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VIABILITY OF INCLUDING FREQUENCY METRICS IN SHORT-TERM SCHEDULING OF ISLAND POWER SYSTEMS

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Abstract - In the current practice of short-term power scheduling, reserve power is used as a tool to address generation mismatch and contingencies. The practice is starting to fall short especially in smaller power systems, as the injection of uncertain renewable sources is growing, there is already a scarcity of primary frequency response, and any contingency leads to relatively big power mismatches. This paper points out the inadequacy of current practice to sufficiently guarantee the frequency dynamic quality after outages. First the UC problem is solved for different levels of reserve requirement. Then a coherent data-set is obtained by simulating the System Frequency Response (SFR) of single outages. The results of the SFR model are statistically analyzed to prove that there are more correlated representatives of frequency quality, compared to the amount of reserve that is used in the current practice.

Keywords - System Inertia, Reserve Requirement, System Frequency Model, Robust Optimization.

I. INTRODUCTION

Variability and uncertainty are becoming a bigger concern in power systems, by ever increasing penetration of renewable energies as a source of power generation. Among power systems, small isolated systems suffer more, as they inherently possess less inertia. Inertia scarcity in island power systems makes them more susceptible to power outages and the fluctuations in uncertain renewable sources. Traditionally online reserve power brought by the conventional units has been the main tool to tackle unforeseen sudden changes of power balance, and maintain the frequency within a tolerable range. This practice is falling short as the conventional units are becoming obsolete by increasing the share of renewable energy sources (RES). Also, the amount of available reserve might vary depending on the changes in RES infeed, which is exposed to forecast errors. To address the volatile nature of RES and include the stochasticities in the scheduling process, usually stochastic and robust models are employed. For stochastic optimization many discrete samples are needed with known probability description. However, in practice it is not easy to obtain an accurate probability distribution of the uncertain variable. Moreover, the computational burden increases massively as the number of samples goes higher. Robust optimization assumes that the upper and lower bound of the uncertain variable is predictable. The goal of the robust optimization is to find the optimal solution under the worst possible scenario for the system, hence the solution might be overconservative [1]. A data-driven adaptive robust UC approach is proposed in [2], that is able to withstand wind power forecast errors and mitigate the conservatism of the solution by reducing operational costs. To further reduce the conservetiveness of the uncertainty set for solving UC problem and enhance the computational efficiency, a partition-combine method is proposed in [3] to build a minimal uncertainty set with the irregularlydistributed historical data. To ensure power balance under the growing level of wind power injection, and also noting that wind power uncertainty reduces over time, the problem is broken into three decision-making problems, which are solved under different degrees of uncertainty in [4]. Numerical results confirm that this approach outperforms existing non-anticipative robust UC models, in both feasibility and optimality. To ensure the provision of sufficient and fast reserves, different solutions are introduced in the literature. In [5], reserved energy in energy storage system (ESS) is proposed as a source of ancillary service, which also takes into account wind speed fluctuations as a source of uncertainty. It concludes that providing reserve by RES can mitigate the need of other types of reserve providers and reduce the operation costs consequently. To quantify how much reserve is required for different uncertainty levels, an endogenous reserve determination method is proposed in [6]. Different sources of uncertainty, including wind generation, load forecast, generator failures, and power flow uncertainties caused by wind power forecast errors, are considered to jointly schedule the generation and reserve. The proposed approach can ensure amount of reserve can sufficiently maintain the operational reliability. To increase the amount of online inertia, the concept of synthetic inertia provided by wind power plants is exploited in [7]. Synthetic inertia and primary frequency response with the support from wind power plants are modeled to actively estimate the system inertia and primary frequency response requirement in a day-ahead stochastic scheduling framework. Result show that the participation of wind sources can increase the overall inertia of the system by 12%. The viability of providing up and down reserve by RES in island power systems is studied in [8].

In this paper the unit commitment problem is solved for different levels of reserve requirement in La Palma island, with an adaptive robust UC formulation. The binary solution is then used to solve economic dispatch (ED) problem for 10 different stochastic scenarios. The result of ED is fed to an SFR model, to simulate the frequency response quality after every single outage. SFR outputs are analyzed to conclude that there are better representatives that can be used in UC problem in Spanish islands, compared to reserve criteria that is currently employed.

The rest of the paper is organized as follows. First the methodology is explained in section II. In this part both adaptive robust UC and the employed SFR model are introduced. In section III, the results of the simulations on real data of La Palma island are presented and analyzed. Finally, the conclusions are drawn after that.

II. METHODOLOGY

An adaptive robust UC with reserve constraint is used in this paper to obtain this data-set, which is explained in II-A. The UC problem is solved for different levels of reserve requirement, and ED is solved for all of the stochastic scenarios. The obtained results predominantly picture the possible feasible solutions that might be encountered in real-time. Using these data dynamic simulations can be carried out to see the quality of frequency response in case of all potential outages. To perform the dynamic simulations an SFR model with no UFLS sceme is used (II-B). As the inputs of SFR model have different levels of reserve and the amount of inertia is ignored, the simulation results will be a broad-ranging mix of tolerablefrequency responses, poor responses and even unstable case. Analyzing the correlation between inputs and outputs of the SFR model is interesting, as it can highlight the most correlated factors of the commitment problem to the frequency response quality.

2.1. Adaptive Robust UC

The Unit Commitment (UC) problem is a mixed integer problem, and is usually solved with MIL Programming solvers after the linearization of nonlinear terms. To solve the UC problem with uncertainty, an adaptive robust formulation is employed in [9] and [10]. The formulation is robust, because it considers all of the possible realizations of the uncertain input, and makes sure that the chosen commitment status of the units, which is decided in the master level, will be feasible for any realization of the uncertain variable. The formulation is adaptive because the subproblem level is a function of the uncertain variables and can adapt the master level decision variable, depending on the different realizations of the uncertain variable. A general representation of UC problem with reserve constraint and uncertain wind power injection isprovided here,

$$\min_{x,p(w)} suc(x_{t,i}) + gc(p_{i,t}) \quad (1)$$

$$x_{t,i} - x_{t-1,i} = y_{t,i} - z_{t,i} \quad t \in \mathcal{T},\ i \in \mathcal{I} \quad (2a)$$

$$y_{i,t} + z_{i,t} \leq 1 \quad t \in \mathcal{T},\ i \in \mathcal{I} \quad (2b)$$

$$\sum_{tt=t-UT_i+1}^{t} y_{tt,i} \leq x_{t,i} \quad t \in \{UT_i, \ldots, \mathcal{T}\} \quad (2c)$$

$$\sum_{tt=t-DT_i+1}^{t} z_{tt,i} \leq 1 - x_{t,i} \quad t \in \{UT_i, \ldots, \mathcal{T}\} \quad (2d)$$

$$p(w)_{t,i} \geq \underline{\mathcal{P}_i}.x_{t,i} \quad t \in \mathcal{T},\ i \in \mathcal{I},\ w \in \mathcal{W},\alpha \quad (3a)$$

$$p(w)_{t,i} + r(w)_{t,i} \leq \overline{\mathcal{P}_i}.x_{t,i} \quad t \in \mathcal{T},\ i \in \mathcal{I},\ w \in \mathcal{W},\ \beta \quad (3b)$$

$$p(w)_{t-1,i} - p(w)_{t,i} \leq \underline{\mathcal{R}_i} \quad t \in \mathcal{T},\ i \in \mathcal{I},\ w \in \mathcal{W},\ \gamma \quad (3c)$$

$$p(w)_{t,i} - p(w)_{t-1,i} \leq \overline{\mathcal{R}_i} \quad t \in \mathcal{T},\ i \in \mathcal{I},\ w \in \mathcal{W},\ \delta \quad (3d)$$

$$\sum^{i \in \mathcal{I}} \left(p(w)_{t,i}\right) + wg(w)_t = d_t \quad t \in \mathcal{T},\ w \in \mathcal{W},\ \zeta \quad (3e)$$

$$wg(w)_t \leq w_t \quad t \in \mathcal{T},\ w \in \mathcal{W},\eta \quad (3f)$$

$$\sum_{ii \neq i}^{ii \in \mathcal{I}} \left(\overline{\mathcal{P}}_i - p(w)_{t,ii}\right) \geq p(w)_{t,i} \ t \in \mathcal{T}, i \in \mathcal{I}, w \in \mathcal{W}, \mu \quad (3g)$$

The aim is to solve (1) subject to (2a)-(2d), which only depends on binary variables, and (3a)-(3g), which depend on both binary and real variables. gc(.) is usually a quadratic cost function, which will be piece-wise linearized to be utilized in an MIL problem. (2a) and (2b) represent the binary logic of the UC problem. (2c) and (2d) are the minimum up-time and minimum down-time constraints of the units. (3a) is the minimum power generation constraint, with dual multiplier α. (3b) is the maximum power generation constraint with dual multiplier β, and states that the summation of power generation and power reserve of every online unit, should be less that maximum output of the unit. (3c) and (3d) are ramp-down and ramp-up constraints, with dual multipliers γ and δ respectively. (3e) is the power balance equation with dual multiplier ζ. (3f) with dual multiplier η makes sure that the scheduled wind power is always less than uncertain forecasted wind. (3g) is the reserve constraint with dual multiplier μ, and makes sure that in case of any contingency, there is enough headroom to compensate lost generation. Note that all the decision variables from (3a) to (3g) are a function of uncertain wind power realization. In practice an iterative delayed constraint generating Benders' decomposition algorithm is used to solve this problem[9]. So, the problem would be broken to a master problem which only depends on binary variables and a subproblem which contains all the other constraint. Then writing the dual formulation of the subproblem will facilitate using the iterative approach. To find out how to properly write the standard form of a problem, and take the dual, have a look at [11]. In case of encountering non-linearity, like a dual variable multiplying the uncertain variable, an iterative outer approximation can be employed [12].

2.2. The SFR Model

This section briefly presents SFR models used to analyze frequency stability of small isolated power systems. The model is able to reflect the underlying short-term frequency dynamics of small isolated power systems. Figure 1 details the power system model used to design UFLS schemes for a small isolated power system, consisting ofI generating units. Each generating unit i is represented by a second-order model approximation of its turbine-governor system. In fact, frequency dynamics are dominated by rotor and turbine-governor system dynamics. Excitation and generator transients can be neglected for being much faster than the turbine-governor dynamics.

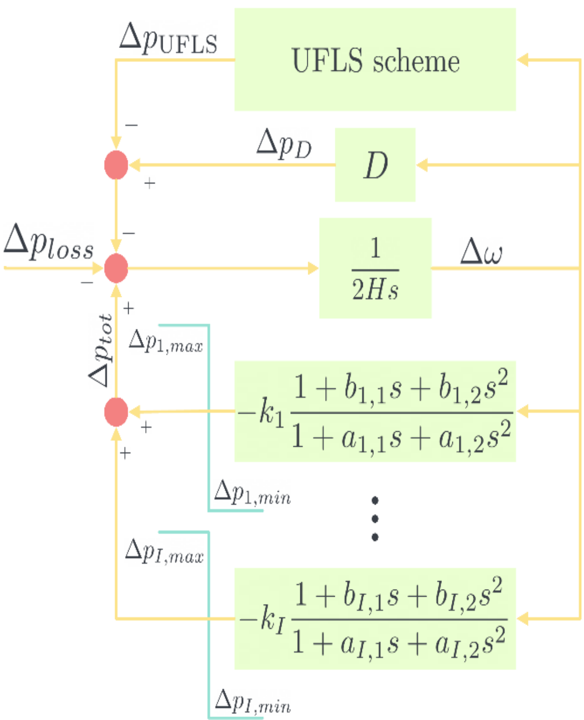

Figure1. SFR model.

The overall response of loads can be considered by means of a load-damping factor D if its value is known. The gain k_i and parameters $a_{i,1}$, $a_{i,2}$, $b_{i,1}$ and $b_{i,2}$, of each generating unit i can be deduced from more accurate models or field tests. Since primary spinning reserve is finite, power output limitations $\Delta p_{i,min}$and $\Delta p_{i,max}$are also modelled. The complete model is explained in [13]. This SFR model uses the outputs of adaptive robust UC as an input, and delivers the frequency response of the system after any single outage of the generators. The obtained results are analyzed to compare the correlation of different metrics.

III. RESULTS

Simulations for the proposed methodology are carried on the real power system of La Palma island, one of Spain's Canary Islands. The yearly demand in 2018 is reported about 277.8 GWh (average hourly demand of 31.7 MWh), supplied by eleven Diesel generators predominantly. According to [14], the installed capacity of the La Palma island power system mounts to 117.7 MW, where about 6% of the installed capacity belongs to wind power generation. Renewable generation covers about 10% of the yearly demand. The input data for solving UC problem is obtained from real data. The forecasted wind generation data of a sample day is chosen, with different scenarios, that also provide us the upper bound and the lower bound of for the robust formulation. Wind data with 10 scenarios is shown in figure 2.

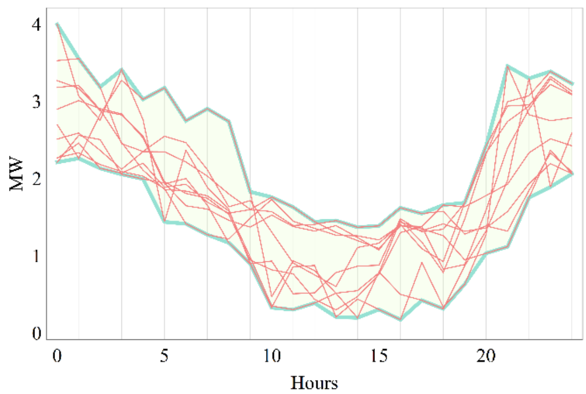

Figure 2: Wind Data

Conventional day-ahead robust UC is solved for ascending reserve requirements levels, starting from zero requirement until the problem becomes infeasible. In the conventional UC, the reserve requirement is the biggestsource of power. A multiplier is defined here for the reserve requirement starting from 0, with 0.1 ascending steps, until 1.5, which is the point that problem becomes infeasible. Then the ED solution of 10 wind scenarios for each reserve requirement level is fed to the SFR model, and all single contingencies are simulated. Obtained results confirm that other system characteristics, like online inertia, lost power, lost power percentage, and normalized gain of turbine governor are more related to the quality of the frequency response, rather that the amount of reserve. Table 1 shows the Pearson's correlation between mentioned characteristics and frequency response metrics, for more than 20000 single outages, simulated by the SFR model. As expected, the ratio of lost generation to hourly demand has the best correlation with frequency metrics, as the big outages relatively to the whole generation tend to disturb frequency considerably. Interestingly enough, the sum of available reserve has a weaker correlation with frequency metrics, compared to the others. So other parameters like total available inertia and power loss ratio, might be better representatives of the system dynamics.

	f_{nadir}	f_{qss}	RoCoF
Total H	0.568	0.558	0.668
Total K	0.286	0.283	0.319
p_{loss}	-0.561	-0.532	-0.876
p_{loss}/d	-0.617	-0.588	-0.965
Total r	0.506	0.516	0.269

Table 1 - Pearson's correlation between parameters

La Palma island, like other power systems, is equipped with UFLS scheme that sheds load depending on the severity of RoCoF (Rate of Change of Frequency) andamount of frequency drop. In bigger systems the purpose is to avoid any incident that leads to load shedding, by providing enough primary frequency response. In islands and smaller system, usually there is not enough primary frequency response, so the aim is to minimize the expected amount of UFLS. The current practice of power schedule in islands only includes the reserve criteria to cover outages, and as mentioned, the correlation of reserve does not have a strong correlation with the frequency response metrics.

IV. CONCLUSION

The paper tries to find out what are the most correlated features in the scheduling process to the post fault frequency. To realize that, day-ahead UC simulations are carries out for La Palma island with the real input data. To cover the variety of possible real-time outcomes, different levels of reserve requirement are considered. Then the economic dispatch problem is solved for 10 stochastic wind realization scenarios. The results are fed to an SFR model to simulate frequency changes after each outage. Analyzing the outputs of the SFR model, confirms that the reserve criteria is much less correlated with the frequency response, compared to other characteristics like the amount of online inertia, turbine-governor constants, and the size of the outage. In island power system that the frequency stability is of high importance, other criteria should be taken into account to better represent the frequency behavior of the system in short-time scheduling process.

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