_{s(t)}\}$ is composed by the optimization variables of problem.

The equation (1) is the objective function that reflect the maximization of profit, generating the optimal dispatch of all elements in VPP for each hour of day.

Two terms compose the objective function:

1) $C_{m(t)} P_{vpp(t)}$: Describe the incomes achieved if power is sold or cost incurred if power is bought in VPP for its participation in day-ahead market

2) $C_{dg(t)}$: Variable that for simplicity is define as:

$$C_{dg(t)} = C_d * \sum_{d=1}^{Nd} (\alpha_d\, P_{d(t)}^2 + \beta_d P_{d(t)})$$

And describe the production cost of diesel power plants generations at time t.

The constraints of the problem are composed by constraint of power balance in (2), constraint (3) which define batteries power, in (4) limit of these power is defined, constraint (5) define the energy variation in batteries which is used to get power in batteries, constraint (6) impose that the energy stored at the last time period must be at least equal to the energy stored at the beginning of the planning horizon, last constrains (7) and (8) set limit for energy in batteries and power in diesel power plant.

This proposed model is general and additional characteristics can be included, for example if is required that the VPP only sell to market the constraint $P_{vpp(t)} \geq 0$ must be included.

C. Stochastic approximation

As aforementioned, the market price and photovoltaic generation are random variables that can be modeled through stochastic approximation.

1) Market price uncertainty

Based on Figure **2** the uncertainty in cost carried out by market price in objective function can be modeled through a normal distribution for each hour of day, hence with $C_{m(t)} \sim N(\mu_c,\ \sigma_c)$ we can maximize the expected value $\bar{C}_{m(t)}P_{vpp(t)}$ taking into account a risk including the variance of the market price defined as $\gamma\left(\sigma_t\, P_{vpp(t)}\right)^2$. Finally the objective function with stochastic approximation of market prices is as follows:

$$\max_{\theta_{(t)}} \sum_{t=1}^{24} \left[\bar{C}_{m(t)}\, P_{vpp(t)} - \gamma\left(\sigma_t\, P_{vpp(t)}\right)^2 - C_{dg(t)}\right]$$

Where the parameter $\gamma > 0$ is called the **risk-aversion** parameter that can be considered as a penalization factor for cost variance.

2) Photovoltaic generation uncertainty

First of all we rewrite the constraint (2) leaving on the right side the photovoltaic generation and expressing that as an inequality equation:

$$P_{vpp(t)} - \sum_{s=1}^{Ns} P_{s(t)} - \sum_{d=1}^{Nd} P_{d(t)} \ \le\ \sum_{pv=1}^{Npv} P_{pv(t)}$$

For simplicity we rewrite the above equation as:

$$g(x) \le b$$

Similar to market prices, the solar radiance shown in figure 3 can be modeled through a normal distribution for each hour of day therefore the photovoltaic generation caused by solar radiance can be define as $b \sim N(\mu_b,\ \sigma_b)$ and we define the follow probability constraint;

$$Prob(g(x)\ \le b)\ \ge n$$

Where we require that previous constraint should hold with a probability exceeding n and according to probability density function we can obtain $b = \phi(1-n)$ and finally the deterministic constraint can be expressed as:

$$P_{vpp(t)} - \textstyle\sum_{s=1}^{Ns} P_{s(t)} - \sum_{d=1}^{Nd} P_{d(t)}\ \le\ \phi^{-1}(1-n) \qquad (9)$$

Where the parameter *n* is considered as a **confidence level**.

D. *Model with stochastic robust approximation*

$$\max_{\theta_t} \sum_{t=1}^{24} \left[\bar{C}_{m(t)}P_{vpp(t)} - \gamma\left(\sigma_t P_{vpp(t)}\right)^2 - C_{dg(t)}\right] \qquad (10)$$

Subject to:

$$P_{vpp(t)} - \textstyle\sum_{s=1}^{Ns} P_{s(t)} - \sum_{d=1}^{Nd} P_{d(t)}\ \le\ \phi^{-1}(1-n) \qquad (11)$$

$$P_{s(t)} = \frac{\Delta E_{s(t)}}{\Delta t} \qquad (12)$$

$$\left|P_{s(t)}\right|\ \le Ps_{max} \qquad (13)$$

$$\Delta E_{s(t)} = E_{s(t-1)} - E\_s(t) \qquad (14)$$

$$E_{s(1)} = E_{s(24)} = E_{fixed} \qquad (15)$$

$$0\ \le E_{s(t)}\ \le Es_{max} \qquad (16)$$

$$0\ \le P_{d(t)}\ \le Pd_{max} \qquad (17)$$

IV. CASE STUDY

A. *Data*

It is considered a price-taker VPP composed by a diesel power plant, photovoltaic generators and an energy storage system with batteries, the capacities of components are shown in Table **1**. Demand response is not considered in VPP. The Colombian electricity market price was observed at each hour during all days of September of 2016 (see Figure 2) and the parameters of normal distribution at each hour was obtained from data, the same process was developed with solar radiance in Pereira city (see Figure 3). The deterministic model was executed with the mean of market price and photovoltaic generation variables and the stochastic approximation model was executed with few values for risk-aversion parameter γ.

Table 1. Parameters of virtual power plant

Data of VPP	
Maximum batteries Power	50 Kw
Maximum diesel power plant	140 Kw
Diesel cost	$2271.87

B. *Results*

The output of deterministic model is shown in figure **4**. Is important to note the behavior of batteries power which buy energy when the market price is low and sold the energy when the market price is high increasing VPP profit, the diesel plant is not dispatched due to the high cost of diesel for that these figure is not shown.

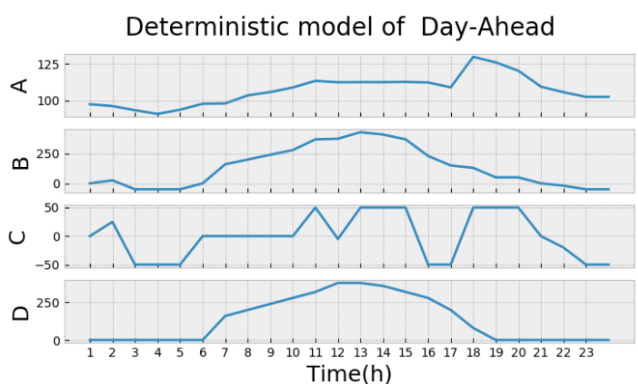

Figure 4. Deterministic outputs where A is the market prices, B is the VPP power, C is the batteries power and D is the photovoltaic generation

In Figure **5** the stochastic robust approximation model output is shown and the profit of VPP is worse than the profit of VPP in deterministic model which is normal, for better understanding of objective function (10) and its behavior is important to say that this is a multi-objective function that can be expressed as:

$$\max_{\theta_t} \sum_{t=1}^{24} [E\left(C_{m(t)}P_{vpp(t)}\right) - \gamma VAR(C_{m(t)}P_{vpp(t)})]$$

Where the first term function is the expected value and the second term function is the variance.

The model will try to maximize *E* and to minimize *VAR*, the behavior of both function is shown in Figure **6** making of the risk-aversion γ a subjective parameter where can be determined following the logic of set it close to zero if the VPP owner can increase the profit regardless of risk or increase γ to be more conservative.

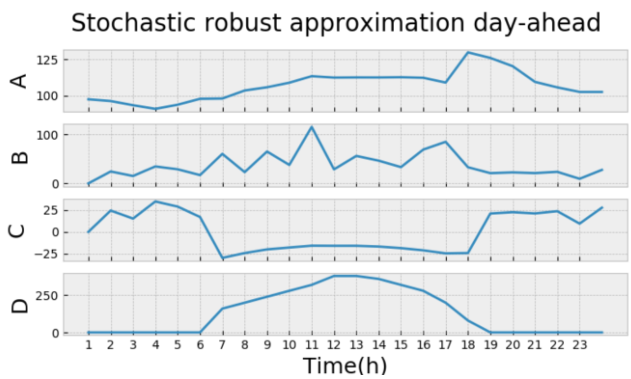

Figure 5. Stochastic robust approximation outputs where A is the market prices, B is the VPP power, C is the batteries power and D is the photovoltaic generation.

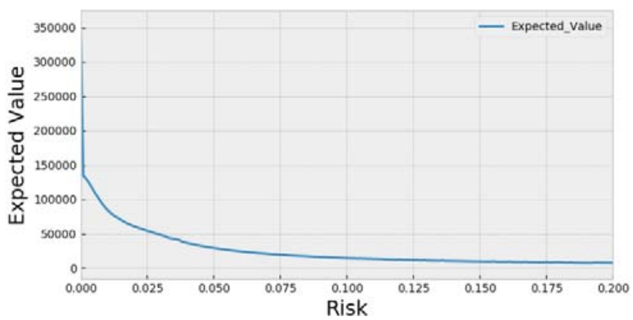

Figure 6. Relationship between the risk-aversion and the expected value

The behavior of n parameter in the stochastic model is shown in Figure **7.** These parameter is used to set the probability of compliance of the power balance constraint (9). It was observed for probabilities between 0.7 and 0.9 where for high probabilities the model is more conservative.

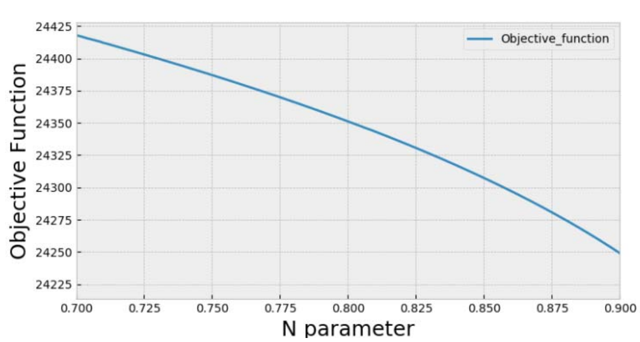

Figure 7. Impact of n parameter of constraint (9) over objective function

V. Conclusions and future works

An optimal day-ahead for a theoretical VPP in Colombian market has been proposed based on convex problem formulation where uncertainties was modeled through stochastic approximation that is convex too, guarantying unique solution that can be reached easily with lower computational cost.

In the stochastic robust approximation model γ is a subjective parameter that represents a penalty to deviation from the expected value therefore the owner of VPP can be set it according its necessities, in a similar way n parameter must be fixed to define the probability with which the power balance constraint holds.

With this day ahead with a time window of one hour is not enough for a real time operation of VPP, more constraints need to be taken into account to avoid deviations from scheduling and to be able to operate in real time. For that reason this work is considered as the first step of a more extensive work which in its first stage does an optimal DER scheduling and in the second stage it adjust the actual power profile with the scheduled in real time through a convex model too.

VI. Acknowledgements

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