

Risk-Based Self-Scheduling of Gencos in Smart Grids considering a New Method for Bilateral Contracts

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Abstract—In this work, the self-scheduling problem of a power producer in smart grids is addressed using a stochastic programming approach. Different uncertainties are considered as price uncertainties, forced-outage of the unit as well as generation reallocation. The conditional value-at-risk index is used for modeling of risk. The markets considered in this study are bilateral contracts, day-ahead and ancillary services, including spinning reserve and regulation, and spot market decisions, while an incomplete competitive market is considered. In this sense, an innovative method for bilateral contracts is proposed to increase the profit of the market without ignoring any regulatory rules. The Monte Carlo method is implemented together with a reduction scenario process to generate scenarios.

Keywords—Self-scheduling; Scenario generation/reduction; Scenario regeneration; Stochastic programming.

I. INTRODUCTION

Due to high intermittency of renewable energy resources in future smart grids, the results of self-scheduling of generation companies (Gencos) are completely influenced by the hourly price forecast [1]. Although, widespread methods considering genetic algorithms [2], and time series [3] are presented to forecast the electricity prices, it is dubious to forecast the electricity prices in a specific hour with zero uncertainty.

In this sense, risk models are used together with price forecasting errors in the self-scheduling problems [4]. In [5], a stochastic self-scheduling framework of Genco is addressed considering the day-ahead electricity markets, energy and reserves, together with the uncertainties of forecasted prices and forced outage of power plants. In [6], a scenario-based stochastic problem background is presented for real-time day-ahead markets with central attention on the operational limits of shiftable demands due to its flexibility features. It described that the presented model may be applied to both demand and supply bids. In [7], a stochastic scheduling of renewable energy resources is proposed considering flexible loads, thermal units, energy storage system, together with environmental and renewable constraints. The time-of-use rates of demand response program are also taken into account, and all the constraints, related with thermal units and energy storage system, are considered under a mixed integer linear programming formulation. Generally, a producer participates in different markets to maximize its profit [8].

The most important concern for participating in different markets is to define the value of power which should be sold in each market [9]. Therefore, it is necessary for a producer to estimate prices before all cleared markets [10]-[12]. Recently, a widespread of different methodologies have been presented using different intelligent methods having high and precise electricity prices forecasting results [13]. Therefore, considering probable scenarios with their probabilities in the stochastic programming may be the best estimation for self-scheduling [14]. In this paper, a Genco with several generating units is considered to take part in bilateral contracts, day-ahead market including, energy market, ancillary service and spot market decisions. So, the Genco should allocate its available power to all these markets in a way that maximizes its profit.

As mentioned above, the proposed strategy requires forecasting results of all markets prices, considering 168 hours for scheduling and enough number of scenarios for each market, turning the analyzed problem in the intractable problem. To overcome the intractability, scenario reduction process is used to facilitate the problem of calculation keeping the new scenario set near to the original scenario set. The performance of the developed framework is investigated using a test model. The attained results confirm the potential of the presented method.

II. SCENARIO REGENERATION

Since the problem is solved by using stochastic programming, scenarios should be generated for different stages. In the present paper, the probability distribution function (PDF) of all individual hour prices including energy price, spinning reserve price and regulation price are constructed from experiences of the system.

Then, it employs the stochastic number of the generation process, spanned in a strategic limit of the price PDF which has a normal distribution behavior. The spot market scenario is also generated by the aforementioned method but PDF of the spot prices is extracted from day-ahead energy market with the same mean value but with higher standard deviation. This results a high number of scenarios and then turns into an intractable problem, therefore, scenario reduction techniques are applied. For this work, a scenario tree is built as shown in Fig. 1.

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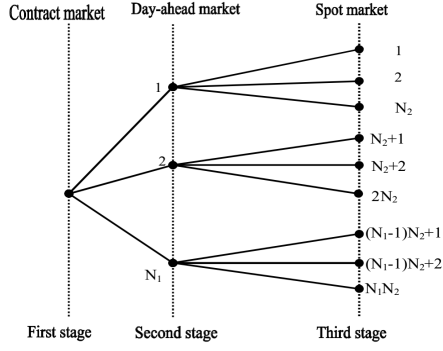


Fig. 1. Scenario-tree example.

The number of first stage scenarios is N_1 , the number of second stage scenarios is N_2 and therefore the total number of scenarios is $N_1 \times N_2$. Then, a reduction process is applied to the stochastic programming considering the lowest distance.

III. PROBLEM FORMULATION

The self-scheduling problem of a price-taker GenCo is discussed in this section. The mathematical formulation of the problem is as following:

$$\text{Maximize: } Inc_1 + Inc_2 + Inc_3 + Inc_4 + Inc_5 - Cost_1 - Cost_2 - Cost_3 + Risk(CVaR) \quad (1)$$

where:

$$Inc_1 = E_w \left\{ \sum_t \sum_c [P_c(t, c, w) \times \lambda_c(t, c, w)] \right\} \quad (2)$$

$$Inc_2 = E_w \left\{ \sum_t P_e(t, w) \times \lambda_e(t, w) \right\} \quad (3)$$

$$Inc_3 = E_w \left\{ \sum_t P_s(t, w) \times \lambda_s(t, w) \right\} \quad (4)$$

$$Inc_4 = E_w \left\{ \sum_t P_r(t, w) \times \lambda_r(t, w) \right\} \quad (5)$$

$$Inc_5 = E_w \left\{ \sum_t \left[P_{del} \times P_s(t, w) + P_{rup} \times P_r(t, w) - P_{rdown} \times P_r(t, w) \right] \lambda_{spot}(t, w) \right\} \quad (6)$$

$$Cost_1 = E_w \left\{ \sum_t \sum_{un} (1 - For(un)) \times C^F(un) \times u(t, un, w) \right\} \quad (7)$$

$$Cost_2 = E_w \left\{ \sum_t \sum_{un} (1 - For(un)) \times c(un) \times \left[P_c(t, un, w) + P_g(t, un, w) + P_{del} \times P_s(t, un, w) + P_{rup} \times P_r(t, w) - P_{rdown} \times P_r(t, w) \right] \right\} \quad (8)$$

$$Cost_3 = E_w \left\{ \sum_t \sum_{un} For(un) \times [P_e(t, un, w) + P_s(t, un, w) + P_r(t, un, w) + P_c(t, un, w)] \times \lambda_{spot}(t, w) \right\} \quad (9)$$

$$Risk = \zeta - \frac{1}{(1 - \alpha)} \sum_{w=1}^{N_w} \pi_w \eta_w \quad (10)$$

The objective function (1) consists five income terms as well as three cost terms. The final term in the objective function represents the risk which is modeled by CVaR. Inc_1 is due to bilateral contract and it is the first stage decision; Inc_2 , Inc_3 and Inc_4 are due to day-ahead market including energy market, spinning reserve and regulation markets, respectively which are the second stage decision; Inc_5 is a probabilistic term which is due to generation reallocation probability for spinning reserve and regulation market.

These incomes may happen at third stage. $Cost_1$ is the fixed cost of unit due to on mode of unit at hour t . $Cost_2$ is the variable cost of units to produce certain power at hour t . $Cost_3$ is due to the forced outage probability. The objective function is maximized subject to the following constraints.

$$P_c(t, un, wi) = P_c(t, un, wj); \forall(t, un) \quad (11)$$

$$P_e(t, un, wi) = P_e(t, un, wj); \forall(t, un) \quad (12)$$

$$P_s(t, un, wi) = P_s(t, un, wj); \forall(t, un) \quad (13)$$

$$P_r(t, un, wi) = P_r(t, un, wj); \forall(t, un) \quad (14)$$

$$P_e(t, un, w) + P_s(t, un, w) + P_r(t, un, w) + P_c(t, un, w) \leq u(t, un, w) \times P_{max}(un) \quad (15)$$

$$P_e(t, un, w) + P_s(t, un, w) + P_r(t, un, w) + P_c(t, un, w) \leq u(t, un, w) \times P_{min}(un) \quad (16)$$

$$\sum_{un} P_e(t, un, w) = P_e(t, w) \quad (17)$$

$$\sum_{un} P_s(t, un, w) = P_s(t, w) \quad (18)$$

$$\sum_{un} P_r(t, un, w) = P_r(t, w) \quad (19)$$

$$\sum_{un} P_c(t, un, w) = P_c(t, w) \quad (20)$$

$$P_e(t, un, w) + P_s(t, un, w) + P_r(t, un, w) + P_c(t, un, w) \leq P_e(t-1, un, w) + P_s(t-1, un, w) + P_r(t-1, un, w) + P_c(t-1, un, w) \quad (21)$$

$$+RU \cdot u(t-1, un, w) + SU \cdot y(t, un, w)$$

$$P_e(t-1, un, w) + P_s(t-1, un, w) + P_r(t-1, un, w) + P_c(t-1, un, w) \leq P_e(t, un, w) +$$

$$P_s(t, un, w) + P_r(t, un, w) + P_c(t, un, w) + RD \cdot u(t-1, un, w) + SD \cdot z(t, un, w) \quad (22)$$

$$u(t, un, w) - u(t-1, un, w) = y(t, un, w) + z(t, un, w) \quad (23)$$

$$y(t, un, w) + z(t, un, w) \leq 1 \quad (24)$$

$$y(t, un, w) + \sum_{i=1}^{MU-1} z(t+i, un, w) \leq 1 \quad (25)$$

$$z(t, un, w) + \sum_{i=1}^{MD-1} y(t+i, un, w) \leq 1 \quad (26)$$

$$P_c^{min}(t) \leq P_c(t, w) \leq P_c^{max}(t) \quad (27)$$

$$P_e(t, un, w) \geq 0 \quad (28)$$

$$P_s(t, un, w) \geq 0 \quad (29)$$

$$P_r(t, un, w) \geq 0 \quad (30)$$

$$P_c(t, un, w) \geq 0 \quad (31)$$

$$-profit_w + \zeta - \eta_w \leq 0; \forall \omega \quad (32)$$

$$\eta_w \geq 0 \quad (33)$$

Constraints (11)-(14) are non-anticipativity constraints due to stages in decisions. Constraints (15) and (16) are generators limit on output power. Constraints (17)-(20) force each generator contribution in different markets.

Constraint (21) are the ramp up and start up limits of generators and constraint (22) is ramp down and shut down limits of generators. Constraints (23) and (24) are logical relation between binary variables. Constraints (25) and (26) are minimum up time and minimum on time limits of generators, respectively. Constraint (27) is contract power limitation for hour t . Constraints (28)–(31) forces the related variables to be positive. Constraints (32) and (33) are CVaR constraints.

IV. NUMERICAL STUDIES

Several markets are taken into account such as bilateral contracts, day-ahead, reserve, and regulation markets based on Spanish electricity market data. In addition, there are some reports that consider spot market decision to maximize the Genco profit by changing policy in contracts. In this study, a power plant with six generators is considered as presented in Table I. Moreover, the contract limits and prices are presented in Table II. As it can be seen, one day period is divided into three levels of load.

The problem is solved without and with considering the risk. Various scenarios are generated by means of the stochastic programming and PDF extracted through system background. All prices for target markets in the paper are split on each hour of a week (1 to 168 hours).

TABLE I. MAIN CHARACTERISTIC OF GENERATORS USED

Type	C_j^F (€/h)	C_j (€/MWh)	P_j^{max} (MW)	P_j^{min} (MW)	R_j^{up} (MW/h)	R_j^{dw} (MW/h)
Coal ₁	126.0	19.810	140.0	75.0	65.0	65.0
CCGT ₁	1097.0	25.170	380.0	160.0	220.0	220.0
CCGT ₂	992.8	25.510	390.0	180.0	210.0	210.0
Coal ₂	575.0	29.370	500.0	250.0	250.0	250.0
Oil ₁	91.5	37.910	50.0	25.0	25.0	25.0
Oil ₂	1800.0	33.910	300.0	200.0	100.0	100.0

TABLE II. CHARACTERISTICS OF CONTRACTS UNDER STUDY

	price (€/MWh)	Max (MW)	Min (MW)
Low load	44.0	400.0	225.0
Medium load	57.4	770.0	500.0
High load	66.5	1120.0	710.0

In order to select enough number of scenarios for generating, first a different number of scenarios are generated, and then the main problem is solved using generated scenarios, where the standard deviation and mean value of profit for scenarios are calculated. The process is repeated for 50 to 160 scenarios with 10 steps between them. For each stage of programming, the following curves described in Fig. 2 are obtained. It can be observed that after 100 scenarios for each stage of programming, standard deviation and the mean value of profits are stabilized in a limited bound.

To show the performance of proposed method and to compare it with the scenario regeneration technique, both methods are implemented to the first stage scenarios of the problem from hour 1 to hour 24 of scheduling horizon to reduce 100 scenarios to 10. Then two sets of reduced scenarios are obtained, considering the Kantorovich distance showing the performance used to find the distance of new sets and the original scenario set. These distances for each 24 hour study are compared with each other by dividing the distance of the set which is obtained from proposed method to the distance of the set which is obtained from corresponding scenario reduction technique. These results are shown in Table III.

Moreover, the study on the percentage of reduction is presented. Note that the proposed method in this work is not the scenario reduction but it regenerates the new set which has a lower number of scenarios. For each percent of reduction, the main problem is solved using new scenario set and the total profit of problem is calculated. More Illustration is shown in Fig. 3. The results of the main problem and the problem with new scenario set are shown in Table IV. Finally, studies on spot market decisions considering aforementioned risks are carried out.

In this study, based on spot market prices at the time of operation, Genco decides to produce the contracted power by its own generators or buy the maximum power of contracts from the spot market and sell it to the buyer.

This results a considerable increment in the optimum value of the objective as indicated in Table V, $\beta=0$, i.e., no risk is taken. Studies on risk with changes in risk coefficient β have been represented and the results are indicated in Table VI.

TABLE III. RATIO OF DISTANCES FROM THE ORIGINAL SCENARIO

hour	Ratio of distances	hour	Ratio of distances	hour	Ratio of distances
1	0.8548	9	0.8972	17	0.8439
2	0.8548	10	0.9372	18	0.8863
3	0.9301	11	0.8153	19	0.8693
4	0.8745	12	0.9030	20	0.8517
5	0.8518	13	0.8186	21	0.8011
6	0.8316	14	0.8919	22	0.8604
7	0.9382	15	0.8492	23	0.9053
8	0.7944	16	0.8514	24	0.8181

TABLE IV. RESULTS FOR MAIN & REDUCED PROBLEM

Profit for reduced problem	Profit for the main problem
€ 8,814,563	€ 8,889,019

TABLE V. COMPARISON BETWEEN PROFITS IN TWO CASES

Profit for First problem	Profit for new problem	Absolute increment	Percentage of increment
€ 8,814,563	€ 8,996,837	€ 182,274	2.06%

TABLE VI. TOTAL PROFIT AND STANDARD DEVIATION OF PROFITS FOR DIFFERENT RISK COEFFICIENTS β

β	Expected profit (€)	Standard deviation of profit
0	8,996,837.0	3.49
0.1	8,987,840.0	3.49
0.2	8,969,846.0	3.48
0.3	8,951,853.0	3.47
0.4	8,942,856.0	3.47
0.5	8,924,862.0	3.46
0.6	8,915,865.0	3.46
0.9	8,906,869.0	3.46
1	8,897,872.0	3.43

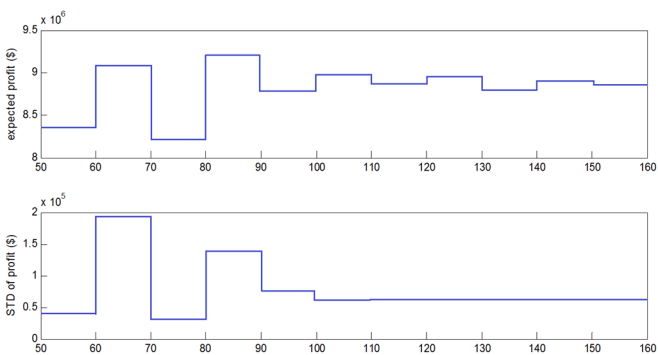


Fig. 2. Standard deviation and mean value of profit versus the number of scenarios

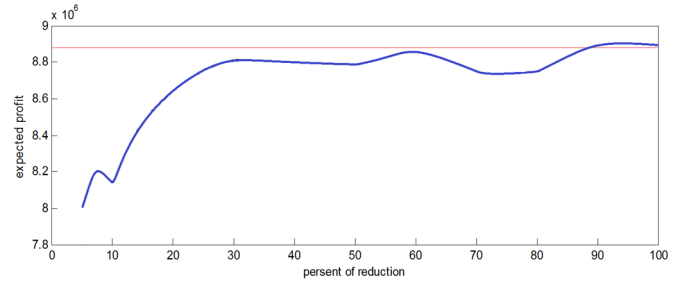


Fig. 3. Total profit for problems with different reduction percentage

V. CONCLUSIONS

In this work, a self-scheduling problem was presented for a Genco who played in a deregulated market. The proposed model improved the accurate results by considering a stochastic programming approach that employed the required number of scenarios due to a generation and reduction process. Finally, a new procedure was developed to determine how to purchase the contracted power based on spot market prices and a considerable increase in the expected profit was obtained.

REFERENCES

- [1] E. Heydarian-Forushani, M. P. Moghaddam, M. K. Sheikh-El-Eslami, M. Shafie-khah, and J. P. S. Catalão, "Risk constrained offering strategy of wind power producers considering intraday demand response exchange," *IEEE Trans. Sust. Energy*, vol. 5, pp. 1036-1047, 2014.
- [2] M. Alamaniotis, D. D. Bargiotas, N. K. Bourbakis, and L. H. Tsoukalas, "Genetic optimal regression of relevance vector machines for electricity pricing signal forecasting in smart grids," *IEEE Smart Grid*, vol. 6, pp. 2997-3005, 2015.
- [3] M. Shafie-khah, M. Parsa Moghaddam, and M. K. Sheikh-El-Eslami, "Price forecasting of day-ahead electricity markets using a hybrid forecast method," *Energy Convers. Manag.*, vol. 52, pp. 2165-2169, 2011.
- [4] B. Mohammadi-Ivatloo, H. Zareipour, N. Amjady, and M. Ehsan, "Application of information-gap decision theory to risk-constrained self-scheduling of GenCos," *IEEE Trans. Power Syst.*, vol. 28, pp. 1093-1102, 2013.
- [5] B. Vatani, N. Amjady, H. Zareipour, "Stochastic self-scheduling of generation companies in day-ahead multi-auction electricity markets considering uncertainty of units and electricity market prices," *IET Gene. Trans. Distr.*, vol. 7, pp. 735-744, 2013.
- [6] M. Kohansal, and H. Mohsenian-Rad, "Price-maker economic bidding in two-settlement pool-based markets: the case of time-shiftable loads," *IEEE Trans. Power Syst.*, vol. 31, pp. 695-705, 2016.
- [7] A. N. Ghalelou, A. P. Fakhri, S. Nojavan, M. Majidi, and H. Hatami, "A stochastic self-scheduling program for compressed air energy storage (CAES) of renewable energy sources (RESs) based on a demand response mechanism," *Energy Conv. Manag.*, vol. 120, pp. 388-396, 2016.
- [8] M. Shafie-khah, and J. P. S. Catalão, "A stochastic multi-layer agent-based model to study electricity market participants behavior," *IEEE Trans. Power Systems*, vol. 30, pp. 867-881, March 2015.
- [9] M. Shafie-khah, M. P. Moghaddam, M. K. Sheikh-El-Eslami, and J. P. S. Catalão, "Optimised performance of a plug-in electric vehicle aggregator in energy and reserve markets," *Energy Conv. Manag.*, vol. 97, pp. 393-408, 2015.
- [10] M. Shafie-khah, M. Parsa Moghaddam, and M. K. Sheikh-El-Eslami, "Development of a virtual power market model to investigate strategic and collusive behavior of market players," *Energy Policy*, vol. 61 pp. 717-728, 2013.
- [11] M. Shafie-khah, M. Parsa Moghaddam, M. K. Sheikh-El-Eslami, and J.P.S. Catalão, "Fast and Accurate solution for the SCUC problem in

large-scale power systems using adapted binary programming and enhanced dual neural network,” *Energy Conv. Manag.*, vol. 78, pp. 477-485, 2014.

[12] M. Shafie-khah, M. P. Moghaddam, and M. K. Sheikh-El-Eslami, “Unified solution of a non-convex SCUC problem using combination of modified branch-and-bound method with quadratic programming,” *Energy Conv. Manag.*, vol. 52, pp. 3425-3432, 2011.

[13] R. Weron, “Electricity price forecasting: A review of the state-of-the-art with a look into the future,” *Int. J. Forecas.*, vol. 30, pp. 1030-1081, 2014.

[14] E. Heydarian-Forushani, M. P. Moghaddam, M. K. Sheikh-El-Eslami, M. Shafie-khah, and J. P. S. Catalão, “A stochastic framework for the grid integration of wind power using flexible load approach,” *Energy Conv. Manag.*, vol. 88, pp. 985-998, 2014.