Final Scientific/Technical Report

STOCHASTIC OPTIMAL POWER FLOW FOR REAL-TIME MANAGEMENT OF DISTRIBUTED RENEWABLE GENERATION AND DEMAND RESPONSE

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Public Executive Summary

To meet the grand challenge of a sustainable energy future, there has been a surge of interest in renewable energy. Today, the uncertainty associated with renewable resources is handled by using operating reserves. The high penetration of renewable resources, however, introduces difficult-to-control dynamics and challenges for power system operation. Decision support tools are necessary at the bulk system operational level to recognize and efficiently utilize renewable resources and distributed demand response products in concert with traditional grid resources. It is envisaged that responsive load can potentially have very significant cost advantages over either spinning or non-spinning ramping reserve. Critical decisions are made during hour(s)-ahead and real-time power system operation regarding the commitment and dispatch of generators to ensure power delivery is both reliable and economic. These decisions are typically made by a security constrained optimal flow, which determines future generator commitments, dispatches, and ensures adequate reserves are available in the event of a contingency (unexpected outage) or if future system conditions deviate from forecasts. However, security has been always based on a pre-specified subset of contingency constraints whose enforcement does not guarantee security under all possible future possibilities while also giving little or no weight to the likelihood of each contingent event or the severity of its consequences. Existing tools, which are based exclusively on deterministic optimization models, do not yield optimal operational decisions to address these new challenges, in terms of both reliability and cost-effectiveness.

This project has focused on developing a stochastic optimal power flow (SOPF) framework, which integrates renewable resource uncertainty, load uncertainty, distributed storage (DS), demand response (DR) products, in a holistic manner to address the uncertainty associated with ever-increasing renewable resources, along with the inclusion of distributed demand response products in future power systems. A proof-of-concept problem was created using the Pennsylvania-Jersey-Maryland (PJM) power system network. Synthetic wind generation was added to the system to simulate 50% wind penetration. A 1-hour test of SOPF operation indicated more than 6% operational cost savings. The project continued by adding the Midwestern Independent System Operator (MISO) as a partner, with focus shifting from SOPF to Stochastic Look-Ahead Unit Commitment (SLAC). Unlike PJM, MISO is faced with significant renewable energy resources within its footprint and is challenged with substantial uncertainty in its operations. The SLAC distinguishes itself from existing tools that operators use. At best, today's tools solve two to three cases independently, where one or two system parameters, such as forecasted load level (e.g., a low, base, and high forecast), are varied and the resulting scenarios are analyzed independently. The stochastic-based optimization of SLAC leverages statistical information from an ensemble of potential operational scenarios and their respective likelihood. The SLAC output can be translated into valuable information to the operator such as suggested commitments, optimal scheduling and dispatch of resources, reserve requirements at both locational and zonal resolutions, ramping availability and requirements, availability of demand response including operational guidance concerning the near-term and real-time coordination between distributed energy resources, and utilization of distributed storage resources.

The developed SOPF/SLAC tool, a stand-alone tool compatible with existing EMSs, will provide system operators with unprecedented visibility, flexibility and predictability to these resources and operational guidance concerning the real-time coordination between DERs and DR/DS products. The game changing and practical impact of this disruptive technology will be dramatic, and will usher in a new era in the electric power industry, wherein green energy concepts are fully embraced and electric power costs are lowered throughout the nation.

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Accomplishments and Objectives

The objective of this project was to develop a stochastic optimal power flow (SOPF) framework, which integrates renewable resource uncertainty, load uncertainty, distributed storage, demand response products, in a holistic manner to address the uncertainty associated with ever-increasing renewable resources, along with the inclusion of distributed demand response products in future power systems.

A number of tasks and milestones were laid out at the beginning of the project. The performance against the stated milestones is summarized here:

Table 1. Key Milestones and Deliverable.

Tasks	Milestones and Deliverables
Task 1: Short term forecast algorithms of wind/solar	Develop stochastic models and forecast algorithms for wind/solar generation
Task 1.1: Formulate and develop data analytics based stochastic models for wind/solar generation	The objective is to develop stochastic models for wind/solar generation, by using spatio-temporal analysis of the historic data to extract the statistical characteristics therein. The desired result is a suite of Markov models, each for an epoch of 3-hour time horizon, where the state space and transition probability matrix are designed based on the statistical distribution and temporal dynamics of wind/solar power learned from historical data.
Milestone 1.1.1: Process historical data to extract statistical characteristics.	Finish data collection and processing of wind/solar generation and extract statistical distribution for different epochs accordingly. Determine stationarity, seasonality and diurnal characteristics and adjust epoch intervals to satisfy stationarity requirement that the variation of the empirical distribution is less than 10%.

	Actual Performance: (Completed 10/10/2016) A variety of historical data from several wind farms and solar farms was used in this project. The wind generation data sets include one 300 MW plant in Colorado with data resolution of 10 minutes. In addition to the Colorado plant, four wind generation sites in the PJM system were available. All PJM generation sites have a data resolution of 5 minutes. Lastly, a large number of wind generation sites are available from the Australian Energy Market Operator (AEMO) in Australia. These generation sites also have a data resolution of 5 minutes. The solar generation data sets include three First Solar sites located in California. However, their exact locations are unknown. These data sets have a data resolution of 5 minutes. In addition to the First Solar plants, a distributed solar dataset is available from the state of California. This is a public dataset that consists of 504 distributed small-scale solar sites. These datasets have a data resolution of 15 minutes.
Milestone 1.1.2: Establish state space model	Build the state space of the Markov models, and quantify the transition probability matrix accordingly. Adjust the average duration of the state to represent the translational behaviors of the wind farm or solar farm real power outputs. The average duration will be determined, by a recursive algorithm, as a solution to an optimization problem. **Actual Performance:** (Completed 4/10/2017) Several innovations were developed regarding the state space of the Markov models. The new Markov model is referred to as the induced Markov chain and has improved state definitions.
Task 1.2: Devise finite-state Markov-chain based forecast algorithms for bulk wind/solar generation	Formulate and develop Markov-model based algorithms for distributional forecast and point forecast of bulk wind/solar generation
Milestone 1.2.1: Work out forecast algorithms for bulk wind farm generation	Devise algorithms for distributional forecast and point forecast, by optimizing finite-state Markov chain models for aggregate wind generation forecast, and test the accuracy using real data traces. For point forecasts, the mean absolute error should be within 5% and the root mean square error to be limited to 7%. **Actual Performance:** (Completed 7/09/2017) Induced Markov chain (IMC) models were developed for bulk wind farm generation forecasting. The IMC was applied to the 300 MW Colorado wind farm for testing. This data has a resolution of 10 minutes. The model was trained with data from all of 2009 and tested on all of 2010. The IMC achieved errors of 4.79% mean absolute percentage error (MAPE) and 8.50% root mean squared percentage error (RMSPE). This performance met the MAPE milestone target but missed the RMSPE

	target. The IMC was then applied to the PJM wind farm data sets. The Colorado wind farm was measured at 10-minute resolution, but the PJM farms were measured at 5-minute resolution. The IMC performed better on the farms with higher data resolution. The IMC achieved errors between 2.81-3.93% MAPE and 6.39-6.96% RMSPE. The IMC met all performance targets when higher resolution data was available.
Milestone 1.2.2: Work out forecast algorithms for a large number of distributed PV solar generation	Devise forecast algorithms based on optimized finite-state Markov chain models for a large number of distributed PV solar generation sites, and quantify the accuracy in terms of mean absolute error using real data traces We will tune the interval of the epoch needed to obtain the desired accuracy and the mean absolute error should be within 5%. **Actual Performance:** (Completed 4/10/2018) Induced Markov chain (IMC) models were developed for PV solar generation sites. The IMC was applied to the 139 MW First Solar (solar PV) site for testing. This data has a resolution of 5 minutes. The model was trained with data from all of 2014 and tested on 2015 data. The IMC achieved errors of 3.87% MAPE. This performance met the milestone target.
Task 1.3: Devise Vector AR based forecast algorithms for bulk wind/solar generation	Leverage VAR model to develop joint forecast algorithms for multiple wind/solar generation in the proximity
Milestone 1.3.1: Devise VAR based forecast algorithms	Develop joint forecast algorithms for multiple wind/solar generation in the proximity by leveraging vector autoregressive (VAR) model to capture spatio-temporal correlation, and test the accuracy. For point forecasts, the mean absolute error should be within 5% and the root mean square error to be limited to 7%. **Actual Performance:** (Completed 4/10/2018) Methods based on vector autoregression (VAR) were explored using the available wind data sets. A vector autoregressive (VAR) model was applied to the individual wind turbines of the Colorado wind farm. The VAR model achieved performance of 4.95% MAPE and 8.757% RMSPE. This met the MAPE milestone target but missed the RMSPE target. The VAR model was also applied to the PJM wind farms. The Colorado wind farm was measured at 10-minute resolution, but the PJM farm was measured at 5-minute resolution. The VAR model performed better on the farm with higher data resolution. The VAR model achieved errors of 4.20% MAPE and 6.937% RMSPE. The VAR model met all performance targets when higher resolution data was available.

	VAR methods were also developed for distributed PV solar distribution sites using data from the California Solar Initiative. In the power system rooftop PV systems are connected to transmission networks through distribution substations. Therefore, it is the sum of solar generation from PV systems connected to each distribution substation that needs to be forecasted. PV systems in California were located using ZIP code location information. The VAR model achieved performance between 3.28 to 3.86% MAPE and 5.65 to 6.35% RMSPE, meeting all milestone targets.
Milestone 1.3.2: Improve forecast accuracy for ramp events	Enhance the forecast accuracy in the presence of ramp events by using support vector machine (SVM) to model ramp patterns and refine the Markov models to obtains mean absolute errors within 3% and root mean square errors within 5%. **Actual Performance:** (Completed 7/9/2018) The IMC model developed for Milestone 1.2.1 was enhanced here with the use of a support vector machine (SVM). The SVM enhanced IMC (SVM-IMC) was applied to the 300 MW Colorado wind farm data. For this milestone, the model was only applied to periods of wind ramping. A downward wind ramp occurs only if the power change in 1 hour is at least 15% of the total capacity. An upward wind ramp occurs only if the power change in 1 hour is at least 20% of the total capacity. The SVM-IMC was able to achieve performance of 2.82% MAPE and 4.20% RMSPE. This performance met both targets set in this milestone.
Task 2: Stochastic SCED algorithms for real- time management of DERs and DR	Formulate and design of stochastic SCED algorithms for real-time management of DERs and DR
Task 2.1: Develop Deterministic SCED	Develop market based deterministic SCED model and algorithm to be used as a baseline for validating and evaluating the performance of Stochastic SCED algorithms. Validation based on collaboration with PJM, validated against PJM's commercial SCED via an internship at PJM and validated PJM.
Milestone 2.1.1: Deterministic SCED	Market based deterministic SCED solving <3 min on large-scale system with >10K bus network like PJM system data (without DER and DR); standard desktop computer – specifications of 12-core processor with 512GB RAM and 1TB hard disk (details to be used going forward); optimality gap: 0.5% **Actual Performance:** (Completed 1/08/2017) The deterministic SCED developed was based on MISO's real-time SCED model, which is available in their business manual, and was modified to satisfy PJM's real-time market clearing procedures. The SCED was tested on a single period using PJM's system data. The test system consisted of

	1,664 generators, 10,188 buses. The total solution time was 20 seconds on a standard desktop computer with Intel® Core® 2.60 GHz CPU and 16 GB memory. The performance of the deterministic SCED meets the milestone target.
Task 2.2: Module 2: Two-stage stochastic SCED model specifications	Two-stage stochastic security constrained economic dispatch tool solved via progressive hedging
Milestone 2.2.1: Module 2 performance	Performance benchmarking of core stochastic SCED: <5 min solve time, standard desktop computer (defined in M2.1.1), medium to large-scale system with >2K bus network (e.g., Polish system); renewable penetration level: >20%. **Actual Performance:** (Completed 7/09/2018) The stochastic SCED optimization problem is solved using a progressive hedging (PH) decomposition algorithm. The PH algorithm was implemented in python/PYOMO. The stochastic SCED was tested using the PJM system data (>10k buses) and solved in under 5 minutes.
Task 2.3: Integration of DR to module 2	Design and classification of distributed demand response products; integration within stochastic SCED model
Milestone 2.3.1: Deterministic SCED with DER and DR	Market based deterministic SCED solving <3 min on large-scale system with >10K bus network like PJM system data (with DER and DR); standard desktop computer (defined in M2.1.1); optimality gap: <0.5%. Specification of DER and DR products to be defined by Task 3. **Actual Performance:** (Completed 10/08/2017) Demand response (DR) has been modeled and integrated into the SCED model as generator resources similar to contemporary industry practices. Since DR corresponds to the same modeling as generators, computational performance does not significantly change (the impact in performance is mild comparatively to other features e.g., the inclusion of uncertainty). The SCED model achieves a solution time of approximately 57 seconds (less than 3 minute, which is the stated target in the milestone).
Task 2.4: PH Algorithm refinement	Refinement to progressive hedging algorithm for stochastic SCED with DER, DR, and storage
Milestone 2.4.1: Module 2 performance	Performance of refined stochastic SCED: <3 min solve time, standard desktop computer (defined in M2.1.1); optimality gap: <2%; large-scale system (PJM); renewable penetration level: >20%.

	Actual Performance: (Completed 7/09/2018) DER, DR, and storage were integrated into the stochastic SCED problem. The PH algorithm was utilized to meet the solution time and optimality gap milestone requirements. Tests were conducted using the PJM system data. DR/DER capacity was determined for 23 buses corresponding to metropolitan areas in the system. Scenarios for renewables were generated using the algorithms from Task 1 with a penetration level of 20.1%. All milestone targets were met.
Task 2.5: Module 3: operator advisory tool specifications	Model specifications for the advisory tool that communicates to the operators and market based SCED
Milestone 2.5.1: Module 3: operator advisory tool specifications	Develop operator advisory tool (Module 3) specifications. Requirements should be reviewed with project's industry advisory board (IAB). Delivery of requirements document to ARPA-E for review and approval by program director. **Actual Performance:** (Completed 12/08/2017) The stochastic SCED tool will provide a spectrum of potential solutions or actions. That output, representing the range of operating cases. The advisory tool then uses the outputs from the stochastic SCED tool to produce various different indicators, e.g., confidence intervals, expectations, etc. that are further leveraged to generate the outputs from the advisory tool for the operator to use as inputs directly to the market SCED or as discretionary advice for out-of-market corrections initiated by the operator (outside the market). The advisory tool will also take inputs from the operator to adjust the means by which the outputs are determined (for instance, choose a different confidence interval when determining the quantity of reserve needed for a particular reserve product). These specifications of the advisory tool have been discussed and reviewed by the industry advisory board and during all of the prior in-person technology-to-market interactions that the team has had with many entities including, but not limited to, PG&E, CAISO, ERCOT, SPP, MISO, PJM, and ISONE. Milestone targets were met.
Task 2.6: Proxy reserve inputs for market SCED	Module 3: advisory tool: inputs for deterministic market SCED: determination of reserve product requirements, ramping requirements, and demand response utilization.
Milestone 2.6.1: Proxy reserve inputs for market SCED	Define input requirements of the Proxy server for market SCED. Requirements should be reviewed with project's industry advisory board (IAB). Delivery of requirements document to ARPA-E for review and approval by program director. **Actual Performance:** (Completed 4/08/2018) In this task, we engaged with the industry to identify the best way to leverage the information

	from the stochastic optimization engine to be of benefit directly for a market based SCED tool. The stochastic optimization engine has more applications than just for the market based real-time SCED tool. In this situation, we focus on the proxy reserve inputs that are there for only the real-time market SCED. This starts with the procurement requirements of all of the typical reserve products: regulation up/down, spin reserve, non- spin reserve, and replacement reserve. These reserve requirements vary throughout industry regarding how they are modeled. The advisory tool was designed to accommodate any of these traditional reserve policies that are commonly used today. Milestone targets were met.
Task 2.7: Rolling Horizon DR model	Rolling horizon testing of stochastic SCED (5 min interval based SCED with look- ahead up to 1 hour, over multiple days) and adaptive flexible (net) load management of DR (i.e., SCED includes DR model and manages its flexibility)
Milestone 2.7.1: Integrated modules	Integrated module testing on large-scale system with >10K bus network like PJM data or similar: <5 min solution time; 3% cost savings; standard desktop computer (defined in M2.1.1); optimality gap: <2%; modules 1-3 **Actual Performance:** (Completed 7/09/2018) A comparison between the deterministic SCED and stochastic SCED was conducted using the PJM system data (>10k buses). A total of 12 subproblems were considered in the stochastic SCED. The test consisted of a single 1-hour period. The stochastic SCED resulted in 3.6% cost savings, solving in 178 seconds with <2% optimality gap. A second test was conducted using 144 subproblems (more renewable scenarios and generator outages considered). Results then increased to 6.2% savings.
Milestone 2.7.2: DR product quality of service testing	Performance testing of flexible load management of DR (large-scale system with >10K bus network like PJM system data); assess the performance relative to the FOA requirements (requirements for: a) Spinning Reserve Products (not Regulation Reserve Products) under Category 2; b) Category 3: Synthetic Ramping Reserves). **Actual Performance:** (Completed 1/18/2019) The stochastic SCED was implemented in a rolling-horizon fashion using the PJM system data (>10k buses). The solution for every interval determines the generator's dispatch setpoints and reserve products for the next 5-minute and second stage decision variables. Once the wind uncertainty is realized, the SCED model is solved again to obtain the generator and DR set-points, using the first stage variables of the stochastic program. This solution is fed back to the DR model which

	generates a new set of the DER capacities and bids that are then used as input to the consecutive SCED solver. The milestone targets were met. A DR (TCLs and batteries) system capacity of 900 MW (<1% system load) yielded a reduction in objective value of 14%.
Task 3: Adaptive flexible load management of DR	Modeling, design and integration of DR products
Task 3.1: Aggregate decision and control model of DR capacity from Thermostatically Control Loads (TCL) and Deferrable Loads	The goal of this activity is to build low order stochastic dynamic models that would allow to control the aggregate response of large population of heterogeneous Thermostatically Controlled Loads and Deferrable Loads Performance simulations will show • MSE error in reproducing the aggregate time response and forecast of future state of the population for a given order of the model and for a given size of the population.
Milestone 3.1.1: Module 1 – Aggregate model of TCL and Deferrable Loads	Simulation program reproducing realistically the dynamic behavior and control of populations of Thermostatically Controlled Loads and Deferrable Loads. Performance targets for both categories that we plan to match or exceed: • MSE <1% representation error compared to detailed model for a population of 1000 loads. **Actual Performance:** (Completed 01/10/2017) Individual thermostatically controlled loads were modeled as thermal circuits. Devices with similar dynamic parameters were then grouped together into clusters to reduce overall problem complexity. The control strategy to shape the aggregate load can be mapped to instructions that are issued to the clusters on how the heat pump should be operated to move between states to obtain the desired load pattern. The disaggregation control is accomplished by sending a message to each cluster that allows each device to determine the probability that it should move to another state. The aggregated control of 10000 individual loads was simulated over the course of 3 hours. The error between the actual load and estimation using the aggregate model was typically below 0.5% with only 759 data points or 0.3% of data violating the 1% threshold. Modeling deferrable loads requires knowing critical information about each load arrival: energy requirements and desired load shape, departure time, and whether the appliance can be interrupted or not. The deferrable load is controlled by modeling the path taken through the deferrable state-space. A simulation of 10,000 homogeneous electric vehicles (EVs) were simulated over a 3-hour period. The aggregate model achieved the 1% MSE target. The simulation of

	10,000 homogeneous washer-dryers also achieved the milestone target.
Task 3.2: Aggregate decision and control model of distributed storage with stochastic in- feed	The goal of this activity is to design aggregate models that would allow to control the aggregate response of distributed storage. The analysis will also explore a randomly changing state of charge due to stochastic in-feed from renewables or local random demand. Performance simulations will show • MSE error in reproducing the aggregate time response of the population for a given order of the model and for a given size of the population. • MSE in the ex-ante forecast of future state from the aggregate model
Milestone 3.2.1: Module 2– Aggregate model storage with stochastic in-feed	Simulation program reproducing realistically the dynamic behavior and control of populations the dynamic behavior and control of DS in a given state at the beginning of the control period for an ideal homogeneous sample population and a given deterministic DS initial charge state with constant, zero in- feed, Gaussian random in-feed Performance targets • MSE <1% error compared to detailed model for a population of 1000 DS. **Actual Performance:** (Completed 07/09/2017) The charge of an individual storage device is assumed to be dependent on a combination of renewable infeed with local inflexible consumption (*k*) and infeed directly from the distribution grid (*p*). It was assumed that the aggregator knows the distribution of *k*. Simulations of a 2-hour period containing 24 time steps was conducted controlling 10,000 households. It was assumed that no households arrive or depart once the simulation begins and the initial state of charge is known. The distribution *k* was assumed to be Gaussian. The objective of the aggregation controller was to minimize the cost of energy over the simulation. A cost curve with sinusoidal noise was used to represent the cost of energy. The simulation was performed with different standard deviations of infeed (*k*). The control model was able to meet the 1% MSE error set by this milestone with standard deviations up to 1000 kW.
Task 3.3: Classification and aggregate modeling of DR resources	The goal of this task is the classification of distributed load resources with a random non-stationary Poisson number of Thermostatically Controlled and Deferrable Loads with mean

	(and variance) from 1000 to 10000 and heterogeneity in the population in order to assess the possible DR and DS services and capacity they can realistically offer to the market; it will also include the analysis of resource deterioration and rebound peaks phenomena for TCL and DL. Interaction with Task 2.4 Performance simulations will determine the following quantities versus population size • Reserve Magnitude (RM) and Duration • Response Time (ResT) average and standard deviation • Ramp Time (RampT) average and standard deviation to 50% and 90% of capacity/max. reserve target possible. • Duration average and STD versus population size
Milestone 3.3.1: Numerical methods to establish DR and DS capacity	Numerical evaluation of the different classes of DR and DS resources performance limits due to their inter- temporal dynamics, heterogeneous physical constraints, response delays and imperfect telemetry Performance targets for TCL and Deferrable Loads • RM >4% of total load for TCL, RM ~50% of Deferrable Load • Tolerance <1% of the RM for populations >=1000 • Average ResT <10 sec , STD ResT < 10 sec for population of 1000 loads and for a population size offering max RM =100MW • Average RampT <10 sec STD <10 sec • Duration average >30 min for TCL and 3 h DL offering 100MW of RM. Performance targets for DS that we plan to match or exceed: 1. Tolerance <1% of the RM for populations >=1000 2. Average ResT <10 sec , STD ResT < 10 sec for population of 1000 storage units and for a population size offering max RM =100MW 3. Average RampT <10 sec STD <10 sec 4. Duration average >4 h for offering 100MW of RM. **Actual Performance:** (Completed 7/10/2017) For the simulation of TCLs a RM > 4% was easily achieved for durations of at least 30 minutes. Average response and ramp times of under 10 seconds were achieved by the proposed aggregation/disaggregation approach. For the simulation of deferrable loads, a RM of 50% was attainable for between 2 and 3 hours. Response and ramp times for deferrable loads were found to be much better than the target of 10 seconds. The target RM (100 MW for 4 hours) was found to be reached at 30,000 batteries, with response and ramp times much better than the target. DR limits were determined for each load type that allow target error tolerances to be met.

Task 3.4: Evaluation of DR dynamics beyond the control period in preparation for Rolling Horizon DR model (in preparation for Task 2.7)	Evaluation of DR dynamics during and beyond the control period • RM characterization for rolling horizon • Rebound peaks % of the peak of reserve capacity used and energy in the rebound peak • MSE in the prediction of the rebound peak
Milestone 3.4.1: Software analysis of DR load trends beyond a performance period of 3h supported with 1000 to 10000	Software analysis of DR load trends beyond a performance period of 3h supported with 1000 to 10000 average number of Thermostatically Controlled Loads and Deferrable Loads Performance targets • Rebound peaks energy neutral, and with peak rebound power 10% of the peak reserve used • MSE in the prediction of the rebound peak < 10% **Actual Performance:** (Completed 1/8/2018) A 60-minute 3.3 GW reserve event was simulated using estimated CAISO controllable load. The rebound peak was not necessarily energy neutral but was far less than the conventional curtailment event. Peak rebound power met the target and further could be controlled (magnitude vs time) by the operator to get the most favorable solution. The modeling error was far less than 10%.
Task 3.5: Algorithm design and stochastic OPF integration OPF (see also Task 2.7)	Design algorithms to select the do-not- exceed (DNE) limits that are inputs to the stochastic SCED, from the aggregate DR and DS model Performance simulations will determine the following quantities versus population size and RM: • DNE calculation
Milestone 3.5.1: Integration with OPF (see also M 2.7.2)	Software tool to numerically select DNE performance limits and analysis of the benefits that can be accrued using Stochastic OPF leveraging DR and DS Performance targets • DNE <%5 for all the relevant performance metrics (RM,ResT,RamT, Duration) **Actual Performance:** (Completed 7/9/2018) The feasible dispatch region (MW with respect to time) is computed for all available resources. This feasible region is then provided to the OPF in the form of a generator being dispatched over the coming horizon. All performance targets were met.

Task 3.6: Validation	Validation the DR and DS aggregation and disaggregation (online-control) via numerical simulation and based on real data and interface to Stochastic OPF program Demonstration of ability of Stochastic OPF to exploit DR and DS resources reliably • Priority 1 (Critical) – Test functionality and robustness of the software performance under batch data (no real time) • Priority 2 (High/Medium) -- Analyze options for real time solution
Milestone 3.6.1: Validation of software and DR product quality of service testing	Test of compliance with Performance Targets Performance testing of flexible load management of DR (large-scale system with >10K bus network like PJM system data); assess the performance relative to the FOA requirements (requirements for: a) Spinning Reserve Products (not Regulation Reserve Products) under Category 2; b) Category 3: Synthetic Ramping Reserves). Same as 2.7.2, meeting or exceeding FOA requirements **Actual Performance:** (Completed 10/1/2018) The DR models were incorporated in a programming bundle that can offer DR capacity bids to the SCED formulation and react to a dispatch decision given by the SCED result. Simulations were done using PJM system data and DR aggregates were added to 60 buses within the system. The simulated response of DR individuals in a rolling horizon fashion was within the 1% performance target and can be maintained by periodically resyncing the state of individuals.
Task 4: Integration and Software development of Stochastic OPF	Define, design, develop and test the Stochastic OPF software.
Task 4.1: SOPF software requirements	Gather minimum functional requirements for the software development phase and required data. This task will be initiated with PJM as the primary source.
Milestone 4.1.1: Functional Requirements Document	Functional requirements document for the Stochastic OPF software. Delivery of requirements document to ARPA-E for review and approval by program director. **Actual Performance:** (Completed 1/08/2017) The functional requirements document for the stochastic OPF software was delivered to ARPA-E on 1/08/2017.

Task 4.2: SOPF software design	Design the necessary functional modules of the SOPF software and create a high level software design document. Prototype development for module 1: deterministic market based SCED for testing.
Milestone 4.2.1: SOPF Design Document	Create a high level software design document that meets the functional requirements gathered in Task 4.1. Delivery of design document to ARPA-E for review and approval by program director. **Actual Performance:** (Completed 4/08/2018) The high level software design document was developed by Nexant and delivered to ARPA-E. The document was continuously updated throughout the project as changes to formulation or model were made.
Milestone 4.2.2: SOPF Performance evaluation	Market based SCED solving in <1 minute on large-scale system with >10K bus network, PJM system size, on a standard desktop computer (defined in M2.1.1) **Actual Performance:** (Completed 1/08/2017) The deterministic SCED developed was based on MISO's real-time SCED model, which is available in their business manual, and was modified to satisfy PJM's real-time market clearing procedures. The SCED was tested on a single period using PJM's system data. The test system consisted of 1,664 generators, 10,188 buses. The total solution time was 20 seconds on a standard desktop computer with Intel® Core® 2.60 GHz CPU and 16 GB memory. The performance of the deterministic SCED meets the milestone target.
Task 4.3: SOPF software development	Develop the prototype version of the SOPF software per the algorithms developed in Tasks 1, 2 and 3 that meet the functional requirements established in Task 4.1. Stochastic SCED refinement; Refinement for PJM specifications; specification for other potential customers engaged via T2M
Milestone 4.3.1: Report on the status of the software development process	Create a high level report outlining the software modules that were developed and a checklist of the functional requirements that were met by these modules. Create a test plan for Task 4.4. Delivery of development and test plan documents to ARPA-E for review and approval by program director. Prototype testing of stochastic SCED (with limited functionality, without DER and DR integrated) on PJM system. **Actual Performance:** (Completed 10/8/2018) Nexant completed this milestone in the 3rd week of July 2018 and a detailed report was

	provided to ARPA-E. Each component of the optimization formulation programmed in Python was tested and all parts passed validation.
Milestone 4.3.2: Report on the status of the software development process	Status update on the software development. Demonstrate system functionality and success metrics of task 2.6 **Actual Performance:** (Completed 10/8/2018) Nexant completed this milestone in the 3rd week of July 2018 and a detailed report was provided to ARPA-E.
Milestone 4.3.3: Report on the status of the software development process	Status update on the software development. Demonstrate system functionality and success metrics of task 2.7. **Actual Performance:** (Completed 7/9/2018) Demand response modeling was implemented into the stochastic SCED for M2.4.1. Demand response capacity was determined for 23 buses, across 5 major metropolitan areas of the PJM system. The capacity was determined for air conditioners (TCLs), following methodology described in past milestones. Within the stochastic SCED the demand response was modeled as a generator. The DR was implemented and was included in the DVP results provided in M5.2.2. In that execution of the stochastic SCED, the general level of LMPs is below the value of $45/MWh and thus the DR consumed more power from the grid. The system functionality and success metrics were demonstrated.
Task 4.4: Initial SOPF software testing	Conduct tests of the prototype software on small test systems (>300 buses) and large-scale system with >10K bus network like PJM system size while ensuring that all functional requirements are correctly addressed.
Milestone 4.4.1: Initial SOPF testing report	Using the prototype software created in Task 4.3, test the software on small systems and PJM system using the following defect priority scale: • Priority 1 (Critical) - Data Loss/Critical Error/ Loss of functionality w/o workaround: Defects that render unavailable the critical functions or partial functionality of the software (with no work-around available) of the software under test. These include errors such as application failures, loss of data, incorrect calculations and missing output files. • Priority 2 (High) - Loss of functionality with workaround: Defects that render unavailable partial functionality of the software under test with a workaround available. These include errors such as incorrect message displayed, optional information missing or not displayed correctly and incorrect defaults.

	• Priority 3 (Medium) - Partial loss of a feature set: Defects that affect a feature that is not executed on a frequent basis and there is not a significant impact on the software. • Priority 4 - Cosmetic/Documentation Error: Defects that are cosmetic and need to be resolved, but are not a factor in the functionality or stability of the software. These include errors such as field alignment and report formatting. Create a report on the tests conducted and assign a pass or fail grade to each test. For each failed test, assign a defect priority as defined above. Allowances will be made for failed software components to be corrected and retested as needed. The exit criteria for this task is zero (0) Priority 1 defects and zero (0) Priority 2 defects. The team (including ARPA/E) will evaluate Priority 3 defects to determine those that will be required to be corrected to advance to Task 4.5. This testing report will be available to APRA/E. **Actual Performance:** (Completed 7/9/2018) The testing was in two forms: 1. Reviewing the code. The code is written in Python using the PYOMO library with PySP extensions. 2. Reviewing the results data. The majority of the results data are associated with constraints (e.g., reserve and flow) and objective function values. Testing found 5 priority 1 defects, 3 priority 2 defects, and 3 priority 3 defects. All of these defects were corrected. Testing found 2 priority 4 defects, of which, 1 was corrected. The testing report was made available to ARPA-E.
Task 4.5: SOPF software testing with PJM data	Continue tests of the prototype software on PJM data and other test systems (obtained through outreach). Refine the software implementation based on the feedback obtained and improve performance.
Milestone 4.5.1: Final SOPF testing report	Create a report on the tests conducted and assign a pass or fail grade to each test. For each failed test, assign a defect priority as defined above. The exit criteria for this task is zero (0) Priority 1 defects and zero (0) Priority 2 defects. Allowances will be made for failed software components to be corrected and retested as needed.

	This testing report will be delivered to APRA-E for review and approval by program director. **Actual Performance:** (Completed 1/18/2019) All software components were thoroughly tested through Q8 using PJM data. Using PJM data is a requirement in this milestone. A report was provided to ARPA-E on the results of this testing in that Q8 report.
Milestone 4.5.2: SOPF software performance evaluation	Evaluate the performance of the SOPF software with large-scale test system and assess performance relative to FOA performance requirements (requirements for: a) Spinning Reserve Products (not Regulation Reserve Products) under Category 2; b) Category 3: Synthetic Ramping Reserves). Utilize test scenarios with various renewable penetration levels including a high- penetration level greater than 50%. **Actual Performance:** (Completed 4/10/2019) Nexant worked with ASU and Sandia to review the results of the tests with the 50% penetration. There were no defects encountered. All software defects that were encountered were documented and subsequently corrected.
Task 5: Program Element 5: Technology Transition	Execute the 'Technology to Market' activities for the project.
Task 5.1: Technology to Market plan development and updates	Development and updates of technology to market plan.
Milestone 5.1.1: Technology to Market plan: (1) T2M plan (2) Qualified T2M contact, (3) Industrial advisory board	Presentation of high-level Technology to Market plan: a) High-level view of the team's plans for technology dissemination and commercialization. b) Appoint a qualified tech-to-market contact person from Nexant to represent and conduct the team's commercialization activities with industry and ARPA-E. c) Invite and select personnel to become members of the Industrial Advisory Board (IAB) d) Select and commit industry advisors to participate in the activities of the project e) Define IAB engagement plan and schedule f) Get IAB commitment to the planned meetings and reviews schedule **Actual Performance:** (Completed 12/08/2017) 1) The revised T2M plan was submitted to ARPA-E on September 27, 2017. 2) The qualified T2M contact has been provided.

	3) The team developed a list of potential IAB members and sent out e-mails in the March 2017 timeframe to these potential members that included the 2-page flyer describing the proposed stochastic SCED process. Upon feedback, an initial set of IAB members were established.
Milestone 5.1.2: Technology to Market plan: (1) Novel Capabilities, (2) Pathways to adoption	Revised Technology to Market Plan, based on discussion with IAB members, is submitted to ARPA-E, presented, and approved by Program Director: a) Inform industry of project – news releases, blogs b) Inform industry of novel capabilities to be provided by the new technology c) Define at least two (2) potential pathways for technology adoption by the power industry. **Actual Performance:** (Completed 10/08/2017) A revised Technology to Market Plan has been submitted to APRA-E on September 27, 2017. Many members of industry were contacted including PJM, MISO, ERCOT, PG&E, CAISO, SPP, and Dominion Energy. The most likely adopters of the proposed technology were CAISO and MISO.
Milestone 5.1.3: Technology to Market plan: Stakeholder and Competitive analysis	Revised Technology to Market Plan: a) Identify early adopters for SOPF b) Identify current/emerging offerings that meet the same needs as technology being developed c) Establish differentiated value proposition (e.g. quantify benefits/costs vs. alternatives/inaction) **Actual Performance:** (Completed 4/08/2018) a) The team identified PJM, MISO, and CAISO as potential early stochastic SCED adopters. b) There are currently no emerging offerings in the industry that are applying this type of stochastic optimization technology. Without this technology, the ISOs will continue to operate conservatively with larger reserve requirements and in potentially the incorrect locations.
Milestone 5.1.4: Technology to Market plan: Post ARPA-E funding	Revised Technology to Market Plan: a) Develop financial model with realistic assumptions, uncertainties, and product development costs b) Develop plans for channel partner development a. EMS vendors b. Integrators

	Actual Performance: (Completed 3/31/2021) Milestones M5.1.4, M6.4.2 and M6.4.3 were all fully completed and all addressed in the Business Plan that was sent to ARPA-E in quarter 19 of this project.
Task 5.2: Technology to Market progress update	Presentation of the team's progress against the Technology to Market plan and objectives.
Milestone 5.2.1: Technology to Market update: (1) Novel capabilities, (2) IP arrangement	Presentation on T2M progress based on discussion with IAB members: a) Highlight novel capabilities to be provided by the new SOPF technology. b) Establish IP agreement among parties **Actual Performance:** (Completed 12/8/2017) a) The team provided the IAB with the novel capabilities that the stochastic SCED tool can provide to the industry in the kick-off Webex presentation on March 31, 2017. This material was provided to ARPA-E on September 27, 2017. b) Nexant has finalized the IP agreement among the parties.
Milestone 5.2.2: Technology to Market update: (1) Stakeholder Analysis (2) Competitive Analysis	Presentation on T2M progress: a) Review of early adopters for SOPF with IAB. b) Differentiated value proposition of SOPF **Actual Performance:** (Completed 7/09/2018) Nexant has reported on the review of early adopters for SOPF with IAB in the Q7 report. The team developed a Differentiated Value Proposition (DVP) framework and provided this in the Q7 report. The team was able to apply the framework to a case that included 9 generator contingencies and 16 wind scenarios. The DVP is based on the cost difference between the costs associated with the stochastic SCED and those of the deterministic SCED (from M2.1.1) when a deliverability approach, through a real-time contingency analysis (for generation) and a simultaneous feasibility test, is applied. The stochastic SCED provided a 6.2% reduction in operating costs.
Milestone 5.2.3: Technology to Market update: Year-end review	Presentation on T2M progress: a) Review of activities to date b) Review of plans for second year **Actual Performance:** (Completed 10/08/2017) a) The team of Nexant, ASU, and Sandia discussed the T2M efforts and progress over the first year. b) The team planned to provide another IAB webinar and hold a general industry webinar. For the general industry webinar, the

	invitees were from Nexant's compiled list of utilities, other ISOs and market participants all of which may benefit from the use of the SLAC tool.
Milestone 5.2.4: Technology to Market update: Update on early adopters	Presentation on T2M progress: a) Update on potential early adopters for SOPF **Actual Performance:** (Completed 12/8/2017) a) Nexant along with ASU and Sandia National Laboratories continue to work with PJM and are also in the process of developing an active partnership with MISO as an early adopter of the SOPF technology.
Milestone 5.2.5: Technology to Market update: Outreach to early adopters	Presentation on T2M progress: a) Discussion of initial tests with PJM data b) Scheduling demonstrations with potential early adopters **Actual Performance:** (Completed 4/08/2018) The team has engaged various potential early adopters over the course of this project. The list below shows these engagements. • PJM: site visit on April 11, 2016 • MISO: site visit on November 21, 2016 • ERCOT: site visit on January 30, 2017 • IAB kickoff meeting on March 31, 2017 • Pacific Gas and Electric: site visit on May 4, 2017 • CAISO: e-mail exchanges in April 2017 – September 2017 • SPP: site visit on May 31, 2017 • Dominion Energy: June 19, 2017 • MISO: Fall 2017 and 2018, MISO has indicated they want to become a Partner in this project • IAB meeting on March 20, 2018 As a result of this outreach, MISO joined the project as a partner.
Milestone 5.2.6: Technology to Market update: Demonstration to potential early adopters	Presentation on T2M progress: a) Execution of demonstration to potential early adopters **Actual Performance:** (Completed 7/9/2018) As part of the T2M effort, the team presented the stochastic SCED project at the FERC Technical Conference in Washington, DC on June 27, 2018 to a diverse audience that included: MISO, SPP, ERCOT, ISO- NE and Hydro-Québec. The Technical Conference is entitled: "Increasing Real-Time and Day-Ahead Market Efficiency and Enhancing Resilience though Improved Software." The attendees of MISO, SPP, ERCOT, ISO-NE and Hydro-Québec provided thoughtful questions and a robust Q/A session was held. All feedback was positive.

Milestone 5.2.7: Technology to Market update: Final assessment	Presentation on T2M progress: a) Assessment of T2M progress and opportunities b) Customer interview report to Program Director for approval (sales opportunities and product feedback) **Actual Performance:** (Completed 3/31/2021) This milestone has been completed and a description was provided in the Q18 report. Nexant feels that there are many opportunities in industry for this technology and the work and compiled results from MISO will help reduce barriers.
Task 5.3: Technology Dissemination and Demonstration	Development of technology demonstrations and prototype software release
Milestone 5.3.1: Technology Dissemination and Demonstration: Develop the Demonstration Scenarios	Presentation of progress in developing technology demonstration: a) Develop suitable demonstration scenarios focused on initial capabilities b) Review demonstration scenarios with IAB and update the scenarios accordingly **Actual Performance:** (Completed 10/08/2017) The demonstration scenarios are effectively the business cases for the technology. a) The demonstration scenarios document was submitted along with the Q5 status report. b) The kick-off IAB Webex presentation provided an overview of the potential demonstration scenarios. Several questions were asked by participants and answered by the team. APRA-E was provided the presentation along with the questions and answers on September 27, 2017. In addition, all of the presentations supporting the technology to market effort that were provided to the ISOs and utilities were provided to ARPA-E on September 27, 2017.
Milestone 5.3.2: Technology Dissemination and Demonstration: Develop Demonstration Scenarios	Presentation of progress in developing technology demonstration: a) Develop and implement suitable demonstration scenarios focused on initial capabilities b) Review demonstration scenarios with IAB and industry audience **Actual Performance:** (Completed 4/08/2018) This milestone is a follow-up to M 5.3.1. The team identified demonstration scenarios for the stochastic SCED. The team held a two-hour IAB review Webex

	on March 20, 2018. The IAB Webex provided fruitful discussion about the project and overall, the IAB provided positive feedback.
Milestone 5.3.3: Technology Dissemination and Demonstration: Publications and planning for workshop demonstrations	Presentation on T2M progress: a) Promoting technology through publications b) Marketing collateral c) Plans for workshop/conference sessions for technology presentation and demonstration to industry **Actual Performance:** (Completed 10/08/2017) a) Nexant along with ASU and Sandia developed 2-page flyers and sent to several ISO, IAB members and handed out at the ARPA-E conference in Colorado in April 2017. b) Nexant along with ASU and Sandia developed 2-page flyers and sent to several ISO, IAB members and handed out at the ARPA-E conference in Colorado in April 2017. c) Nexant held a general industry Webinar in the early part of 2018 that discussed the SLAC technology and gained additional general industry feedback.
Milestone 5.3.4: Technology Dissemination and Demonstration: Publications and planning for workshop demonstrations	Presentation of T2M progress: a) Technology publications b) Featured articles in trade magazines c) Update to plans for workshop/conference sessions for technology presentation and demonstration to industry **Actual Performance:** (Completed 12/8/2017) a) Nexant along with ASU and Sandia National Laboratories developed 2-page flyers and sent to several ISO, IAB members and handed out at the ARPA-E conference in Colorado in April 2017. b) Nexant along with ASU and Sandia National Laboratories developed 2-page flyers and sent to several ISO, IAB members and handed out at the ARPA-E conference in Colorado in April 2017. c) Nexant held a Webinar in the early part of 2018 to discuss the stochastic SCED technology and gained additional general industry feedback.
Milestone 5.3.5: Technology Dissemination and Demonstration: Workshops	Presentation on T2M progress: a) Workshops to publicize the technology and results of initial tests **Actual Performance:** (Completed 4/08/2018) The team pursued the T2M effort at the ARPA-E Innovation Summit. The team met with members from CAISO and Lartra Inc and discussed the project and facilitated future discussions.

Milestone 5.3.6: Technology Dissemination and Demonstration: (1) Marketing Collateral and (2) Review of results	Presentation of progress in developing technology demonstration: a) Update on technology publications a. Marketing collateral b. Featured articles in trade magazines b) Demonstration results - review, analysis, and conclusions c) Customer report to Program Director for approval (feedback from demonstrations to potential early adopters) **Actual Performance:** (Completed 4/10/2019) Nexant, ASU and Sandia National Laboratories developed the slide deck for the industry wide webinar and presented it on February 27, 2019. Nexant originally developed a list of 2,700 potential invitees from its inventory from customer contacts in all corners of the electric industry. Based on the likelihood of success, this list was pruned, and invitations were sent to approximately 1,900 people. 82 people registered and 40 people attended the webinar (excluding Nexant, ASU and Sandia staff members). We received positive feedback from the webinar attendees and several excellent questions were asked.
Milestone 5.3.7: Technology Dissemination and Demonstration: (1) industry engagement (2) Technology Publications	Presentation of progress in developing technology demonstration: a) Updates on industry engagement and future plans a) Product realization strategy & roadmap b) Update on technology publications b) Case studies c) Journal articles c) Updated plans for converting industry engagement to industry adoption **Actual Performance:** (Completed 3/31/2021) This milestone has been completed. We gave a webinar on March 31 and it was well received. There were more than 140 attendees from industry and academia. We answered 24 questions. Specifically, the team presented an Industry Wide Webinar (IWW) on March 31, 2021 that was attended by several dozen industry participants. The product roadmap is contained in the Business Plan that was provided as part of the quarter 19 report. Nexant believes that the stochastic optimization is a valid technology to pursue. The team is working on an industry paper for the forecasting and scenario development associated with load, wind production and net scheduled interchange levels. The team is also work on an industry paper for the application of the stochastic optimization including progressive hedging to MISO's look ahead commitment process.

Task 6: Joint Industry Partnership: Midcontinent ISO	Jointly identify data, case studies, use cases, purpose for SLAC tool; validation of tools; jointly conduct case studies and process results; prepare final report with business plan and value proposition
Task 6.1: Scoping analysis	Mutually agreed upon (MISO, ASU, Nexant, Sandia National Laboratories) scope of work, use cases, study design, and performance metrics.
Milestone 6.1.1: Targeted use cases, tool performance and uncertainty modeling metrics are defined	A report describing targeted use cases (example: normal operational cases with extreme events (extreme renewable ramps)), and selection justification based on SLAC functionality delivered to ARPA- E for approval. The following required performance metrics for all tools (SCED, LAC, SLAC): computer specifications (including number of cores), computational performance, type of uncertain events modeled, number of uncertain events modeled for each category, and optimality gap, are defined. In addition, required performance metrics for all uncertainty modeling ("Interchange and loop flow" and "extreme weather" may not be explicitly considered.): a) renewable resources; b) interchange and loop flow; c) extreme weather; d) demand response; e) generator non-compliance; f) contingencies, are defined. **Actual Performance:** (Completed 03/31/2021) The main purpose of the SLAC tool is to make better commitment decisions under uncertainty and serve as a better advisory tool for operators. In this project, three main sources of uncertainty were modeled; namely, uncertainty from wind generation, load, and net scheduled interchange. In addition, uncertainty from generator startup and shutdown MWs was modeled and incorporated into the SLAC using historical data and machine learning techniques. In the deterministic LAC, it was expected that on days with more uncertainty, operators would tend to act conservatively and commit more units to better deal with uncertainty in order to maintain system reliability. In such days in particular, modeling uncertainty coming from different sources into the optimization processes is shown to be beneficial in terms of production costs savings and improving system reliability. MISO selected a set of 15 "stressed" days from different seasons in 2018 and 2019 to evaluate the performance of SLAC

	against deterministic LACs under MISO and ASU point forecasts. These days included operation days with higher number of real-time unit commitments, extreme hot weather and severe cold weather events that impacted renewable generation, load, and net scheduled interchange. Our goal was to see if SLAC can perform better in terms of cost savings and reliability metrics by taking uncertainties from wind generation, load, and net scheduled interchange into account. MISO generated around 1440 deterministic LACs (96 LACs/day) from production cases and benchmarked it using EGRET developed by the team in a laptop PC with typical specifications and availed it as base cases for the SLAC tool simulations. To speed up the computation time, parallel optimization techniques was used within the SLAC tool to solve the problems decoupled by scenario in parallel. The SLAC tool was utilized to study the 15 days (as well as many other small and large cases) in a rolling-horizon fashion on a Linux server at MISO with 32 cores and 256 GB of RAM. Considering MISO's operational practices, a maximum of 15-minute solve time under 40 joint scenarios from wind, load, and net scheduled interchange and a 0.1% relative optimality gap was considered for SLAC performance evaluation. In addition to the above considerations, the following performance evaluation on uncertainty modeling was conducted by MISO and the team: a) The scenario generation approach was applied to a test case from September 2018, for a period when extreme weather resulted in emergency event in MISO. Scenarios were generated for 152 wind farms and performance metrics were evaluated using Energy, Integrated distance and Variogram scores. b) Scenarios were generated for the MISO aggregate Net Scheduled Interchange (NSI) with all its neighbors. Loop flows were not considered. c) Extreme hot weather and severe cold weather days with impacts on wind, load, and net scheduled interchange captured through a set of scenarios were evaluated and analyzed to see under which days SLAC performs better; either in terms of production cost savings or reliability improvements, e.g., avoiding reserve shortfalls or transmission flow violations.

	d) Instead of demand response, we generated scenarios for load for each control area in MISO. Scenarios for wind and load were applied to the stranded capacity use case. e) For generator non-compliance, we identified generators while they are in startup or shutdown process as uncontrollable units. They pose another source of uncertainties in the SLAC problem since they are not considered as variables in the optimization. We propose using machine learning techniques to capture the non-compliance generators' uncertainties and applying them to the SLAC as fixed predicted values. The timeseries prediction of the startup or shutdown curves is different with the wind forecast. It has its unique obstacles such as the uncertain length of horizon, uncertain state estimation starting point, noise-dominant raw data, and generator-specific feature selections. We first query and export 6-year generator market data from the MISO database. The raw data is highly polluted by estimation errors and noises, which means it cannot be directly used for prediction analyses. Hence, we conduct data preprocessing before loading them to the machine learning module. Since the generator data patterns vary greatly, we have to perform the preprocessing for each individual unit. There are generally three steps for a typical data preprocessing: Identify whether the curve is longer than 15 minutes (for startup/shutdown curve eligibility), check the curve gradient direction (confirm the curve classification), and remove outliers (reduce the data noises and marginal cases). After the data preprocessing, we conduct the prediction analyses using machine learning techniques. Due to the different timeframes of LAC and UDS, we use a static method for 15-minute LAC curves and a dynamic method for 5-minute real time dispatch (UDS) curves. The LAC curve method is built upon the Gradient Boosting Tree (GBT), which is the state-of-the-art regression method with one-hot encoding. GBT predicts

	values with index labels and feature labels created from the data preprocessing stage. The UDS curve method is built upon the Long Short Term Memory network, which uses the last-interval realization data to guide the current prediction and thus achieves real-time error correction. Theoretically, the dynamic method should be more useful and accurate than the static method because we could use the latest information to support our prediction. Regarding the results and performance, we mainly focus on the static method because both the SLAC and UDS in the simulations are with a 15-minute resolution. We conduct our analyses for 840 generators in the database. After preprocessing, for startup curve, 90.78% eligible generators can achieve with the prediction performance of MAPE < 10%, while for shutdown curve, 87.41% eligible generators can achieve with the same performance. Then these curves are produced as fixed timeseries values and prepared for being loaded into the SLAC or UDS module. Though we do not apply the real-time error correction-based prediction in SLAC, we also test the performance of the dynamic method, which could reduce the general prediction error to 3% in real time. Lastly, we apply the predicted startup and shutdown curves to the SLAC and UDS coordination. These curves are used as fixed timeseries values and we slightly modify the generator power output constraints to adopt the curves for future awareness of startup/shutdown in the upcoming intervals. In the whole-day run of SLAC simulations for Sept. 15-20 cases, when applying the curves, the average daily cost saving of the production cost is around $60,000. We also observe that SLAC could better utilize the curves (achieve a higher cost saving) than deterministic LAC, which proves the cost-effectiveness of the predicted curves in the 15-minute scheduling and its synergy with the stochastic optimization.

	f) To ensure post-contingency reserve deployment while accounting for loss of generator events, MISO implements post-zonal reserve deployment constraints in production. These constraints ensure different reserves (e.g., regulation, contingency reserve, short-term reserve) can be delivered to meet zonal reserve requirements under import transmission limitation in case of contingencies. MISO and the SLAC team implemented these constraints into the EGRET tool and benchmarked a few deterministic LAC cases. However, these constraints were not included in the deterministic LAC and SLAC simulations.
Milestone 6.1.2: SLAC features to address identified use cases	MISO identified SLAC tool features: a) defined time stage and time intervals; b) composition of the subproblems; c) input data requirements; d) utilization of SLAC outputs in MISO operations (generation loss distribution factors, ancillary services products, critical contingency selection) and interaction with existing tools and personnel. A subsection of the design specification report from Task 4 is dedicated to describe the SLAC features identified by MISO. **Actual Performance:** (Completed 03/31/2020). With the team, MISO identified the SLAC tool features as follows: a) As with regular LAC run, the SLAC would have a three-hour look-ahead with fifteen-minute time-intervals. b) The stochastic subproblems determined by MISO are equivalent to MISO's existing deterministic LAC, which was validated under Milestone 6.2.1. c) The input data requirements determined by MISO are: (1) state information (current and future generator commitments, current generator production levels), (2) information equivalent between LAC and SLAC (reserve requirements, monitored transmission constraints pre- and post-contingency), and (3) scenarios generated by ASU which set load, available wind power, and net-scheduled interchange on a per-scenario basis.

	d) Two major outputs identified by MISO (1) the recommended SLAC generator commitments, which can be evaluated against the existing LAC tool solution and (2) critical scenarios, e.g., those with reserve or transmission violations, which could warn operators well in advance about a potentially critical event. These scenarios could be identified either as part of the SLAC solution process or as a post-analysis of a given (S)LAC commitment.
Milestone 6.1.3: Specialized SLAC: refinement of functionality and associated metrics	MISO, ASU, Nexant and Sandia National Laboratories identified required refinements to enhance value proposition of general SLAC based on performance from M6.4.1. This includes new performance metrics to be met, including the metrics for the rolling horizon testing. Metrics to be approved by ARPA-E PD. **Actual Performance:** (Completed 12/30/2020) The performance metrics of the specialized SLAC with MISO-customized features on a rolling-horizon basis were defined as the computation time (e.g. ability to solve under 15 minutes for operational purposes), solution quality (ability to achieve a reasonable and acceptable optimality gap), production cost savings over the entire study period, and reliability improvements (e.g., transmission flow violation or reserve shortfall reduction). With MISO's input, the SLAC solution time was set to 15 minutes and the relative optimality gap was set to 0.1%. For each studied period (e.g., an entire day), the measuring stick in terms of cost and reliability improvements were defined as the total production cost of the underlying SCEDs for the entire study period. For example, for September 15, 2018, the total production cost of 96 SCEDS under the commitments from SLAC with 40 scenarios from wind, load, and net scheduled interchange, deterministic LAC with MISO point forecast, and deterministic LAC with ASU point forecasts were computed and compared. The results showed that in general SLAC performs better and appropriately trades off between cost and reliability by prepositioning the system for uncertainties stemming from wind generation, load, and net scheduled interchange.

	Quantitative performance of these results are given elsewhere in this report.
Task 6.2: Validation of Deterministic Tool	MISO to work with ASU, Nexant, Sandia National Laboratories to validate deterministic tools used for confirmation of SLAC benefit and also validate SLAC input and modeling information related to uncertain events.
Milestone 6.2.1: Deterministic tool validation	MISO, ASU, Nexant, Sandia National Laboratories to benchmark SLAC with MISO production look-ahead commitment (LAC) and security- constrained economic dispatch (SCED) based on MISO data and systems. Qualitative performance evaluation: MISO review and approval with report to ARPA-E. Quantitative performance evaluation: Satisfied performance metrics stated in M6.1.1. 6.2.1a: Implement specialized features of MISO's deterministic LAC into EGRET 6.2.1b: Implement specialized features of MISO's deterministic SCED into EGRET 6.2.1c: Develop a method to simulate MISO's current response to a given scenario using the specialized deterministic LAC and SCED consecutively in a rolling horizon fashion **Actual Performance:** (Completed 12/30/2020) MISO worked with the SLAC team to produce deterministic LAC cases from production and benchmark it using the EGRET tool. MISO took a bottom-up approach and started the benchmarking process from a simple energy-only small test case of 5-generator system. This was followed by including more MISO-customized features (e.g., different reserve types such as regulation, spin, and, flexible ramp, and supplemental reserves) and scaling the test system to tens and hundreds of generators all the way to the full-size MISO system with around 1200 generators, all reserve types, and around 40 production watchlist transmission constraints. The benchmarking criteria were to obtain the same (or close enough) objective value and the same or equivalent unit commitments, energy/reserve schedules, and transmission flow/violations results for all units and lines in both MISO LAC

	and EGRET tools. Further benchmarking details can be found in prior quarterly reports. MISO then selected 15-days from different seasons and benchmarked 96 consecutive deterministic LAC cases per day with specialized features as the base cases for rolling-window SLAC simulations. For milestone 6.2.1a, Sandia National Laboratories implemented the features utilized in MISO's current implementation of LAC into EGRET's version of LAC including reserve requirements for each reserve type, transmission constraints, post contingency reserve deployment constraints, future/past on/off time constraints, etc. The EGRET implementation was validated against MISO's LAC using test cases developed by MISO. By the completion date the team had scaled up validation to full-sized MISO cases that represented the actual data used in practice and included over one thousand generators. The EGRET and MISO LACs resulted in the same solutions or solutions that matched very closely. For milestone 6.2.1b, Sandia National Laboratories executed a straightforward extension of 6.2.1a. This extension was straight forward because the SCED uses many of the same specialized features as the LAC. The specialized SCED in EGRET represents the specialized LAC in EGRET restricted to a single time interval, with a 15-minute time interval length, and with different violation penalties for reserve constraints. Validation was not needed because the specialized features were already validated through the LAC. For milestone 6.2.1c, Sandia National Laboratories connected EGRETs specialized LAC and SCED using a rolling horizon simulation framework. Using 15-minute intervals, the LAC passed generator commitment statuses to the SCED during each interval and the SCED passed the generator output levels to initialize the LAC in the next interval. The input data was updated in each interval, which includes parameters for each available generator, transmission line parameters, demand trajectories, reserve requirements, etc. This input data matched the input data used in practice for the 15 days studied in 2018-2019.

Milestone 6.2.2: Uncertainty modeling validation	MISO, ASU, Nexant, Sandia National Laboratories to validate uncertainty modeling approaches. Qualitative performance evaluation: MISO review and approval with report to ARPA-E. Quantitative performance evaluation: Satisfy performance metrics stated in M6.1.1. **Actual Performance:** (Completed 06/30/2020) The point forecast generated by the model was compared to the existing MISO point forecast using the root-mean-squared error (RMSE) metric, and showed forecast improvement over all intervals of the look-ahead commitment horizon. The spatial and temporal correlations between wind farms estimated by the model were compared to the real data, and were found to be consistent. **Actual Performance:** (Completed 03/30/2021) The startup/shutdown curve predictions were evaluated using the mean average percentage error (MAPE) metric in both the training and testing stages. The predictions of curve-eligible generators are further validated by inducing the curves into LAC and UDS operation pipelines. The result validates that using the startup/shutdown curves leads to more cost-savings and reliability improvements.
Task 6.3: SLAC implementation and performance evaluation	Implementation of SLAC tool based on MISO data; identified use cases, modeling of uncertain events; initial testing of the generic SLAC followed by a specialized, enhanced SLAC.
Milestone 6.3.1: Generic SLAC implementation and evaluation for single snapshot studies	SLAC tool implemented on identified use cases and MISO data (single snapshot results and comparison). Qualitative performance evaluation: MISO review and approval with report to ARPA-E. Quantitative performance evaluation: Satisfied performance metrics stated in M6.1.1. 6.3.1a: Establish a precise stochastic optimization formulation for this application 6.3.1b: Implement the generic SLAC on simple small test cases by embedding the generic deterministic LAC and SCED into the inner stage of the stochastic framework **Actual Performance:** (Completed 03/31/2021) Under 6.3.1a, MISO, NREL, and the project team developed a detailed mathematical SLAC formulation; the first and second stage

	variables, parameters, and constraints were clearly defined over the appropriate sets. The SLAC tool precisely implements this mathematical formulation and has the capability to implement and simulate single snapshot and rolling-horizon SLAC and SCED on small as well as large full-day cases. The SLAC tool is also generic in nature in the sense that, depending on whether or not the inputs to the tool include specialized LAC features, the underlying stochastic optimization framework can implement the two-stage SLAC/SCED problem. Under 6.3.1b, NREL and the team implemented the SLAC tool to simulate single snapshot, partial day (consecutive cases, e.g., 11:00 AM to 3:00 PM), and full-day specialized LAC and SCED cases on a rolling-window basis. In each study, the generated scenario data from stochastic variables (e.g., wind units' generation, load, and net scheduled interchange) was appropriately embedded into the stochastic optimization framework. The benefits of SLAC over deterministic LACs were more tangible in rolling-horizon simulations that had longer time horizon (e.g., an entire day).
Milestone 6.3.2: Specialized SLAC implementation and evaluation for single snapshot studies	SLAC tool implemented on identified use cases and MISO data (single snapshot results and comparison). Qualitative performance evaluation: MISO review and approval with report to ARPA-E. Quantitative performance evaluation: Satisfied performance metrics stated in M6.1.3. 6.3.2a: Implement the specialized SLAC on simple small test cases 6.3.2b: Evaluate performance of the SLAC from Tasks M6.3.2.a and M6.3.2.c using the simulation techniques from Task M6.2.1.c as a benchmark 6.3.2c: Implement the specialized SLAC on large test cases and validate using deterministic rolling horizon methods **Actual Performance:** (Completed 03/31/2021) For milestone 6.3.2a and 6.3.2c, NREL implemented the stochastic programming techniques and specialization using a parallelized progressive hedging algorithm to solve the specialized SLAC

	problems. NREL tuned the performance of the SLAC solution algorithm to both MISO data and the Linux workstation provided by MISO, utilizing 20-way parallelism to solve the 40-scenario SLAC instances detailed below. The exact customized algorithmic approach is detailed in the Q19 Quarterly Progress Report. The specialized SLAC with MISO-customized features were simulated on a rolling-horizon basis for 15 operation days selected by MISO. MISO provided an entire year of historical wind generation, load, and net scheduled interchange data from 2018 to 2019 to generate scenarios for the 15 days using the scenario generation tool developed under this project. For each simulated day, around 96 SLACs (a total of 1436 cases) plus two deterministic LACs each followed by a SCED were run and the total production cost, transmission violation cost, and reserve shortfall violation costs were reported and compared. For each specialized SLAC solve, MISO defined the following performance evaluation metrics under 40 scenarios for wind generation, load, and net scheduled interchange: • Each SLAC needed to run under 15-minute time limit • Each SLAC solve needed to reach a relative optimality gap of 0.1% As detailed elsewhere, the team found that in the 1436 cases, the above metrics were met 99.7% of the time (all but four cases) for these 40-scenario specialized SLAC problems. In those four cases, the established time limit of 15-minutes was met, but the optimality gap was over 0.1%. In all cases, the optimality gap was within 0.5%. For milestone 6.3.2b, Sandia National Laboratories simulated the LAC and the SLAC using the rolling horizon framework from Task 6.2.1c using 15 days from 2018-2019. The performance of the SLAC was analyzed in the context of reducing reserve constraint violations, reducing transmission constraint violations, and reducing production costs as compared to the LAC. In these results we only see improvements by the SLAC during days where the system is particularly stressed, otherwise

	the SLAC performs very similar to the LAC model. During non-stressful days we see a very small increase in production cost when using the SLAC of approximately 0.01% of the total production costs in the system. During the stressful days, the most common observed improvement increases reliability by reducing either reserve constraint violations or transmission constraint violations. The alternative improvement that we occasionally observe decreases productions costs as compared to the LAC model. We observe production cost reductions of up to 5% of the total productions costs in the system.
Task 6.4: Final reporting	Final reporting on MISO partnership and future business path.
Milestone 6.4.1: SLAC broader impacts	Documentation on MISO partnership, main findings, benefits, and conclusions. Documentation of general SLAC applications outside of MISO and identification of other market targets. **Actual Performance:** (Completed 03/31/2021) The SLAC project team believes MISO partnership has been a success. The main findings are noted below: • Overall, SLAC provides a net benefit and robustness for managing uncertainty. • SLAC exhibits economic benefit over the deterministic LAC variants with decreased costs and little or no change in reserve or transmission flow violations under certain full-day cases simulation. • SLAC also exhibits a reliability benefit, i.e., decreased reserve or transmission flow violations, over the deterministic LAC, with increased production costs in certain other full-day case simulations. • At all other times, SLAC has similar performance to deterministic LAC. In summary, SLAC provides reliability (the ability to meet operational standards) and/or economic (the ability to avoid over-commitment of units and over-procurement of reserves) benefits. Outside of MISO, the prime targets are SPP, ERCOT and CAISO (all rich in terms of wind generation) as well as utilities who need to make day-to-day operational decisions based on uncertainties (e.g., weather-based uncertainty) in the system.

Milestone 6.4.2: Documentation of remaining T2M barriers and risks	Documentation in final report on remaining practical barriers, SWOT/NABC analysis; team to collect industry feedback. **Actual Performance:** (Completed 03/31/2021) SLAC is an intra-day advisory tool. All ISOs have some type of deterministic advisory based tool today. The main barrier we see is to convince ISOs that this technology is sound, validated and workable, and that the results can be translated for practical use for system operators. For example, SPP seemed very interested, but needed to prioritize various projects and stated they could not take on a partnership at that time. The MISO partnership was a great opportunity because they do have a focus on R&D that are willing to go outside of traditional vendor relationships to research new technology. This successful partnership with MISO, which yielded positive results, will lower the barriers going forward. Milestones M5.1.4, M6.4.2 and M6.4.3 were all addressed in the Business Plan (that includes a section on the remaining practical barriers) that was submitted in the quarter 19 report. The SWOT analysis was submitted in the quarter 19 report. As part of the T2M process the team has met with many industry members. All feedback has been positive as reported in previous reports. Our current partner MISO states that this project has been successful and they will continue to investigate the SLAC technology
Milestone 6.4.3: Business plan	Documentation of future business plan and value proposition. **Actual Performance:** (Completed 03/31/2021) Nexant will continue to evaluate the SLAC prototype as a promising technology and pursue it for commercial use. Nexant realizes that more R&D work is needed for this purpose including conducting pilot as well as commercial projects with target market participants. Nexant provided a business plan and value proposition as part of the quarter 19 report.

	MISO plans to pursue this technology and leverage the tools developed in this project with potential near-term applications including: • Scenario generation and its application on different operational tools • Generate startup and shutdown curves and include them in operational tools • Further develop EGRET for real time simulation. Define dynamic reserve requirements and uncertainty events in a better way based on simulations on meaningful scenarios. MISO will continue research and development on market simulation tools and plans to conduct research on longer horizon uncertainty quantification (e.g., 7-day) as well as other uncertain factors (e.g., generation outage) and evaluate viable stochastic optimization approaches in terms of computation time and applicability on market processes and clearing engines.

Project Outputs

A. Journal Articles

Trevor Werho, Junshan Zhang, and Vijay Vittal, *Yonghong Chen, Anupam Thatte, Long Zhao*. "Scenario Generation of Wind Farm Power for Real-Time System Operation". Submitted to IEEE Transactions on Power Systems.

B. Papers

Knueven, Bernard, et al. "A Parallel Hub-and-Spoke System for Large-Scale Scenario-Based Optimization Under Uncertainty." Submitted to *Mathematical Programming Computation*.

C. Status Reports

Q1 Quarterly Progress Report. November 4, 2016.
Q2 Quarterly Progress Report. April 10, 2017.
Q3 Quarterly Progress Report. January 8, 2017.
Q4 Quarterly Progress Report. July 10, 2017.

Q5 Quarterly Progress Report. October 8, 2017.
Q6 Quarterly Progress Report. December 8, 2017.
Q7 Quarterly Progress Report. April 8, 2018.
Q8 Quarterly Progress Report. July 9, 2018.
Q9 Quarterly Progress Report. October 8, 2018.
Q10 Quarterly Progress Report. January 18, 2019.
Q11 Quarterly Progress Report. April 10, 2019.
Q12 Quarterly Progress Report. July 20, 2019.
Q13 Quarterly Progress Report. October 15, 2019.
Q14 Quarterly Progress Report. January 9, 2020.
Q15 Quarterly Progress Report. April 9, 2020.
Q16 Quarterly Progress Report. July 9, 2020.
Q17 Quarterly Progress Report. October 12, 2020.
Q18 Quarterly Progress Report. January 12, 2021.
Q19 Quarterly Progress Report. April 2021.

D. Media Reports

N/A

E. Invention Disclosures

N/A

F. Patent Applications

Werho, T., Zhang, J., Vittal, V., Induced Markov Chain for Wind Farm Generation Forecasting, United States Patent Application No. 10,796,252. August 29, 2019.

G. Licensed Technologies

N/A

H. Networks/Collaborations Fostered

N/A

I. Websites Featuring Project Work Results

N/A

J. Other Products (e.g. Databases, Physical Collections, Audio/Video, Software, Models, Educational Aids or Curricula, Equipment or Instruments)

Performance and feature enhancements to the open-source software package *EGRET* (Electrical Grid Research and Engineering Tools). Available: https://github.com/grid-parity-exchange/Egret.

Performance and feature enhancements to the open-source software package *mpi-sppy*: optimization under uncertainty for Pyomo models. Available: https://github.com/Pyomo/mpi-sppy.

K. Awards, Prizes, and Recognitions

N/A

Follow-On Funding

N/A