Optimal Electric Grid Black Start Restoration Subject to Threats

Kevin L. Stamber, Bryan Arguello, Richard Garrett, Walter E. Beyeler, Casey Doyle, David Schoenwald
Sandia National Laboratories
Albuquerque, NM
klstamb@sandia.gov, barguel@sandia.gov, ragarre@sandia.gov, webeyel@sandia.gov, cldoyle@sandia.gov, daschoe@sandia.gov

ABSTRACT

Efficient restoration of the electric grid from significant disruptions – both those natural and manmade – that lead to the grid entering a failed state is essential to maintaining economic resilience under a wide range of threats. Restoration requires the use of a black start plan tailored to meet the constraints imposed on the system by the disruption. A goal of the restoration plan is to restore all loads as rapidly as possible subject to those constraints. The current state-of-the-art for restoration modeling breaks the problem into multiple parts and assumes that system operators have full observability and control of the grid, and that the network is in a known state. These assumptions are not guaranteed under some threats.

This paper focuses on a novel integration of modeling capabilities to aid operators in restoration. A power flow-informed restoration framework, comprised of a restoration mixed-integer program informed by power flow models to identify restoration alternatives, interacts with a dynamic representation of the grid through a cognitive model of operator decision-making, to identify an optimal restoration path. Application of this integration against exemplar systems is reviewed.

ABOUT THE AUTHORS

Kevin L. Stamber is a Distinguished Member of the Technical Staff at Sandia National Laboratories. He has worked for over two decades on the development of models for consequence analysis of critical infrastructure systems and modeling of physical and information supply chains for a range of Federal customers.

Bryan Arguello is a Senior Member of R&D Computer Science Staff at Sandia National Laboratories. His research focuses on applying optimization to problems in scheduling, power grid resiliency, and national security in general.

Richard Garrett studies operations research problems of complex systems for national security at Sandia National Laboratories. His background includes discrete optimization, simulation methods, and industrial engineering methodologies.

Walter E. Beyeler is a systems analyst at Sandia National Laboratories, who develops and applies simulation models to improve infrastructure resilience.

Casey Doyle is a systems analyst at Sandia National Laboratories that focuses on modeling and simulation of social and human elements in complex systems.

David Schoenwald is a Principal Member of the Technical Staff at Sandia National Laboratories. His research focuses on control system design and implementation to improve dynamic stability and resilience of power systems.

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INTRODUCTION

There exists a long and well-documented history of substantial events impacting the performance of the electric grid in many locations around the world (Larsson and Ek, 2004; Andersson et al., 2005; Li, Sun, and Chen, 2007; Atputharajah and Saha, 2009; Wu, Chang, and Hu, 2017). This literature indicates many identified causes for such disruptions Carrier et al, 2000; Hines, Balasuaramaniam, and Sanchez, 2009), including damaging natural events, such as hurricanes (Lopez-Cardalda and Lugo-Alvarez, 2018) and manmade causes, such as cyber attacks (Sullivan and Kamensky, 2017).

In the event of a complete disruption of a transmission and distribution area, as in the 1965 northeast blackout (Loehr, 2017) there exists a need to have black start generators, ones that do not require connectivity to the rest of the grid (and corresponding support from the grid) in order to bring a generator back into service which, under normal conditions, would leverage power in the transmission system to assist in plant activation. A range of resources - diesel generators associated with a larger generator, hydroelectric generation facilities, and battery sets supporting gas turbines - all can be leveraged for the purpose of supporting black start operations (Farmer and Allen, 2007).

Planning for restoration from a fully failed state involves the regional identification of black start resources. In many cases black start units are defined through commercial agreements or market structures (Isemonger, 2007). Black start restoration, in turn, follows a defined process of energization and connection of black start units, so as to in turn energize busses and transmission lines and add loads, provided a range of performance parameters (voltage, phase angle, frequency) for components and the energized system are satisfied (Feltes and Grande-Moran, 2008).

The ability to restore from a failed state (and to improve said restorations, so as to minimize the impact of disruptions) has long been a subject of research (Liu, Fan, and Terzija, 2016), including a variety of technologies within the grid considered for process improvement (El-Zonkoly, 2015; Fazel Darbandi, 2021; Pasais et al, 2021) and a range of techniques applied to the problem (Liu et al, 2005; Liu, Fan, and Terzija, 2016).

Optimization is a frequent method of choice for the development of black start restoration plans, and home to some of the most cutting-edge research on the problem (Coffrin and Van Hentenryck, 2014; Patsakis et al, 2018). These existing techniques often work from an assumption of full observability and control of the grid on the part of the operator, implying the network is in a known state (Aravena et al, 2019). Under many of the causal circumstances described above, full observability cannot be assured. Similarly, and especially for cyber-based incidents, control of the grid on the part of the operator is not confirmable. Techniques are required to accommodate for these uncertainties in improving modeling of restoration of the grid from black start events.

RESEARCH CONCEPTS

The research, discussed in this section, builds on the concepts of the state of the art in optimization, creating a novel integration of restoration through static power flow models with network dynamics and cognitive modeling. It leverages an integration of a mixed inter linear programming model of restoration (leveraged from work described in Aravena et al., 2019) with power flow modeling (from a range of sources, including Tan, Cai, and Lou, 2012; Coffrin et al., 2018; and Aravena et al., 2018) through a feasibility oracle (also as described in Aravena et al., 2019) for the development of restoration plans. These are provided to an Operator Cognitive Model developed in the ACT-R framework (Anderson, 1996) to work with both the optimized restoration plan and a Network Dynamic Model of the system, monitoring the system to implement the schedule at the proper pace and adapting to any deviations from planned behavior. This section will describe each of these components in more detail.

Power Flow-Informed Restoration Model

A key goal of power flow-informed restoration models is to provide useable schedules for a utility operator to bring a power system back online after a full or partial blackout event. A candidate schedule should account for power flow physics during the restoration to ensure that, as components become energized, the system enters into a stable state. Linear steady-state power flow models are desirable for restoration because they are scalable for use in this application and these models have been well-studied (Coffrin and Van Hentenryck, 2014; Patsakis et al, 2018; Aravena et al, 2019). The work by Aravena et al., 2019 was selected as an appropriate modeling paradigm for the consideration of linearized alternating current (AC) power flows during blackout events. This model benefits from recent advances in AC power flow models to provide enhanced realism over direct current (DC) models with respect to the steady state power physics during the restoration process and is solvable at scale. A summary of Aravena et. al., 2019 is provided given that model's application in the next section. The reader is directed to their work for the formulation and a presentation of their notation (excluded here for brevity).

Restoration Model

The Restoration Model from Aravena et. al., 2019 was solved to determine how a power system's components become energized over time. Here, we define these components as black start generators, non-black start generators, buses, and lines. The model constrains the energization decisions for these components based on relationships between them and their place within the topology of the power system. These energization decisions reflect the temporal scale at which an operator would respond (e.g., minutes to hours). How power flow feasibility informs this model is discussed in the next section. We define the optimal solution to this problem as a *restoration schedule*, comprised of the binary energization state of each component (e.g., energized or de-energized) at each time period in the time horizon. This schedule is used by the Operator Cognitive Model in later sections of this paper.

The restoration process of the IEEE Reliability Test System (RTS-96) (Grigg et al., 1996) is illustrated in Figure 1 below. Assume a power system has experienced a catastrophic insult and is fully blacked out. Additionally, assume the state of each component is known, e.g., energized or de-energized. One possible path of restoration, following the process of Aravena et al., 2019, against a portion of the RTS-96 network, consists of these steps:

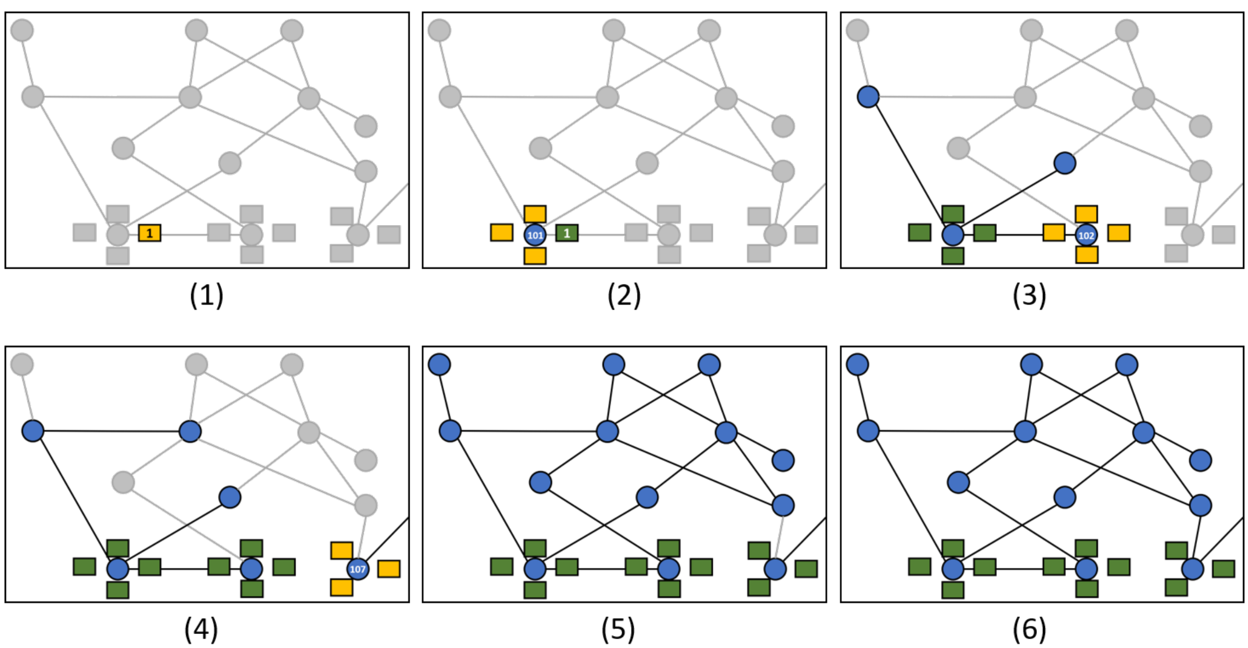

Figure 1. Example restoration sequence of the RTS-96 system. Each figure represents the energization state of components within the system at different snapshots in time. Generators are represented by rectangles (yellow=cranking, green=energized), buses by blue circles, and power lines by black lines between buses. Components in gray are not yet energized at the given point in time.

(1) Black start generator 1 begins cranking.
(2) Generator 1 is energized and provides power to bus 101 and its other attached generators.
(3) Power reaches other buses across energized lines, and the generators at bus 102 can now crank.
(4) Power has reached the generators at bus 107, in a nearby island, and they begin cranking.
(5) The island including the generator cranked in (1) is completely energized.
(6) Finally, a line between the two islands is energized. The system is fully restored when all lines between all islands are energized (not pictured).

The authors note the objective function models how the power system "returns to a normal operational state…in terms of stability and coverage." This objective strives for power system restoration as rapidly as possible while maintaining stable dynamics through the process. For the purposes of this work, shunt compensators and series compensators were not modeled, and discussion of that functionality in their work is omitted. Therefore, the restoration model discussed here consists of an objective function to drive the energization scheduling decisions for generators, buses, and lines. The reader is advised to review Aravena et al., 2019 for a detailed explanation of the restoration model, which is omitted here for brevity.

Power Flow Model
An optimal steady state for the bulk power grid can be obtained using AC optimal power flow (AC-OPF), detailed in Cain, O'Neill, and Castillo, 2012. We focus on the polar formulation where the model nonlinearities are found in the line flows shown in Equations 1 and 2:

$$p_i^{ij} = v_i^2 g_{ij} - v_i v_j g_{ij} cos(\theta_i - \theta_j) - v_i v_j b_{ij} sin(\theta_i - \theta_j) \quad (1)$$
$$q_i^{ij} = -v_i^2 b_{ij} + v_i v_j b_{ij} cos(\theta_i - \theta_j) - v_i v_j g_{ij} sin(\theta_i - \theta_j) \quad (2)$$

When using optimal power flow in a time-based restoration scheduling model, we choose to use only linear approximations of AC-OPF. Specifically, we compare the use of DC Optimal power flow (DC-OPF) (Tan, Cai, and Lou, 2012), LPAC (Coffrin et al., 2018), and a mixed-integer linear approximation (Aravena et al., 2018) in restoration modeling.

The DC-OPF model is obtained though the assumptions: Bus voltages being approximate to one, as in Equation 3; Elements of the conductance matrix being approximate to zero, as in Equation 4; and voltage angle differences between buses *i* and *j* approximating zero, as in Equation 5.

$$v \approx 1 \quad (3)$$
$$g_{ij} \approx 0 \quad (4)$$
$$\theta_i - \theta_j \approx 0 \quad (5)$$

Under these assumptions and Taylor Series approximations of sin and cos, line flows are approximated as in Equations 6 and 7:

$$p^{ij} = b_{ij}(\theta_i - \theta_j) \quad (6)$$
$$q^{ij} = 0 \quad (7)$$

This linear model is widely used within difficult planning models where linear power flow models are desirable. Under black start or severe outages, DC-OPF is inaccurate since its assumptions are violated, as discussed in Aravena et al., 2018.

Another linear optimal power flow model, LPAC (Coffrin et al., 2018), was developed with the intent of including reactive power and allowing voltages to deviate from unity. This model is obtained through a piece-wise linear approximation of the cosine function (as shown in Figure 2).

The optimization objective must be chosen carefully in this model to ensure that cosine is approximated by a point that falls on one of the approximation lines.

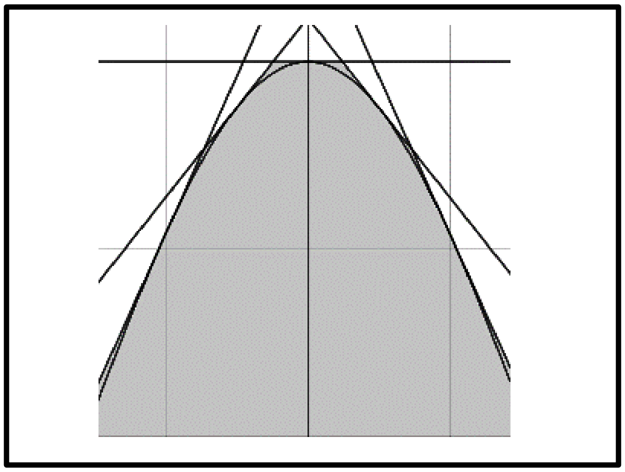

Figure 2. Piecewise Linear Approximation of Cosine Function

$$\kappa_{p_{ij}} = \frac{\left|p''_{ij}\right|}{\left(1+p'^{2}_{ij}\right)^{\frac{3}{2}}} \quad (8)$$

$$\kappa_{q_{ij}} = \frac{\left|q''_{ij}\right|}{\left(1+q'^{2}_{ij}\right)^{\frac{3}{2}}} \quad (9)$$

to carefully partition their domains so that fine partitioning only occurs when p_i^{ij} or q_i^{ij} have large curvature. This partitioning is reflected in Figure 3.

Finally, line flows can be even more carefully approximated through a mixed-integer linear multiple-choice approximation model as described in Aravena et al., 2018. This model regards p_i^{ij} and q_i^{ij} as functions of three variables: v_i, v_j, and $\delta_{ij} = \theta_i - \theta_j$. The three-dimensional domain is then partitioned into cubes and the functions are each approximated with a hyperplane in each cube. The model then uses binary variables to pick a single cube and uses the linear hyperplane within that cube to approximate power flow. This mixed-integer formulation and LPAC can both use curvature, as shown in Equations 8 and 9

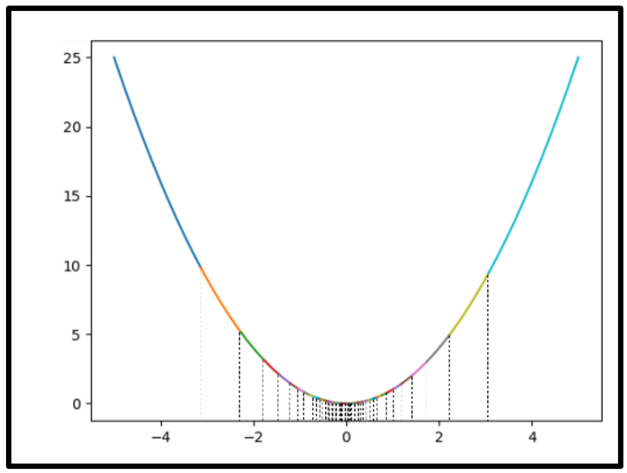

Figure 3. Domain Partition of Line Flow Function Based on Curvature

Integration of Restoration and Power Flow Models

The goal of the restoration model is to obtain a restoration schedule that can be acted on by a power utility operator. We use quasi-static power flow calculations to help ensure islands generated by a schedule are physically possible. Towards this end, Aravena et al., 2019 embed the restoration model in a decomposition algorithm with certain features akin to Benders decomposition. Specifically, their algorithm is similar in how a candidate solution is passed from a main problem to a subproblem to provide cuts to the branch-and-bound (B&B) tree (Laporte and Louveau, 1993; Angulo, Ahmed and Dey, 2016). However, the decomposition algorithm in Aravena et al., 2019 has significant differences from a Benders algorithm.

The decomposition algorithm begins by solving the Master restoration problem in a mixed-integer program (MIP) B&B solver (Wolsey, 2007). Anytime an integer solution is found, a callback is used to extract the schedule and send it to the *Feasibility Oracle*. The Feasibility Oracle constructs and solves a *sequence* of increasingly rigorous subproblems to check for power flow feasibility in each island. As noted in their work, this decomposition algorithm allows for fast solution times at scale. Figure 4 provides an overview of the Feasibility Oracle.

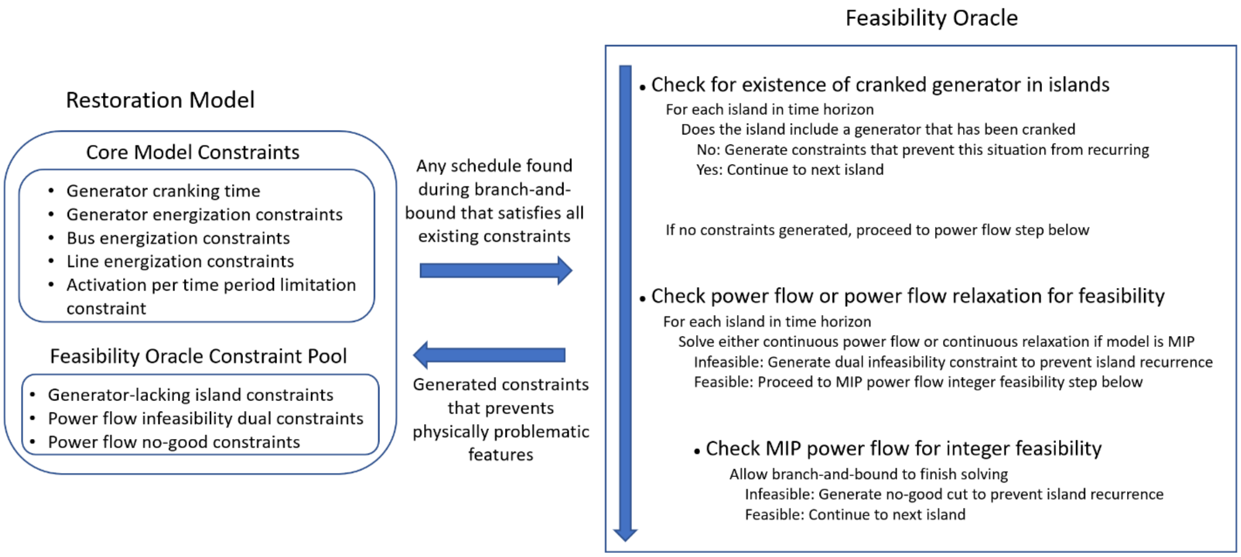

Figure 4. Overview of the Feasibility Oracle

The Feasibility Oracle is designed to detect any sources of infeasibility in a restoration schedule and generate constraints that will prevent these sources of infeasibility in any future schedules in the B&B solve. The Feasibility Oracle proceeds in a 4-step sequence to ensure power flow feasibility within each island:

1. Extract all islands that exist throughout the time horizon of the schedule. These islands are connected components of grid components containing transmission lines, connected buses, and generators along with the state of restoration schedule binary variables pertaining to these respective components.
2. Check to see if any of the islands do not have fully cranked generators. If no such generators exist, the island is infeasible since there is no source of power generation in the island. In this case, one constraint per island bus as well as a single constraint for the whole island are generated to prevent this island from recurring. An additional benefit of these constraints is that no sub-island of the original island will occur with these constraints. If constraints are generated, go to step 3.
3. If no constraints were generated in step 2, a power flow model is solved for each island. If the model is not infeasible, the restoration model B&B proceeds. Otherwise, a constraint is generated as follows:
   a. If the power flow is continuous or an infeasibility is detected at the root node where the continuous relaxation of a MIP is solved, a hybrid Benders integer constraint can be constructed using both the dual unbounded ray given by the B&B solver and the grid component binary variables. This constraint prevents this island from recurring along with other problematic sub-islands
   b. If the power flow is a MIP and the infeasibility is not detected by the continuous relaxation sub-solve, then a no-good cut is generated. This constraint prevents only this exact island from recurring.
4. Any generated constraints are added to the Restoration Model and the B&B solve is allowed to proceed.

As the Restoration Model progresses, its set of core model constraints are appended with a pool of constraints generated by the Feasibility Oracle. In this way, the Restoration Model becomes more well-informed and finds more physically feasible restoration schedules until it terminates with an optimal restoration schedule.

Network Dynamic Modeling

During implementation of a restoration plan, actual conditions on the system typically depart from the idealizations used to develop the plan. These deviations can delay or sometimes preclude restoration as envisioned in the plan, requiring operators to draw on heuristics, experience, and other sources of expert judgement. Our goal is to provide restoration plans that are robust considering all elements of the system (grid, operator, information flow, planning) and their interactions, as well as the pragmatics of implementation. To assess the interactions among a plan, the system, and the system operator, we require a "ground truth" simulator for the system that can present the kinds of problematic behaviors operators are likely to encounter. Such behaviors include power system dynamics, variability in load, and deviation of system conditions from those assumed in developing the plan.

Because the purpose of the ground truth simulator is to present the operator with a set of plausible unexpected conditions that might arise in the course of restart, the ability to efficiently create a set of alternative trajectories resulting from a diverse range of processes is essential. Simulating the behavior of a single fully-specified system under ideal conditions is not the goal. To meet this distinct requirement, we have adapted a network simulation model originally developed to study disruptions on fluid transportation networks (Corbet et al., 2018). In the present application nodal storage represents rotational energy of generators, with terms added to model frequency stabilization following disruption (Beyeler et al., 2020). The resulting model exhibits oscillatory responses to discrete events such as closure and line tripping, potentially inducing disruptive cascades. Stochastic variations in load can also activate problematic dynamics and create system balancing challenges for the operator. The overall modeling architecture allows other simulators to be used to define the ground truth, just as different models might be used to simulate operator behavior and to generate optimal plans. The only requirement for these components is that they implement the appropriate framework interfaces.

Operator Cognitive Modeling

As mentioned in the previous section, further complexity in modeling is required to increase simulation fidelity beyond idealized systems and accurately capture how events unfold during real world failures. In addition to variability in load and system conditions, there is a strong human element controlling the overall behavior and recovery speed of the system. Decisions made by the grid operator when it is appropriate to connect generators, close lines, and introduce loads into the system all affect the state of the system moving forwards, and many of these decisions cannot be entirely automated or prescribed in detail via the restoration schedule. To this end, our model includes a human Operator Cognitive Model developed in the ACT-R framework (Anderson, 1996). ACT-R is a cognitive modeling framework used to simulate the decision making and actions taken by a cognitive agent in response to varied stimulus; in this case we build our agent to read in restoration schedules and system state information from a console and make decisions about cranking generators, connecting them to the grid, and managing lines and loads in the system. This agent represents a grid operator working to bring the system back online and serves as the intermediary between the idealized model represented in the restoration schedule built via the system optimizer and the 'ground truth' system represented in the dynamic grid model. Prior work has outlined the decision framework operators undergo when implementing grid restoration (Hou et al., 2010), and cognitive modeling has a deep history of diagnostic (Böhm and Mehlhorn, 2009; Mehlhorn et al., 2011) and strategic decision making (Gonzales et al., 2009; Thomson et al., 2015; Lebiere and Anderson, 2011). Still, the two have not been integrated into a single power systems model that takes into account the operator ability (and speed) for recognizing, diagnosing, and adapting to deviations from expected behavior.

To address this need we have developed a cognitive model to work with both the optimized restoration plan and the dynamic system, monitoring the system to implement the schedule at the proper pace and adapting to any deviations from planned behavior. This operator interfaces with a virtual system console where they have control over the system to implement changes such as cranking generators, connecting energized generators, adding loads, and energizing lines. All these must be done in the proper order and at the proper times to ensure the system is balanced. Additionally, the cognitive architecture is highly extensible and has the capability to support further planning and strategic decision making in the future to make more detailed models as they become necessary.

DISCUSSION

This section reviews both integration of the models (e.g., how inputs and outputs are used) and application of the models performed to date.

Model Integration

Our model has three distinct pieces that run in conjunction with each other: the power flow-informed restoration model leveraging the Feasibility Oracle; the Network Dynamic Model of the grid, and the Operator Cognitive Model. This combination, as applied to the system they are modeling, is shown in Figure 5. The three work in conjunction to simulate a realistic grid restoration procedure, beginning with the restoration model which produces an optimal schedule for the system in question. This schedule is then passed to the Operator Cognitive Model, which runs in conjunction with the dynamic grid model to attempt the implementation of the schedule. The Network Dynamic Model contains the information about what the system is expected to look like after the prescribed failure mode, and is connected to the Operator Cognitive Model via a virtual console through which it reports a variety of summary statistics including the voltage, angle, and frequency of the system. Further, the virtual console also contains hooks for the Operator Cognitive Model to affect the system via actions such as cranking generators, energizing lines, connecting generators, and adding loads. These actions affect the dynamic grid model which is then reported back to the operator for further monitoring to ensure that the system is behaving as desired. The operator reads through the restoration script, attempting to implement the prescribed actions as appropriate for the system under question.

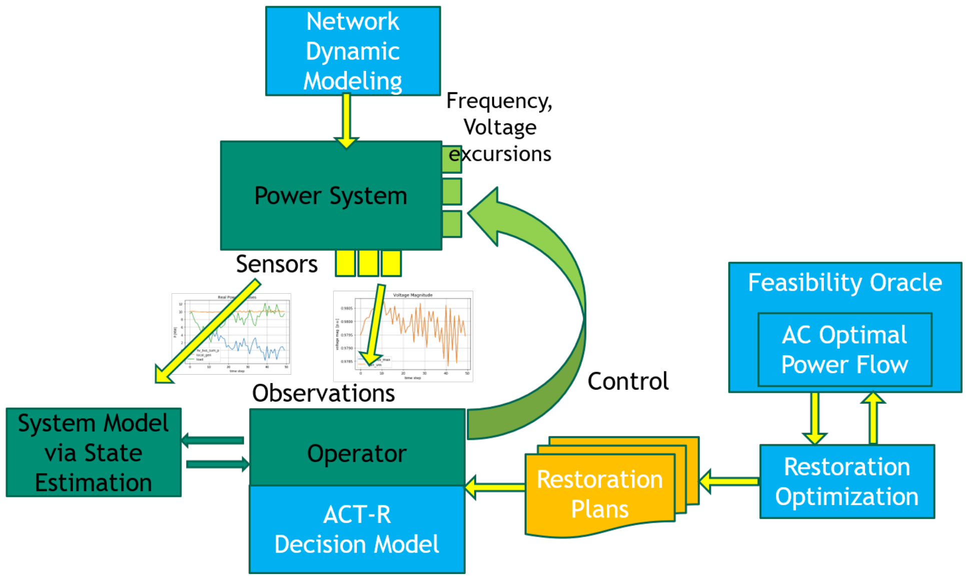

Figure 5. Model Integration Relative to Interacting Systems and Information Paths

Application
The analytic process, as shown in Figure 5, is performed as follows:

First, as shown in Figure 1, the initial focus of the effort was on development of restoration plans for the RTS-96 system (Grigg et al., 1996) relative to the Feasibility Oracle, leveraging an optimal power flow model. Initial efforts in this space utilized concepts from the DC-OPF model (Tan, Cai, and Lou, 2012), with later efforts leveraging MCM (Aravena et al., 2019) model.

Next, the resultant restoration plans are used, in turn, by the ACT-R Operator Cognitive Model, which assumes the system is in a stable state prior to the performance of any action. Actions are chosen based on the restoration plan (e.g., cranking generators, connecting generators, energizing lines, adding loads) and stability checks are performed using the Network Dynamic Model of the system, to check for any issues (e.g., voltage, phase angle, frequency) affecting system stability resulting from the action chosen. If issues are found based on feedback provided from the Network Dynamic Model to the Operator Cognitive Model, corrective actions can, in turn, be made, until stability is reached. At this point, the Operator Cognitive Model can move on to the next step of the restoration plan; this process is repeated until the restoration plan is complete. The detail included in the Operator Cognitive Model has gradually increased, with external subject matter experts providing guidance to the team on the ways in which system operators work with limited information to restore systems following significant disruptive events. Similarly, the Network Dynamic Model has been enhanced to capture departures from expected operation via tripping behaviors, which in turn provide feedback to the Operator Cognitive Model for necessary corrective actions based on the operator's previous action.

Figure 6 shows an example of a restoration simulation using the integrated system. Generator reconnection at time 10 induces system transients, which the operator uses to assess the condition of the overall system, and to verify pre-conditions for the next restoration step, connecting load at time 140.

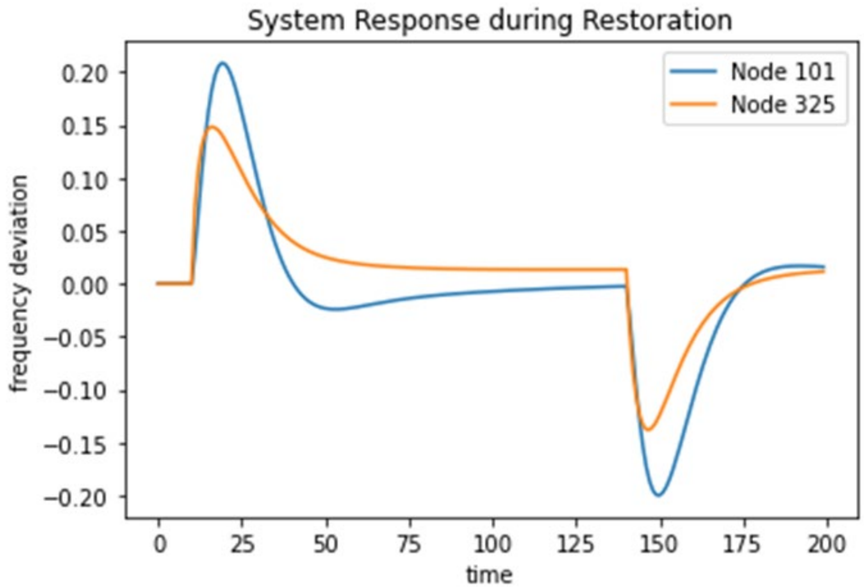

Figure 6. Frequency Deviation as a Function of Time in Restoration Sequence at Two Network Nodes of the RTS-96 System

A more detailed discussion of the consequence and resilience analysis results for this modeling integration will be presented at MODSIM World 2022.

CONCLUSION

The research described in this paper has drawn on multiple modeling techniques in order to assemble a novel integration of these techniques for a 'whole of response' modeling of black start response and action. The modular nature of the approach allows for substitution of modeling techniques and for component-level validation. Incorporation of the Feasibility Oracle in conjunction with the restoration model and the optimal power flow model, enables the development of restoration plans that integrate the restoration modeling process with its' implementation, in this case via the Operator Cognitive Model and its' interaction with the Network Dynamic Model representation of the power system. Results of this work (and potential successor work) will enable more comprehensive and technically accurate development and implementation of restoration plans, allow for the development of those plans considering uncertainties on situational awareness, and reduce restoration time for large disruptive events that impact individuals, industry, and the economy.

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