Scenario Creation and Power-Conditioning Strategies for Operating Power Grids with Two-Stage Stochastic Economic Dispatch

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Scenario creation and power-conditioning strategies for operating power grids with two-stage stochastic economic dispatch

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***Abstract*—A significant difficulty associated with the use of stochastic programming to solve optimal power flow problems on a 5-minute timescale is the quality of renewable energy scenarios input by the user. This is especially true when considering power systems with high penetrations of renewable energy, e.g. wind power. This paper introduces the use of stochastic programming to solve the DC optimal power flow problem with scenarios drawn directly from high-fidelity data sets. Hence, the proposed method avoids the problem of lost physics by finding high-fidelity analogs that can describe future states of the system. Furthermore, this method can be simply extended to output multi-period scenarios to the stochastic program. We demonstrate the effectiveness of this technique by simulating dispatch operations on a synthetic test system over the course of a week.**

***Index Terms*—Stochastic optimization, high penetrations of renewables, data-driven forecasting, scenario-based optimization**

I. Introduction

As the penetration of renewable energy resources on power grids increase, so does uncertainty in available generation. Due to this fact, new methods for operating grids warrant consideration. Power generation from wind provides an excellent example of this point: ramping events over the span of minutes can cause large swings in the available power supply. For grids with high penetrations of wind, such events can be compared to losing multiple generators on a more conventional network. Classically, events involving the loss of generators are planned for via the use of security constraints, see e.g. [1]. However, when considering power grids with high penetrations of wind, operational methodologies which explicitly consider the uncertainty in wind power output should be considered. In this paper we propose a tool for representing the uncertainty caused by a high penetration of wind power on a grid.

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Our approach to addressing uncertainty caused by high penetrations of wind power begins with the application of multi-stage stochastic programming to economic dispatch problems. Stochastic programming is a well known tool to the power systems community, having found applications in, e.g. stochastic unit commitment problems, economic dispatch, and power systems planning. Here we apply the technique to multi-period economic dispatch under wind uncertainty at a 5-minute timescale.

A significant challenge when using multi-stage stochastic programming is the construction of scenarios which accurately represent uncertainties in the problem. In the case of wind power, uncertainty scenarios must capture spatial and temporal relationships between different wind power resources. Such samples can be obtained by constructing and sampling a high-dimensional joint probability density function (PDF). Constructing a high-dimensional joint PDF is difficult for our test case since it requires 132 dimensions (22 wind farms and 6 time steps). One method for constructing joint PDFs is to use copulas [2], [3]. However, copulas, to our knowledge, do not scale well to such high dimensions. We pursue another method: analog forecasting, where samples come from either real wind data or high fidelity weather models. In the remainder of this paper we present a technique which leverages large volumes of high fidelity data to circumvent the need to construct high-dimensional PDFs to represent wind uncertainty.

This paper is divided into the following sections: in Section II we briefly review two-stage stochastic programming and the economic dispatch problem. In Section III we describe our approaches to conditioning on current power and sampling multi-period wind power scenarios. In Section IV we demonstrate our economic dispatch approach on the Reliability Test System of the Grid Modernization Laboratory Consortium (RTS-GMLC) [4]. In Section V we state our conclusions and propose future work.

II. Background

Computing effective solutions to 5-minute economic dispatch problems for power grids with high-penetrations of wind power requires a decision-making process that accounts for the uncertainty inherit in renewable sources of energy. There are many problem formulations and algorithms used to address uncertainty in optimization problems. Robust optimization plans against all possible realizations of unknown variables leading to potentially very conservative solutions [5]. Chance constrained problems, where constraints formulated with unknown variables can be relaxed to hold with high probability, offer a less conservative approach [5], [6], [7]. However, these problems are almost always computationally difficult. The approach we choose to address uncertainties caused by wind power generation in the 5-minute economic dispatch problem is a two-stage stochastic program, which has useful properties both in terms of computation and modeling uncertainties in power grid operations.

The two-stage stochastic program [8], [7] is defined as:

$$\min_{\boldsymbol{x}} \quad f(\boldsymbol{x}) + \mathbb{E}_{\boldsymbol{\xi}}\left[L(\boldsymbol{x},\boldsymbol{\xi})\right] \tag{1}$$

$$\text{s. t.} \quad \boldsymbol{g}(\boldsymbol{x}) \leq \boldsymbol{0} \tag{2}$$

where

$$L(\boldsymbol{x},\boldsymbol{\xi}) = \min_{\boldsymbol{y}} \quad l(\boldsymbol{x},\boldsymbol{y},\boldsymbol{\xi}) \tag{3}$$

$$\text{s. t.} \quad \boldsymbol{g}_{\boldsymbol{\xi}}(\boldsymbol{x},\boldsymbol{y}) \leq \boldsymbol{0}. \tag{4}$$

The first stage of the program (1) is an optimization problem with decision variables $\boldsymbol{x}$, constraints $\mathbf{g}$, and objective function that includes the expectation of the second stage cost function $L(\boldsymbol{x},\boldsymbol{\xi})$, defined in (3), integrated against random variables $\boldsymbol{\xi}$. The second-stage optimization problem, $L(\boldsymbol{x},\boldsymbol{\xi})$, is a deterministic optimization problem with respect to the decision variables $\boldsymbol{x}$ and random variables $\boldsymbol{\xi}$. For this paper we restrict ourselves to the DC optimal power flow model (DCOPF), and thus only consider linear programs.

The expectation in (1) is not trivial to optimize over, thus approximations are often employed to ensure computational tractability. One example of such is the well-known sample average approximation (SAA) [7], where a sample average is used to approximate the expectation $\mathbb{E}_{\boldsymbol{\xi}}\left[L(\boldsymbol{x},\boldsymbol{\xi})\right]$ in (1). More formally, given samples $\{\boldsymbol{\xi}_i\}_{i=1}^N$, the expectation is approximated via $\mathbb{E}_{\boldsymbol{\xi}}\left[L(\boldsymbol{x},\boldsymbol{\xi})\right] \approx \frac{1}{N}\sum_{i=1}^N L(\boldsymbol{x},\boldsymbol{\xi}_i)$. Using the SAA with (1) and (3) reduces the two-stage stochastic program to a structured deterministic program.

Computing solutions to two-stage stochastic programs via the SAA requires scenarios that sufficiently capture the uncertainty of the problem. Specifically, in the context of using the SAA and two-stage stochastic programming to compute economic dispatch solutions in the presence of high penetrations of wind power, scenarios must accurately capture the uncertainty in wind farm generation over time from geographically distributed wind farms. Furthermore, the uncertainty must be characterized in a manner compatible with the computational tools used to solve the economic dispatch problem. E.g., if we are solving the AC or DCOPF problem, and thus considering power flow physics, a characterization of wind power uncertainty that only works for a copper sheet model will not be sufficient.

The scenario creation problem has been studied for power systems problems. See [9], [10] for work on scenarios for stochastic unit commitment and [11], [12] for work on economic dispatch scenarios.

III. Two-stage stochastic economic dispatch and data-driven scenarios

A. Two-stage stochastic economic dispatch formulation

Our approach to solving the economic dispatch problem using stochastic programming is to assign generator set points as first stage decision variables x, while relegating variables such as wind dispatched ω, wind spilled ω^{spl}, and slack variables describing loss-of-load and overload $y_i^{\pm}$ to the second stage. Intuitively, this division makes sense: generator set points must be decided before we know how much wind power will be generated. However, the amount of wind dispatched and spilled, slack variables, etc. are computed only once the random variables describing wind power output are realized.

The division of constraints between the first and second stage follows similar logic: ramping constraints in our model only apply to the generator set points, thus they can be placed either in the first or second stage. Constraints controlling the balance between wind power, spilling, dispatched, and forecast, along with power balance constraints at the nodes, and power flow constraints are all relegated to second stage constraints, as they are functions of the random variables describing wind power output from the wind farms. We note that while generator set points are first stage decision variables in our model, adjustments to generator set points to employ reserve quantities can be added as second stage decision variables. In such models, ramping constraints should be moved to the second stage to account for ramping in reserve use.

The mathematical formulation for the first stage of our model is,

$$\min_{\boldsymbol{x}} \quad \sum_{g\in G}\left(c_g x_g + \mathbb{E}_{\boldsymbol{\xi}}\left[L(\boldsymbol{x},\boldsymbol{\xi})\right]\right) \tag{5}$$

$$\text{s. t.} \quad x_g^{min} \leq x_g \leq x_g^{max} \quad \forall\, g \tag{6}$$

$$-R_g^{down} \leq x_g - I_g \leq R_g^{up} \quad \forall\, g, \tag{7}$$

where we have restricted ourselves to linear thermal generator costs c_g in (5), (6) are the minimum and maximum generation bounds for each dispatchable thermal generator, and (7) are the ramping constraints on the thermal generators that limit the amount a generator set point can change in a time period (I_g is the set point of generator g from the previous decision). The second stage costs, $L(\boldsymbol{x},\boldsymbol{\xi})$ in (5) are modeled by the loss function

$$
\begin{aligned}
L(\boldsymbol{x},\boldsymbol{\xi}) = & \\
\min_{\boldsymbol{y}^{\pm},\boldsymbol{\omega},\boldsymbol{\omega}^{spl}} \quad & \sum_{w\in W}\left(c_w\omega_w + c_w^{spl}\omega_w^{spl}\right) \quad + \qquad (8)\\
& \sum_{i\in\phi}\left(c_i^+ y_i^+ + c_i^- y_i^-\right)\\
\text{s. t.} \quad & 0 \le y_i^{\pm} \quad \forall\, i\in\phi \qquad (9)\\
& 0 \le \omega_w \le \omega_w^{fcst} + \xi_w \quad \forall\, w\in W \qquad (10)\\
& \omega_w^{spl} = \left(\omega_w^{fcst} + \xi_w\right) \qquad (11)\\
& \qquad - (\omega_w) \quad \forall\, w\in W\\
& \sum_{w\in W_i}\omega_w + \sum_{g\in G_i} x_g + \sum_{e\in\mathcal{E}_{in}(i)} f_e - \sum_{e\in\mathcal{E}_{out}(i)} f_e \qquad (12)\\
& \qquad = d_i + y_i^+ - y_i^- \quad \forall\, i\in\phi.\\
& \underline{F}_e \le f_e \le \overline{F}_e \quad \forall e\in\mathcal{E} \qquad (13)\\
& B_e(\theta_i - \theta_j) - f_e = 0 \quad \forall e = (i,j)\in\mathcal{E}. \qquad (14)
\end{aligned}
$$

Equation (8) contains the second-stage costs for our model, consisting of costs for slack variables $c_i^{\pm}$, wind generation c_w, and spilling wind c_w^{spl}. Bounds on slack variables are expressed in (9), while equations (10) and (11) contain bounds on the amount of wind dispatched and power-balance equations for the wind respectively, with ω_w^{fcst} being the forecast for wind power and ξ_w the deviation of realized wind power from the forecast at wind plant w in the set of wind plants W. The power balance for each bus is modeled via (12), and the line limits are modeled by (13), where ϕ is the set of buses, $\mathcal{E}$ is the set of lines with arbitrary directions assigned, θ_i is the voltage angle at bus i, and f_e is the power flow on line e. Finally, $\mathcal{E}_{in}(i)$ and $\mathcal{E}_{out}(i)$ represent directed lines into and out of bus i respectively, while W_i and G_i represent wind and thermal generators at bus i. For this work, we use the DC approximation to AC power flow, as expressed by (14).

Equations (5)-(14) describe our model for evolving economic dispatch problems by looking ahead for a single 5-minute time period. However, the real power of combining two-stage stochastic programming and data-driven scenario creation (described in the next subsection) is the ability to look ahead for multiple time periods. This approach allows us to consider ramping events contained within scenarios during the decision-making process. Updating our model to include multiple periods involves introducing time-dependence in the following variables,

$$
\left(x_g, \xi_w, \omega_w, \omega_w^{spl}, y_i^{\pm}, d_i, f_e, \theta_i\right) \mapsto \left(x_{g,t}, \xi_{w,t}, \omega_{w,t}, \omega_{w,t}^{spl}, y_{i,t}^{\pm}, d_{i,t}, f_{e,t}, \theta_{i,t}\right),
$$

introducing sums in (5) and (8) over periods $t_1,\ldots,t_M$, where M is the number of periods that we look ahead, and modifying ramping constraints such that

$$
-R_g^{down} \le x_{g,t_m} - x_{g,t_{m-1}} \le R_g^{up}
$$

for $m = 1,\ldots,M$ and x_{t_0} is equivalent to I_g in (7).

The benefits of taking ramping events and transmission physics from scenarios into consideration during the decision-making process become clear when choosing the amount of generation room to hold. Setting aside a percentage of generation capacity to hold for reserves does not take ramping nor transmission constraints into account when the generator set points are computed. Thus, while generation capacity is held, the extra power may be limited by transmission physics or ramping capabilities of generators. Since our multi-period approach computes transmission-constrained economic dispatch decisions using scenarios with ramping events, generator set points can be chosen to hedge against ramping events and limitations due to power flow physics.

B. Data-driven scenarios

The process of producing meaningful deviations from persistence forecasts for creating scenarios requires partitioning the set of candidate scenarios based on the amount of wind power present in the system. The reason for this partition is that deviations from persistence depend strongly on the current power. Wind-ramp events that increase power in a system that is producing near its capacity should not occur. Similarly, if there is a small amount of wind power supplied to a system, i.e. the wind is barely blowing, ramp events that lead to large decreases in power should not occur either.

Before defining the partitioning, the following definitions are required: the set of candidate scenarios is denoted by $S = \{s^j\}_{j=1}^{N_{\text{scen}}}$, where $s^j \in \mathbb{R}^{N_{\text{w}}\times N_{\text{t}}}$, N_{scen} is the number of candidate scenarios, N_{w} is the number of wind farms, and N_{t} is the number of time steps in each scenario, including current state of the wind (consequently, all scenarios will have $N_{\text{t}} \ge 2$). To generate a partition of the candidate scenario set, we first define the functional q (which enables us to condition on power)

$$
q\left(\boldsymbol{s}^j\right) = \sum_{w=1}^{N_{\text{w}}} s^j(w,1),
$$

and constants $p_{w,\text{high}} > p_{w,\text{low}} > 0$. The set of candidate scenarios are then partitioned such that

$$
\begin{aligned}
S_{\text{low}} &= \left\{s^j \mid q\left(\boldsymbol{s}^j\right) < p_{w,\text{low}}\right\}\\
S_{\text{med}} &= \left\{s^j \mid p_{w,\text{low}} \le q\left(\boldsymbol{s}^j\right) \le p_{w,\text{high}}\right\}\\
S_{\text{high}} &= \left\{s^j \mid q\left(\boldsymbol{s}^j\right) > p_{w,\text{high}}\right\}.
\end{aligned}
$$

Given S_{low}, S_{med}, and S_{high}, we modify the data so that the partitions contain deviations from the persistence forecast. This is accomplished by subtracting from each vector-element in the time series the first vector $s^j(:,1)$, i.e. the last known state of wind power, and replacing the entries in the partitioned data sets with

$$
\tilde{s}^j(:,n) = s^j(:,n) - s^j(:,1) \quad \forall n = 1,\ldots,N_t.
$$

We remark that $\tilde{s}^j(:,1) = \mathbf{0}$ for all $j = 1,\ldots,N_{\text{scen}}$. These vectors correspond to the current wind power on the system, and the subsequent values of n correspond to the deviations from the persistence forecast that assumes the wind power does not change from its value at $n = 1$.

C. Sampling from the scenario set

The process of drawing scenarios from partitions described in the last subsection begins with the selection of a partition to sample. A partition is chosen based upon which partition the last recorded actual wind power value would fall into. Once the appropriate data set to draw from has been chosen, samples are drawn at random, with replacement, from the partition and passed on to the two-stage stochastic program.

A powerful feature of our sampling technique is the ability to extend our approach to generate multi-period scenarios. This ability stems from how scenario sets S are stored in memory during computation. Candidate scenarios are stored as a list of time stamps that reference a historical data set. Thus extracting a scenario involves using a time stamp as an index and pulling out subsequent data. For single period, two time steps are drawn (one for current power, one for deviation from persistence). For multi-period, the only change required is to draw more time stamps.

Using multi-period scenarios enables the two-stage stochastic program to better incorporate ramping into the decision making process. As an illustrative example, consider a system operating near rated wind power, implying it is likely that wind power will drop. If multi-period scenarios containing significant wind power drops were passed to a two-stage stochastic program, the program would compute steps to economically mitigate ramp-down events therefore decreasing the likelihood of loss-of-load events. This is accomplished by holding extra thermal generation in a manner that preserves headroom across multiple generators to enable fast thermal ramping during subsequent time steps.

IV. Computational tests of performance

We tested our economic dispatch approach on a modified version of the RTS-GMLC (see Figure 1). The RTS-GMLC wind data were replaced by data from the Wind Integration National Dataset (WIND) Toolkit [13]. Furthermore, solar generation data were also replaced with WIND Toolkit data. The RTS-GMLC data were replaced using the following approach: for a bus with either wind or solar generation, the nearest WIND Toolkit sites to the geo-spatial location of the bus were aggregated and attached to the bus until the maximum capacity of renewables from the RTS-GMLC at that bus were met. Using WIND Toolkit data in place of the RTS-GMLC renewables data enables access to 7 years of high-fidelity synthetic data to run experiments with.

After replacing renewables data from the RTS-GMLC, we divided the wind power data into two partitions: 1 year of data were assigned to be a source of actuals, i.e. realizations of the wind power during our test period. The other 6 years were assigned as historical data, i.e. data that were used as the source of scenarios. Examples of multi-period scenarios drawn from the aggregation of WIND Toolkit sites are provided in Figure 2. We emphasize that this approach conserves the spatial-temporal fidelity of the WIND Toolkit data.

The tests consisted of solving the 5-minute economic dispatch problem for the RTS-GMLC over the course of a

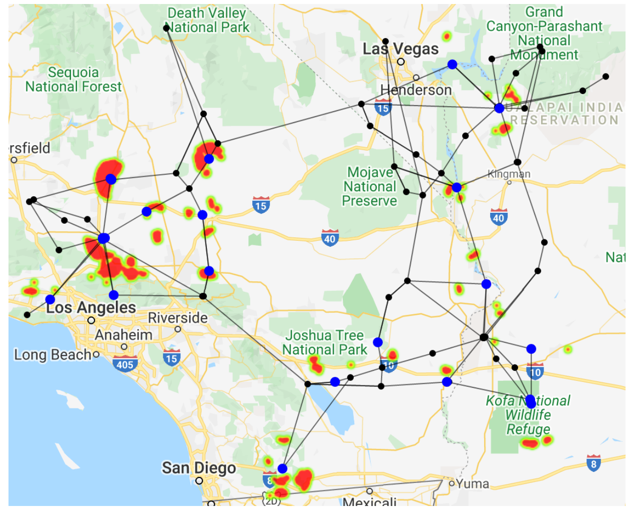

Fig. 1: RTS-GMLC network: 51 buses (black dots), 22 buses with wind generation (blue dots), 445 WTK wind sites (heat map), 104 transmission lines (black lines)

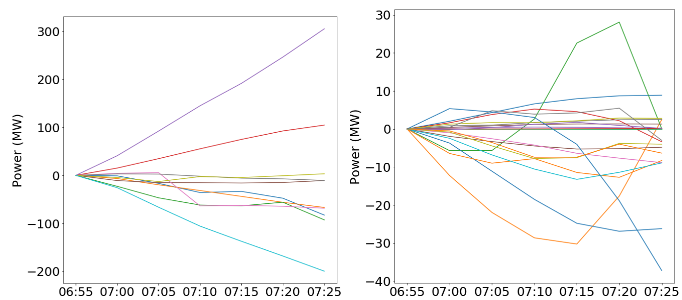

Fig. 2: Examples of deviations from persistence for wind power on the RTS-GMLC. (Left) 10 scenarios of total wind power on the grid, $\sum_w s^j(w,t)$, $j = 1,\ldots,10$. (Right) A single scenario displayed for all 22 wind farms, $s^1(w,t)$, $w = 1,\ldots,22$.

simulated week. Tests were run using two types of scenarios: single-period and six-period. Operational costs, including first and second stage costs, are provided in Table I and Table II. Plots of second stage costs are provided in Figure 3. In the tables, stochastic economic dispatch is compared with a deterministic approach that uses a persistence forecast. We observe that stochastic programs using both types of scenarios outperform (i.e. operations are conducted with a lower cost) the deterministic approach over the course of the week in terms of second stage and total costs. However, we remark that in every case the first stage operational costs of the stochastic economic dispatch are more expensive than the deterministic approach. This difference is small compared to the amount of savings from the second stage optimization problems. Thus the total costs of operations are lower.

The phenomena of stochastic economic dispatch producing slightly higher first stage costs and much lower second stage costs is due to the pricing of loss-of-load compared with the

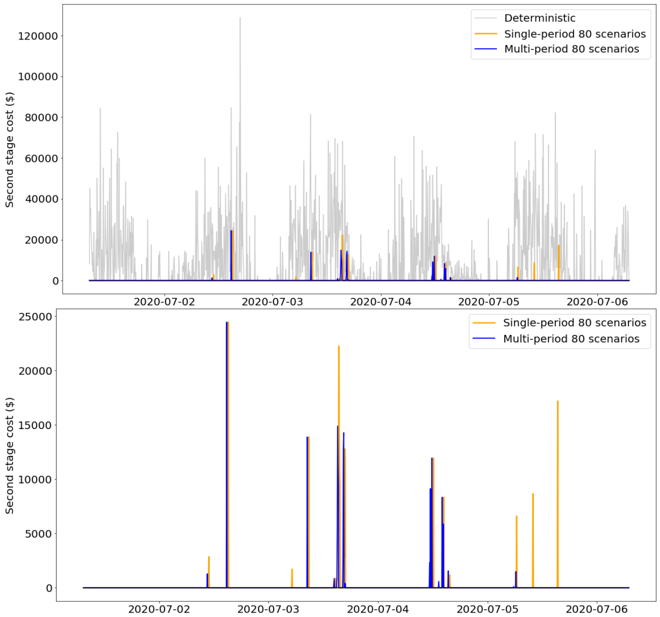

Fig. 3: Second stage costs from one-week economic dispatch experiments including (top) and excluding (bottom) deterministic results. We observe that both our stochastic approach and increasing the number of periods lowers operational costs.

TABLE I: Single Period Economic Dispatch Costs

	Single Period Dispatch Costs ($)		
# of Scenarios	1st stage	2nd stage	Total Costs
deterministic	3.138×10^6	1.455×10^7	1.769×10^7
20	3.181×10^6	8.813×10^5	4.062×10^6
40	3.190×10^6	4.714×10^5	3.661×10^6
80	3.201×10^6	1.976×10^5	3.399×10^6

price of overload or spilling wind. Loss-of-load is by far the most expensive ($833 per MW compared to $42 per MW for overload, spilling wind is essentially free), thus the inclusion of the expectation of the loss function $L(\mathbf{x}, \xi)$ in (5) enables the algorithm to hedge against the potential of loss-of-load by increasing the values of the first stage decision variables subject only to resource, overload, and wind-spilling costs.

We also notice that increasing the sampling rate in the stochastic economic dispatch experiments leads to lower second stage costs. This is due to our use of relatively low sampling rates for scenarios. Assuming the existence of a probability distribution function describing the space of multi-period scenarios, it is highly unlikely that we are sampling at sufficient rates to compute the expectation to a high degree of accuracy. Despite this shortcoming, our approach still shows a dramatic improvement over using only a persistence forecast. For details on sufficient sampling for the SAA see [7].

V. Conclusion

In this work we have demonstrated that coupling stochastic programming with scenarios drawn from high-fidelity synthetic data sets yields an effective approach to computing 5-minute economic dispatch solutions. Such an approach could

TABLE II: Multi-Period Economic Dispatch Costs

	Multiple Period Dispatch Costs ($)		
# of Scenarios	1st stage	2nd stage	Total Costs
deterministic	3.138×10^6	1.455×10^7	1.769×10^7
20	3.180×10^6	8.083×10^5	3.988×10^6
40	3.189×10^6	4.072×10^5	3.596×10^6
80	3.198×10^6	1.543×10^5	3.3523×10^6

also be applied to a power grid with historical wind power data. Our experiments illustrate an example where using scenarios built from data with stochastic economic dispatch leads to more cost-effective dispatch decisions than those produced with a simple economic dispatch using only a persistence forecast. Due to the expense of loss-of-load, the stochastic program decides to strategically over-produce, preferring to incur cheaper overload and wind-spilling costs instead of risking loss-of-load events.

Future work will include refinement of how to select scenarios from the provided population of time series data. Due to the structure of the loss function, some scenarios will not affect the expectation term in the first stage loss function and should not be selected from the population for use in the stochastic program. Also of interest for future work is the application of these techniques to problems with real wind data.

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