Data Driven Unit Commitment problem with High Renewable Penetration

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1 Introduction

Making optimal decisions under uncertainty is an important problem and needs more sophisticated algorithms to apply in real world. The output of a generator is its on/off status under constraints such as load balance, generator constraints and transmission line constraints. Renewable penetration tends to increase in the next few decades and more than 50 percentage of demand will be provided by renewable energy resources. To account for the fluctuations in power output, a number fo measures are proposed to overcome the operation and planning problem. These include demand side management, usage of fast ramp generators, battery storages.In addition to the physical means, updating current systems' planning and operation with stochastic and probabilistic methods has been particularly recommended as a promising solution to help maintain and improve system reliability with increasing penetration of variable energy resources. This report is to investigate why stochastic optimization methods are not widely used in markets, and what could be done to mitigate this issue.

2 Deterministic method

In real time, the Independent System Operator perform economic dispatch every 5 min and Unit Commitment for the day-ahead (1 hour interval). The economic dispatch and Unit commitment problem is formulated as co-optimization of energy and ancillary services. The deterministic formulation method has evolved over the years and the most commonly used ones are mixed integer programming. It is typically modelled as follows:

$$\min_{x,y} c^T x + b^T y$$

$$Fx \leq f \tag{1}$$

$$Hy \leq h \tag{2}$$

$$Ax + By \leq g \tag{3}$$

$$\begin{aligned} I_u y &= \bar{d} \\ x \;\; & binary \end{aligned} \tag{4}$$

The binary variable x is a vector of commitment related decisions for the generators including on/off and start-up/shut-down status of each participating generation unit in the market for each time interval. y is a continuous variable which represents dispatch related decision including the generator output, spinning reserve output, non spinning reserve output, regulation level for each time interval. (1) corresponds to min up time, min down time, startup and shutdown constraints. (2) represents energy balance, reserve requirements, ramping constraints, transmission limits constraints. (3) integrates the commitment and dispatch decisions including the generation capacity constraints. The last constraint (4) represents the uncertain net nodal injection. Since this is a deterministic problem formulation, we have a constant $\bar{d}$.

3 Adjustable Robust Joint Dispatch Model

3.1 Problem Formulation

This section presents joint dispatch of energy and ancillary service in real time electricity market. Traditionally, economic dispatch problem is solved using deterministic method like mixed integer programming. In recent years, there has been an increase in the penetration of renewables generation which has drawn many researchers to look at the unit commitment and economic dispatch problems with uncertainty. To address this uncertainty, [3] proposed a robust optimization model with the goal of finding a solution which reduces the impact of uncertainties. Here, we use participation factors to signal the participating generators to provide regulation services.The problem is formulated as a single stage linear programming with uncertainties quantified in a closed set. It is typically modelled as follows:

$$\min_{P_i^{sch}, A_s^+, A_s^-} \sum_{i=1}^{N_g} a_i P_i^{sch} + \sum_{s=1}^{N_s} b_s (A_s^+ + A_s^-) + \sum_{i=1}^{N_g} c_i R_i \tag{5}$$

$$s.t. \sum_{j=1}^{N_d} D_j - \sum_{k=1}^{N_w} W_k^f = \sum_{i=1}^{N_g} P_i^{sch} \tag{6}$$

$$\sum_{i=1}^{N_g} R_i \geq D_R, R_i \geq 0 \tag{7}$$

$$\sum_{s=1}^{N_s} A_s^+ \geq D_A, \sum_{s=1}^{N_s} A_s^- \geq D_A \tag{8}$$

$$P_r^{min} \leq P_r^{sch} + R_r \leq P_r^{max}, \quad \forall r \tag{9}$$

$$P_s^{min} \leq P_s^{sch} + R_s - A_s^-, \quad \forall s \tag{10}$$

$$P_s^{sch} + R_s + A_s^+ \leq P_s^{max}, \quad \forall s \tag{11}$$

$$0 \leq A_s^+ \leq Ru_s, 0 \leq A_s^- \leq Rd_s, \quad \forall s \tag{12}$$

$$P_s^{sch} + A_s^+ \leq A_s^{max}, P_s^{sch} - A_s^- \leq A_s^{min}, \quad \forall s \tag{13}$$

$$\sum_{s=1}^{N_s} \beta_s = 1 \tag{14}$$

$$\begin{gathered} z_{1,s} \sum_{k=1}^{N_w} E_k^{max} + z_{2,s} \sum_{k=1}^{N_w} E_k^{min} \leq A_s^+, \\ z_{1,s} \sum_{k=1}^{N_w} E_k^{min} + z_{2,s} \sum_{k=1}^{N_w} E_k^{max} \geq -A_s^- \qquad \forall s \\ z_{1,s} \geq 0, z_{1,s} \geq \beta_s \\ z_{2,s} \leq 0, z_{2,s} \leq \beta_s \end{gathered} \tag{15}$$

$$\sum_{i=1}^{N_g} G_{l,i}^P P_i^{sch} + \sum_{k=1}^{N_w} G_{l,k}^W W_k^f - \sum_{j=1}^{N_d} G_{l,j}^D D_j + \sum_{k=1}^{N_k} y_{l,k}^+ E_k^{max} + y_{l,k}^- E_k^{min} \leq F_l^{max}, l = 1, ..., N_l \tag{16}$$

$$\sum_{i=1}^{N_g} G_{l,i}^P P_i^{sch} + \sum_{k=1}^{N_w} G_{l,k}^W W_k^f - \sum_{j=1}^{N_d} G_{l,j}^D D_j + \sum_{k=1}^{N_k} y_{l,k}^+ E_k^{min} + y_{l,k}^- E_k^{max} \geq -F_l^{max}, l = 1, ..., N_l \tag{17}$$

$$\begin{gathered} y_{l,k}^+ \geq 0, y_{l,k}^+ \geq \sum_{s=1}^{N_s} G_{l,s}^P \beta_s + G_{l,k}^W \\ y_{l,k}^- \leq 0, y_{l,k}^- \leq \sum_{s=1}^{N_s} G_{l,s}^P \beta_s + G_{l,k}^W \\ l = 1, ..., N_l, \\ k = 1, ..., N_w \end{gathered} \tag{18}$$

In the above problem formulation, (5) represents the joint dispatch of energy and ancillary service market, (6-18) refers to the load balancing, transmission line constraints, generator ramping constraints.

3.2 Results

The results were obtained using MATLAB and cvx tools on macbook pro 13 inch 2016 model.

For the case study, IEEE 30 bus system with 2 wind farms is tested using deterministic method and robust optimization based method. The information about the IEEE network is taken from [2], and the characteristics of generator is given in Table 1. Regulating reserve demand is 20 MW, spinning reserve is 30 MW. The location of wind farm is at bus 13 and bus 20 with point forecast of 20 MW and 40 MW respectively. The error distribution for wind farm 1 and 2 is a uniform distribution with uncertainty set as [-4,4] and [-8,8] respectively.

Table 1: Generator characteristics for IEEE 30 bus system

Bus	**Energy**	**Pmax**	**Pmin**	**Ru**	**Rd**	**AGC**	**Amax**	**A**	**Reserve**
	yuan/MW	MW	MW	MW/5min	MW/5min	yuan/MW	MW	MW	yuan/MW
1	150	80	0	12	-12	120	75	15	120
2	180	80	0	16	-16	200	70	10	150
22	200	50	0	15	-15	180	50	10	100
23	250	30	0	8	-8	0	0	0	80
27	300	55	0	10	-10	0	0	0	90

Table 2: Comparison table for deterministic and robust optimization based methods

	P(MW)		**A^+(MW)**		**A^-(MW)**		**R(MW)**	
Bus	**D**	**RO**	**D**	**RO**	**D**	**RO**	**D**	**RO**
1	63	63	12	12	12	12	0	0
2	10	25.773	0	4	0	4	0	0
22	38.86	14	8	4	8	4	0	0
23	0	4.3363	0	0	0	0	30	25.664
27	17.34	22.091	0	0	0	0	0	4.336

Table 3: Cost Comparison Table

	Cost (yuan)	
Service type	**D**	**RO**
Energy	24224	24600.47
Regulation	5760	5920
Spin	2400	2443.4
Total	32384	32963.87

4 Data Driven Optimization

The goal of the stochastic programming is to make optimal decisions under uncertainty. For a single stage stochastic program, we usually assume a probability distribution P for uncertain parameter or the error parameter. This probability distribution is constructed using historical datasets. Therefore, we can conclude that the decision making under uncertainty depends on the dataset. We construct dataset D_1 and D_2 from the same distribution and get the optimal decision from stochastic programming using dataset D_1. Now, we check the performance of the optimal decision we got with dataset D_2 and the result is often disappointing. This phenomenon is called **optimizer's curse** [4]. This is why we introduce data-driven optimization models. A data-drive solution of a problem is found using the training data set.

4.1 Sample Average Approximation method

A natural approach to generate data-driven solutions is to approximate P (probability distribution) with the discrete empirical probability distribution or the uniform distribution [4].

$$P_N := \frac{1}{N} \sum_{i=1}^{N} \delta_{\xi_i} \tag{19}$$

$$\hat{J}_{SAA} := \inf_{x} \{ E^{P_N} \left[h\left(x, \xi\right) \right] = \frac{1}{N} \sum_{i=1}^{N} h\left(x, \hat{\xi}\right) \} \tag{20}$$

We refer to $\hat{J}$ as out of sample performance. This method has been used when the probability distribution is known and getting more dataset is cheaper. However, when getting additional dataset tends to be costlier or N is small, SAA offer poor out of sample performance. Therefore, we need a more robust distribution P which can deal with the optimizer's curse problem.

4.2 Distributionally Robust Optimization

Due to incomplete information about the uncertain variable, it is very difficult to construct an accurate probability distribution. Therefore, we need an alternate approach to eliminate the need of finding true probability distribution to solve the unit commitment problem. The basic idea behind distributionally robust optimization (DRO) is to construct an ambiguity set which has a set of probability distributions constructed using the training datasets δ_ξ with high confidence [4]. To summarize the problem formulation, we minimize the total worst case expected cost. Data driven Unit commitment formulation is discussed in [5]

4.3 Bootstrap based Distributionally Robust Optimization

The difficulty in constructing the ambiguity set is high when data procuring is expensive. Therefore, I propose a bootstrap based construction of ambiguity set which uses the available data and resample the same data multiple times to construct the ambiguity set of probability distributions P. The bootstrap concept is a computer intensive approach used in statistics to derive the mean and standard deviation when available data δ is small. We sample a small dataset δ_{ξ_1} from the original dataset δ with replacement and get a probability distribution which fits the data with high confidence. We sample again and again to get a set of probability distributions. Now, we can minimize the total worst case expected cost using the constructed ambiguity set.

$$\min_x \max_P \{E^P\left[h\left(x,\xi\right)\right]\} \tag{21}$$

$$P := \{P_{\delta_{\xi_1}}, P_{\delta_{\xi_2}}, ...P_{\delta_{\xi_n}}\} \tag{22}$$

$P_{\delta_{\xi_1}}$ is a probability distribution constructed using δ_{ξ_1} bootstrap data set

5 Conclusion

There is an increasing demand in developing more sophisticated tools to make decisions under uncertainty. This report was developed in order to review the existing literatures on Unit Commitment under uncertainty and improvise the algorithms if need be. There are multiple sources of uncertainties such as variation in demand, contingencies, renewable output fluctuations and fuel input price variations. More detailed modeling of the uncertainties is essential to make optimal decisions and bring academic models closer to the real world implementations.

6 Appendix

References

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Nomenclature

β_s Participation factor of AGC unit s.

a_i Fuel cost coefficients of dispatchable unit i.

A_s^+, S_s^- Up and down regulating reserve of unit AGC s

$A_s^{max}, A_s min$ Maximum/minimum AGC limit of AGC unit s.

b_s AGC bidding price of unit AGC s.

c_i Reserve bidding price of dispatchable unit i.

D_A Total AGC requirement.

D_R^f Total reserve requirement.

$D_{j,t}$ Forecasted load demand of site j.

F_l^{max} Transmission capacity of line l.

$G_{l,i}^P$ Distribution factor of dispatchable generation at bus i on line l.

$G_{l,j}^D$ Distribution factor of dispatchable generation at bus i on line l.

$G_{l,k}^W$ Distribution factor of wind farm at bus k on line l.

N_d Total number of load sites.

N_g Total number of dispatchable units.

N_l Total number of transmission lines.

N_s Total number of AGC units.

N_w Total number of wind farms.

P_i^{max}, P_i^{min} Maximum/minimum output of dispatchable unit i.

P_i^{sch} Scheduled generation of dispatchable unit i.

R_i Spinning reserve for dispatchable unit i.

Ru_s, Rd_s 5 min up and down regulating speed of AGC unit s.

W_k^f Forecasted wind generation of farm k.