IMPACT OF LARGE-SCALE STOCHASTIC GENERATION AND FLEXIBLE DEMAND ON NETWORK DESIGN AND PROPOSALS ON MID- AND LONG-TERM ASSET MANAGEMENT

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ABSTRACT

A successful asset management during time horizons of mid- and long-term strongly depends on a proper representation for the impacts of large-scale stochastic generation and flexible demand on network design. The use of stochastic methods is necessarily unavoidable in addition to the basic deterministic methods due to the aggregate uncertainty of stochastic generation outputs. In this paper, the variability of renewable generation is considered as part of the load variation. This evaluation of flexibility is a fundamentally important step, as it has a direct impact on the system's operating costs. According to this new scheme, the contribution of this paper is centred on characterizing the variability of the stochastic distributed generation (SDG) power output more precisely by considering the realistic interdependence structure between them and between the consumers' load profiles. This subject is thoroughly examined using some illustrative context about sizing of a small power system components to reach an optimal total cost considering large-scale wind power uncertainty.

INTRODUCTION

Asset management strategies in power systems fall into four different time horizons: real-time, short-term, midterm, and long-term asset management. Among these time scales, mid-term and long-term asset management covers monthly/seasonal and yearly management respectively. Asset management for the mid-term scale includes optimal allocation of resources (e.g., fuel and renewables). Besides, the long-term is about facility planning and acquisition [1]. A successful asset management during these time horizons strongly depends on a proper representation for the impacts of large-scale stochastic generation and flexible demand on network design.

Conventional asset management routines were aimed at ensuring the least-cost operation within a pre-specified level of system risk. However, in today's increasingly competitive electricity markets, with large-scale penetration of stochastic distributed generation units, competitors should be able to participate actively in the planning and operation of such generation and distribution systems.

Stochastic distributed generation (SDG) devices interact with the planning, operation, and control of the distribution feeder at which they are installed [2]-[3]. The produced electrical power via a variety of these generation units is stochastic by a non-dispatchable primary energy source. Therefore, DG systems inherently provide some benefits and produce some potentially unwanted effects. Although the practical capacity of these systems is smaller than the conventional generation units, their integration may significantly alter the behavior of the system across which they are installed. Deterministic modeling of such a system with stochastic non-dispatchable DG units (e.g. wind or photovoltaics) is not trivial, mainly due to the aggregate uncertainty of stochastic generation outputs in a time-independent manner [4], [5]. Hence, the use of stochastic methods (e.g. statistical data analysis and Monte Carlo simulation) is necessarily unavoidable in addition to the basic deterministic methods.

Therefore, the gradual increase of DG penetration, especially of renewable and stochastic type, will determine a deep revision of methodologies for planning and management of electrical distribution networks. Generation planning is shifting from planning for peak load towards planning for system energy [6]. This shift is centered on using net load as a basis for capacity planning and this creates a set of requirements for reliable and large sets of renewable resource data analysis. This needs an increased flexibility by providing effective load control, energy storage, and proper portfolio management. This paper contributes directly to the first case. Quantifying the variability to determine required flexibility also requires correlated historic load and resource data at the time scales that currently are not being collected.

To further examine the net load applicability in the power system planning, we consider an emerging practice to include renewable energy supply early in the planning process and consider it during energy growth forecast. In this manner, the variability of renewable generation is considered as part of the load variation. It is readily appeared that the system load is reduced to account for contribution from renewable generation. Generation and distribution are then planned relative to this net load with sufficient flexibility to meet the net load requirements. This evaluation of flexibility is a fundamentally important step, as it has a direct impact on the system's operating costs.

According to this scheme, the contribution of this paper is centered on characterizing the variability of wind/PV power output more precisely by considering the realistic interdependence structure between them and between the consumers' load profiles. This characterization is then used to place wind/PV distributed generation. Based on this, the coordination between long-term planning (facility

construction/planning) and mid-term asset management (allocation of resources) could be addressed in view of both technical and economical indices. This subject is examined using an illustrative example about sizing components of a small real power system to reach an optimal total cost considering large-scale wind power uncertainty. The placement of wind turbines in this real system is according to the first stage mentioned above (characterizing the variability in the framework of mid- and long-term asset management).

CHARACTERIZING VARIABILITY OF SDG DATA: WIND/PV UNITS ALLOCATION

Just as consumer demands are smoothed by aggregation, so is the output from wind or PV plant, and geographic dispersion dramatically reduces the wind speed or solar radiation fluctuations. However, the DG-enhanced distribution system planning (e.g. for the calculation of the system net load distribution) should completely take into account the dependence structure between the relevant determinants as follows:

1. Wind speed in different locations;
2. converted wind power in the wind turbine output if not available;
3. PV output power;
4. system load curve data in different localities.

Therefore, the system net load distributions should be obtained by using a multivariate data modeling tool such as the copula algorithm as presented in [4]. The results can be used for accurately estimating the real capacity credit added to the generation system due to the integration of wind and PV distributed power. In addition, the multivariate data modeling could be employed in conjunction with the system design programs (such as probabilistic load flow algorithms) to make known the necessary system reinforcements and policy changes due to the incorporation of renewable distributed PV and wind powers. Here, we use a rank correlation analysis to make a proper placement of wind/PV units.

For the application of the method, the 11×11 rank correlation matrix is calculated and presented in Table I. Seven rows and columns correspond to the active powers in accordance with the locations in Fig. 1; three rows and columns correspond to the wind speeds at three different hub heights; and the last row and column corresponds to the solar radiation. A moderate correlation between the wind and solar activity and the system load is observed, ranging from 0.00 two 0.77. Also, it should be noted that the wind resources are correlated throughout the area and the solar activity can potentially makes a good correlation with the system load at some locations with a specific typical load profile.

This correlation matrix provides a good measure to place the PV/wind units in the Fig. 1. This is done by choosing the TLPs, more correlated to the wind/solar activity. The chosen TLPs correspond to the substations with a good potential to utilize the wind/PV generation. For example, consider the eighth column of Table 1. As seen, the TLP 1 and the TLP 6 are strongly correlated with the wind activity; while, the TLP 2 and the TLP 3 do not practically correlated with the produced wind power. Thus, it is reasonable not to choose the substations with the TLPs 2 and 3 as a candidate for wind turbine installation. On the other hand, the same reasoning shall be applied to the solar radiation. For example, the TLP 7 is the worst case to use the PV units; since, its correlation with the solar radiation is 0.001 (consider the last row and the seventh column of Table 1). The locations of Fig. 1 are chosen based on this reasoning.

Table I: The rank correlation matrix (RCM) of the real data.

	TLP1	TLP2	TLP3	TLP4	TLP5	TLP6	TLP7	WP1	WP2	WP3	SR
TLP1	1.00	0.38	0.42	0.41	0.72	0.78	0.60	0.71	0.71	0.69	0.40
TLP2	0.38	1.00	0.88	0.51	0.55	0.01	0.67	0.09	0.07	0.07	0.40
TLP3	0.42	0.88	1.00	0.38	0.70	0.15	0.88	0.24	0.29	0.26	0.29
TLP4	0.41	0.51	0.38	1.00	0.18	0.51	0.05	0.51	0.58	0.63	0.77
TLP5	0.72	0.51	0.70	0.18	1.00	0.61	0.88	0.54	0.54	0.53	0.21
TLP6	0.78	0.01	0.15	0.51	0.61	1.00	0.41	0.74	0.64	0.64	0.61
TLP7	0.60	0.67	0.88	0.05	0.88	0.41	1.00	0.41	0.41	0.40	0.00
WP1	0.71	0.09	0.24	0.51	0.54	0.74	0.41	1.00	0.92	0.91	0.53
WP2	0.71	0.07	0.29	0.58	0.54	0.64	0.41	0.92	1.00	0.98	0.54
WP3	0.69	0.07	0.26	0.63	0.53	0.64	0.40	0.91	0.98	1.00	0.57
SR	0.40	0.40	0.29	0.77	0.21	0.61	0.00	0.53	0.54	0.57	1.00

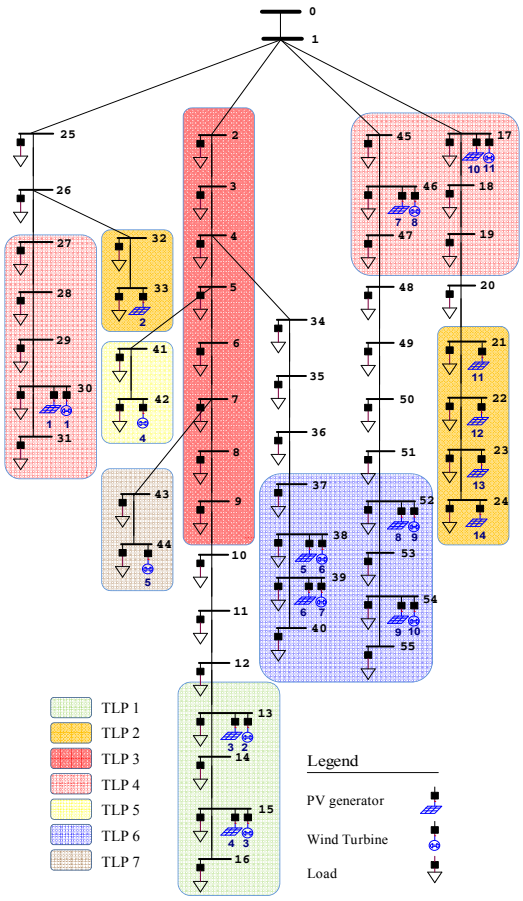

Fig. 1. SDG (wind/PV) placement using RCM of Table I.

OPTIMAL SIZING OF A HYBRID SYSTEM WITH LARGE SCALE WIND PENETRATION

The great capacity of intermittent generation in stand-alone power systems has increased the uncertainty in sizing, planning, and operation of such systems. These uncertainties affect both the long- and the medium-term system asset planning, and the day-ahead operation. Considering the uncertainty earlier in the planning stage makes the whole system less expensive and more secure.

Anticipated high penetration of stochastic energy flows spatially distributed throughout the network or stand-alone microgrids should be optimized by using hybrid stochastic-heuristic simulation methods. Both the uncertainty caused by a renewable power producer and the non-linearity of the objective function could be completely treated in this way. The most popular method that takes the uncertainty properly into account is the Monte Carlo simulation.

Generally speaking, many factors can introduce uncertainties in solving the problem of sizing of hybrid system components in a given scheme; such as power production, cost of energy, cost of gas or fuel, environmental constraints, load growth, and etc. In this paper, without loss of generality, it has been hypothesized that the power production of wind turbines is the main cause of uncertainty. The other factors (cost of energy, cost of gas or fuel, and so on) are considered deterministic variables, assuming for them values derived from the experience of the *decision maker*.

In this paper, the optimal sizing of a wind-fuel cell hybrid system is considered. We first consider the hybrid power system and then the cost of the system presented by an objective function. For a proper and reliable representation of uncertainty, a statistical/stochastic simulation is presented; which involves generating a vast number of scenarios/samples to model the uncertain behavior of wind variability along with the associated prediction error over a year. Optimization of all these samples using PSO algorithm results in a cluster of optimal sizes which provides a wide knowledge of all possible outcomes stemming from multivariate wind power uncertainty. The final mostly optimal sizes can then be calculated based on proper statistical moments of the size sets. These sizes are advisable to be optimal with a greater probability considering the wind power uncertainty. This study is performed for Namin site in north-west Iran (the same network of Fig. 1). It is located in a small city with a population of 10,000.

System Description

The hybrid system involves some wind turbines (placed using the method presented in the previous section), some fuel cells, some electrolyzers, and some hydrogen tanks and assumed to be a grid-connected small power system. The objective function and operation strategies for this grid-connected hybrid system are somehow identical to the autonomous system of [7] with the below distinctions, mainly due to the grid connection of the system:

- Emission is another variable to be minimized in addition to the environmental credit.
- It should be optimized the electricity production cost and the load should be secured while the power purchased from the grid is minimum.
- If there is an excess energy, it should be sold to the grid.

The system's power output should meet the demand and the costs are minimized. Strategies of different outcomes when trying to meet the load, cost calculations and objective function are selected according to [7]. The system operation is dictated based on its working conditions. The control strategy for grid-connected system is similar to the one discussed in [7] in the sense that renewable energy must be exploited first and excess energy should be stored in the hydrogen tanks, however, if there is still excess energy then, it should be sold to the grid. Real spilled energy is the energy that cannot go to the grid because of the rating limit of the electric substation. If the renewable energy is not sufficient to supply the load in a given sub-period, the operational policies of [7] are applied but with the grid now replacing the fuel cells.

Addressing Wind Power Uncertainty

A stochastic simulation is proposed to evaluate the uncertainty of wind power and its prediction error applied to the problem of optimal sizing. The general stages of the presented analysis are as follows:

1. *Statistical analysis of wind power forecast error*: the persistence method is applied and the forecast error are statistically modeled and calculated.
2. *Statistical modeling of weekly wind and load time series using correlation analysis covering a whole year*.
3. *Making realistic samples for Monte Carlo simulation*: combining the information obtained from steps 1 and 2, the weekly scenarios are generated as stochastic infeeds.
4. *PSO-embedded Monte Carlo simulation*: using the samples obtained from step 3, the Monte Carlo simulation is performed and the optimal cluster of sizes for each component is achieved.
5. *Statistical analysis of optimal sizes' sets*: a proper criterion should be employed to decide a single installation size (one simple way is to use expected values).

The general optimization outline is presented in Fig. 2. Some of the results are shown in Fig. 3. These optimal sets could be used to help the decision maker in a more appropriate and optimal system design and planning. It

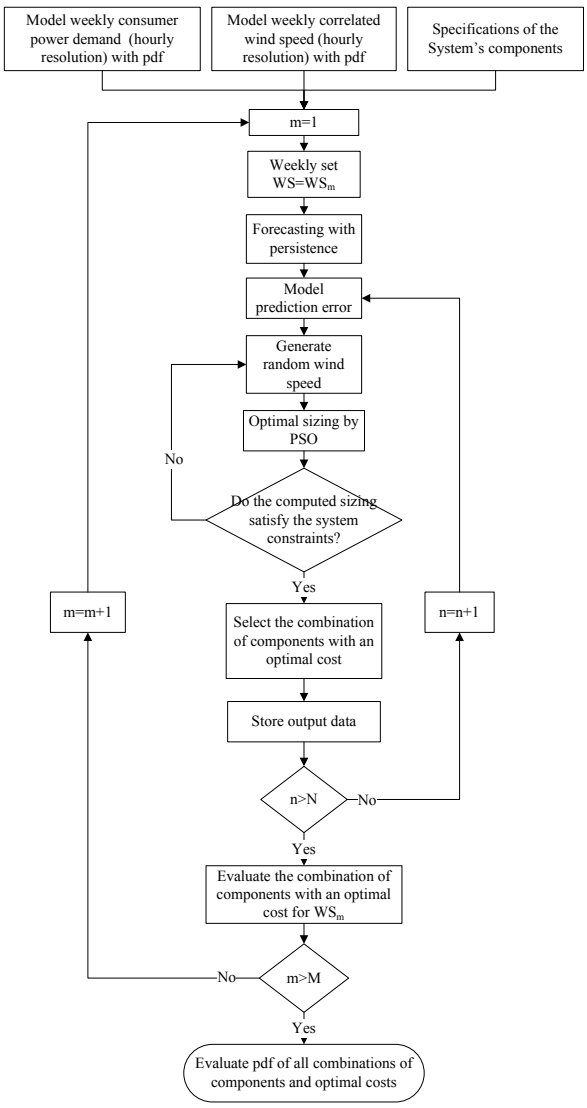

Fig. 2. Flowchart of the optimization process.

should be mentioned that the post-simulation data analysis would contribute to a more optimal decision other than selecting the mean value by default (as shown on the graphs of Fig. 3). The application of the presented method in power system planning and asset management could be further clarified considering the emerging viewpoint in which the contribution of this paper is centered on characterizing the variability of wind power output more precisely. Such a new perspective is being addressed in the emerging framework of active/smarter networks with a high penetration of renewable stochastic generation [6].

CONCLUSION

Facing uncertainties, power system asset planners could apply rigorous stochastic optimization methods to manage the probabilistic nature of generation asset planning. The risk-based planning solutions provide planners with a list of risk-based alternatives for optimizing expected payoffs in electricity markets. This subject is examined in this paper, using an illustrative example about sizing and placement of the components of a small real power system to reach an optimal total cost considering large-scale wind power uncertainty.

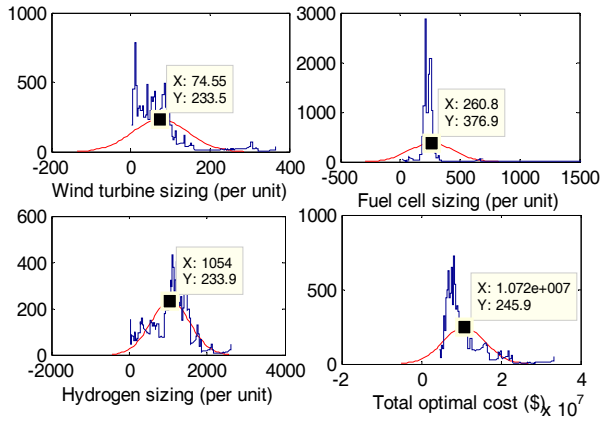

Fig. 3. Sizing results along with the optimal cost.

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