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# Using System Dynamics to Define, Study, and Implement Smart Control Strategies on the Electric Power Grid

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**Abstract**
*The United States electric power grid is the most complex and expansive control system in the world. Control of individual generators is based on unit inertia and governor characteristics, larger regional control coordinates unit response based on unit economics and error conditions, and higher level large-area regional control is administered by a network of humans guided by economic and resiliency related factors. Under normal operating conditions, the grid is a relatively slow moving entity that exhibits high inertia to outside stimuli, and behaves along repeatable diurnal and seasonal patterns. However, that paradigm is changing due to increasing implementation of renewable generation sources. Renewable generators by nature cannot be tightly controlled or scheduled and appear like a negative load to the system with all of the variability associated with load on a larger scale. In response, grid-reactive loads (i.e. smart devices) can alter their consumption based on price or demand rules, thereby balancing this variability. This paper demonstrates how a system dynamics modeling approach capable of operating over multiple time scales can provide valuable insight into developing new "smart-grid" control strategies and new ancillary services for smart devices to accommodate renewable generation and regulate the frequency of the grid.*

**Key Words**
Smart Grid, power systems, load management

**Introduction**
Electric utilities throughout the United States and the world are progressing towards higher levels of intermittent and distributed renewable energy. With higher levels of intermittent generation, power system planners and operators are struggling to provide the ancillary grid services needed to integrate this renewable energy. This trend will increase the value of ancillary services, especially those that respond on timescales similar to those of intermittent generation, such as the frequency regulation service. From traditional energy storage systems alone, revenues from ancillary services applications are forecasted to rise from $20 billion in 2012 to between $30 and $55 billion by 2022 [1]. Large-scale grid energy storage has been heralded as the breakthrough needed for economic integration of renewable energy sources. However, utilities are currently finding large-scale grid storage technologies that can respond quickly enough to integrate intermittent generation to be prohibitively expensive [2]. While battery-based grid storage may reach a technology breakthrough in the next decade, the potential for intelligently-controlled load (herein: *load management*) to provide these services should also be considered as a readily-accessible option.

The current paradigm for considering load management as a resource does not adequately take into account emerging technologies that would allow load to provide highly valuable frequency regulation services. In fact, the behavior of traditional load at sub-hourly timescales is underrepresented by the current state-of-the-art power system modeling tools. These modeling shortcomings have lead to a misrepresentation of the potential for load management technologies, which ultimately results in a very shallow innovation learning curve.

In order to shift toward a more aggressive learning curve that will change the way the industry approaches load and lead to a robust capability to integrate renewable generation in a short amount of time, we have developed a modeling tool based on system dynamics principals that utilizes a multi-timescale modeling approach for power systems. This model is able to simulate technology innovations and integrate economic impacts with power system operation constraints over multiple relevant timescales. This has significant impact to the way the power industry approaches ancillary services for frequency regulation.

Using this modeling tool, utilities will be able to model system-wide impact of load management technologies on grid stability. Regulators will be able to collaborate with utilities to set new pricing structures that capture the true value of new ancillary services. Policy-makers will be able to utilize the simplified model interface to help them make legislative decisions regarding the support of renewable energy and the impacts that load management devices will have on the economy. By providing a deeper understanding to these high level issues, the electric industry can eliminate roadblocks in the slow cycle of load management development, which will dramatically decrease the cost of ancillary services critical to intermittent generation integration and the growth of renewable energy.

**National Needs and Problems Encountered**

The United States has aggressively pursued renewable energy generation technologies to meet the Presidential Directive [3] of increasing our energy security and to reduce the generation of greenhouse gases. Other than the mature technologies of hydro-electric generation and pumped hydro-electric generation, the leading candidates for large quantities of renewable generated electricity are wind and photo-voltaic (PV) or solar farms. This mentality has filtered down to the state level of implementation and the majority of the states in the United States have Renewable Portfolio Standards (RPS) and goals for the implementation of renewable generators [4].

A renewable portfolio standard is a policy that requires electricity retailers to provide a minimum percentage or quantity of their electricity supplies from renewable energy sources. An RPS establishes a base level of demand but allows the market to determine which renewable energy resources will meet that demand. Historically, state legislatures and regulatory agencies have been the driving force behind RPS policy formulation, although some RPS polices have been adopted through citizen ballot initiatives. Initially proposed as a mechanism to support renewable energy development in competitively restructured electricity markets, the RPS model today serves additional policy aims such as fuel diversity and in-state economic development. By the end of 2007, 25 states and the District of Columbia had enacted RPS policies, ranging from 2% of the electricity supply in Iowa to 40% in Maine (Figure 1). Three other states, Illinois, Virginia and Vermont, have established nonbinding renewable energy goals. The time horizon for achieving the RPS varies among states.

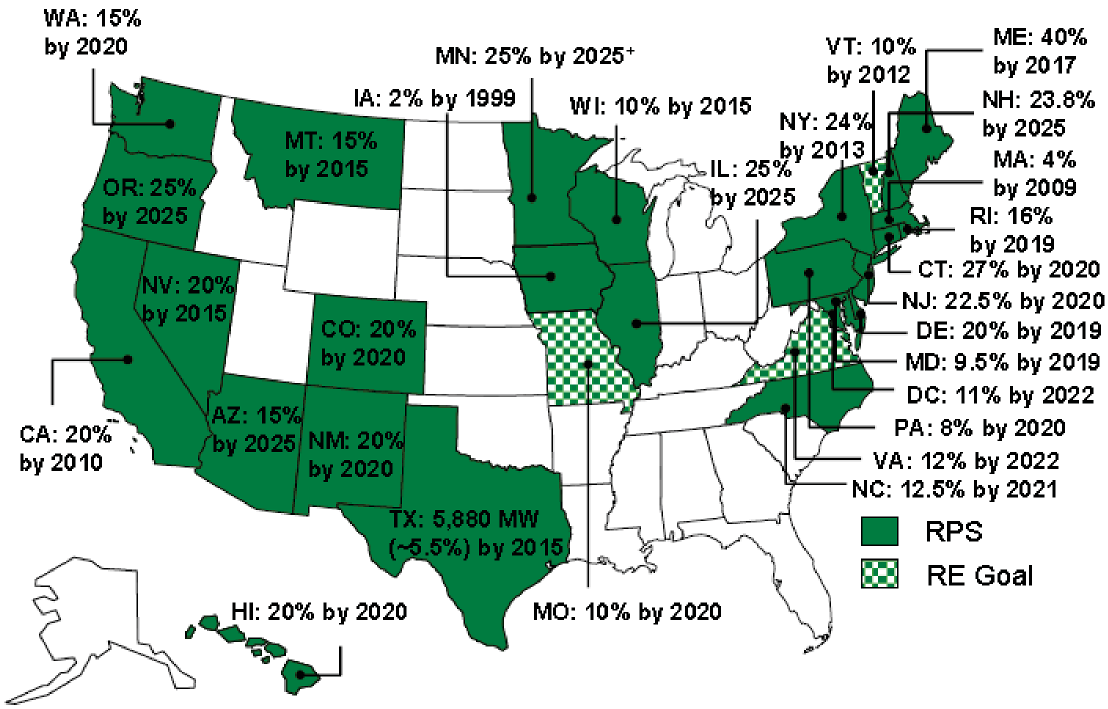


**Figure 1.** RPS goals and participation by state [4].

The nature of electric power is that whatever is generated must either be consumed immediately or stored for later use. One mature method of storage is pumped hydro-electric systems where water is pumped to a higher potential energy during times of excess generation for use at a later time. While this technology is viable, suitable sites are limited and capital costs are high. Battery storage is a topic of intense research, but remains an expensive and real-estate intensive option. So, currently most power systems in the world operate under the premise that generation and consumption must be matched nearly instantaneously. This is done by close monitoring of power system frequency and voltage, accurate load forecasting, and control of generation output to match current load conditions.

In reality however, there are always minor imbalances in the generation and consumption. This is because consumption, or load, has a random element to it that is unpredictable within a given range or percentage of total load. Generation/load mismatches are absorbed by the rotating machinery of the generators in the form of kinetic energy. Too much generation causes the generators to speed up, increasing the frequency of the generated electricity. Too little generation (or too much load) causes the generators to slow down, decreasing the frequency of the system. Ideally, frequency of the system is maintained within one-tenth of percentage point of 60 Hz in the United States to protect sensitive electronics and provide adequate power quality.

Unfortunately, wind and PV renewable generators can and often have a large random component to their output. This is the nature of wind and PV as the wind can change speed and direction randomly, and clouds can occlude PV farms in a random fashion. Therefore, renewable generation appears to the electric utility as a negative load owing to its randomness. They can also have a much larger random component compared to normal loads as illustrated in figure 2

[5]. The left plot in Figure 2 demonstrates how quickly significant wind generation can be lost. At approximately 6:00 AM, a total of 400 MW of wind generation is lost in a matter of minutes. Because this loss of generation is likely not forecasted, the utility must hold extra capacity online as spinning reserve (online generators operating below their maximum output) to absorb these random fluctuations. This capacity is sometimes referred to as incremental reserve. The right plot in Figure 2 demonstrates that wind can also increase output quickly, requiring the utility to scrub generation from responsive plants. Utilities must have machines online that can quickly decrease their output, termed decremental reserve. Ultimately, the inefficiency of this operation costs both valuable natural resources and money.

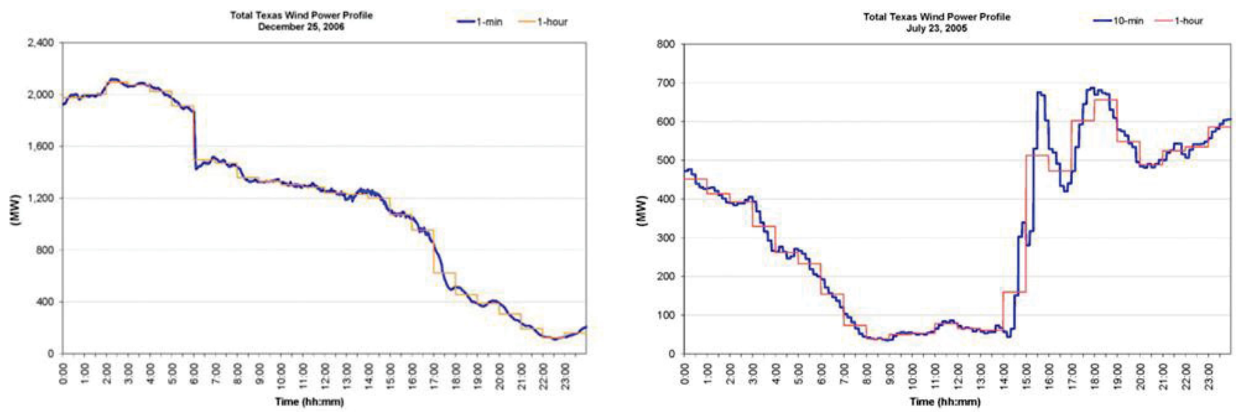


**Figure 2.** Wind profiles showing dramatic decrease and increase of overall wind generation during a day [5].

Solar power ramps tend to be even faster than the wind ramps shown here. Frequency regulation is an ancillary service provided by incremental and decremental reserves that are able to respond on timescales of a few seconds to minutes. It is so-called because the electrical frequency of the system is proportional to the amount of kinetic energy stored in the rotating masses of generators, and is therefore the integral of net power imbalance over time. On timescales of minutes to hours, the service of slower-responding reserves is marketed as load following. Fast-ramping frequency regulation is the most valuable ancillary service because it is the most expensive to provide. This is because fast-responding plants such as gas turbines nominally have higher operating costs than slow-responding plants such as the common coal and nuclear technologies. Grid storage technologies such as advanced batteries are theoretically excellent frequency regulation providers because they offer both quick response and precise control. However, to provide frequency regulation at the scale required for large utilities, advanced battery storage remains very expensive [6].

Frequency regulation services required to maintain sub-second energy balance in the electric grid have traditionally been supplied by generators and are often procured as an ancillary service in organized markets. However as the imbalances increase in both frequency and amplitude due to renewable generation, it becomes very expensive to do this with traditional generation units. However, this can be accomplished more efficiently and economically using intelligent load management techniques [7]. The model developed herein aims to provide a method and framework by which frequency regulation schemes can be postulated and analyzed using distributed load management techniques incorporating the behavioral aggregate of smart homes and devices while including traditional load following and other ancillary frequency regulation services.

**The Need for New Power Modeling Techniques – Top Level Design of MEGS**

Currently, there are no commercially-available power simulation platforms available that assess the multi-scale, multi-system impact of distributed load management technologies. To address these issues, we developed the Model for Electric Grid Strategies (MEGS) using a hybrid modeling approach. Our approach numerically solves only the most salient power system equations at appropriate levels of detail in conjunction with agent-based models of consumers including non-linear human response algorithms. In this way, MEGS captures the coupled contribution of distributed control, centralized control, and human response to the dynamic power balance in the face of added variability from wind and solar generators. To simulate the economic impact of high penetrations of intermittent generation, MEGS uses four components illustrated in figure 4. The object-oriented systems implementation of these four components is shown in figure 5.

**System Dynamics Simulation of Power System Phenomena**

Figure 6 illustrates the classical power system feedback loops present in MEGS. Component behavior as outlined in figure 4 is color coded in figure 6. Renewable generation has a largely exogenous effect on total generation and therefore is not included in the loop diagram. Figure 7 shows the implementation of the stock-and-flow structure of power grid physics within MEGS. This implementation represents the blue variables in figure 6. Equations that describe both physical and human behavior are implemented using the system dynamics methodology described by Sterman [8] and Ford [9]. System dynamics is useful for computer simulation of complex interactions between disparate variables with explicit implementation of feedback. The ease with which disparate variables are incorporated allows MEGS to simulate, for example, the impact of weather events on renewable generation or the impact of adjusted holiday schedules on load profiles. This allows the modeler is able to construct a hypothesis about evolving causal interactions through time using a visual programming language consisting of accumulators (stocks), flows, and delay-inclusive feedback.

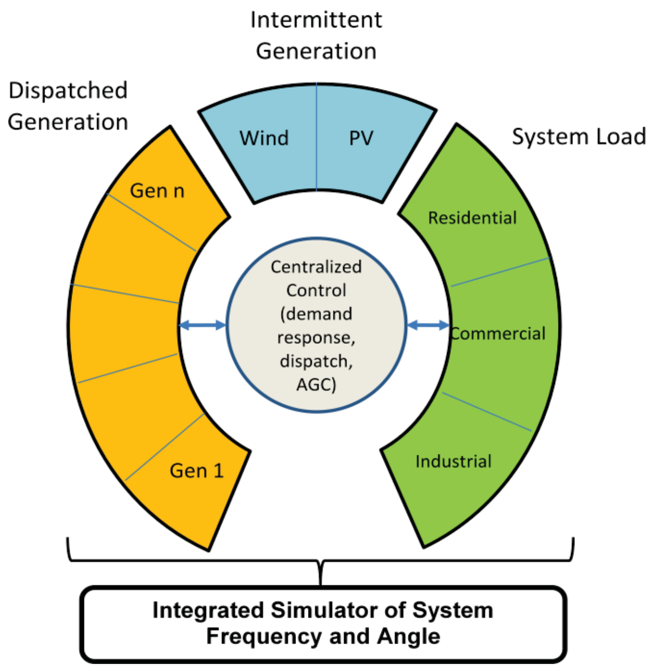


**Figure 4.** Top-level components of the MEGS modeling platform

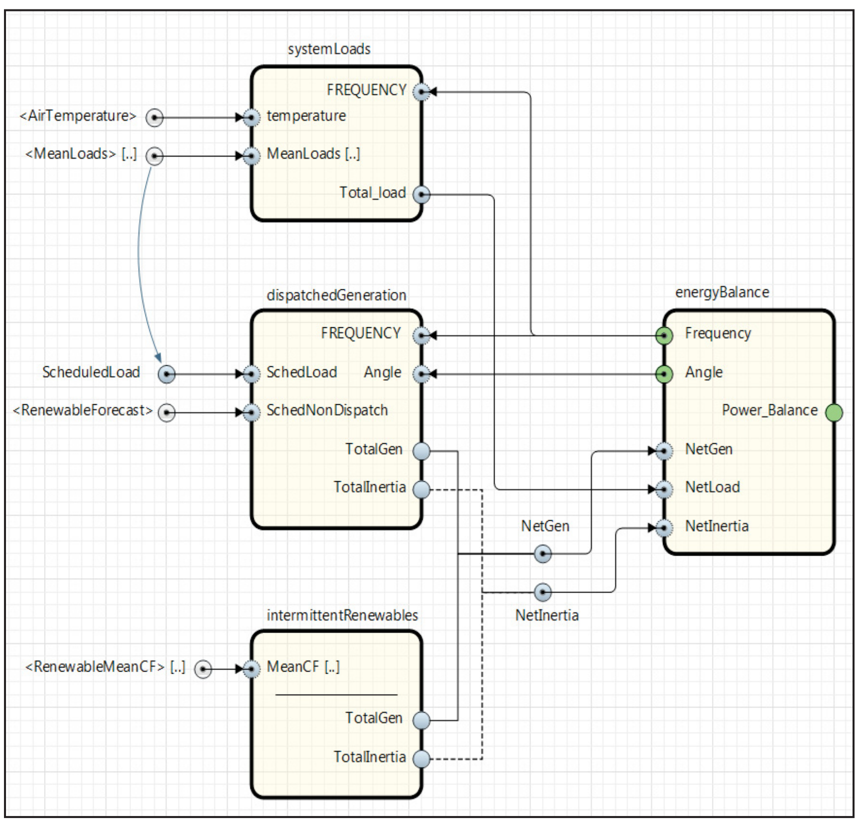


**Figure 5.** Multi-object structure of the Model for Electric Grid Strategies (MEGS) showing feedback between system physics, generation, and load. MEGS contains a visual object structure that allows algorithms to be easily exchanged and feedback to be visualized.

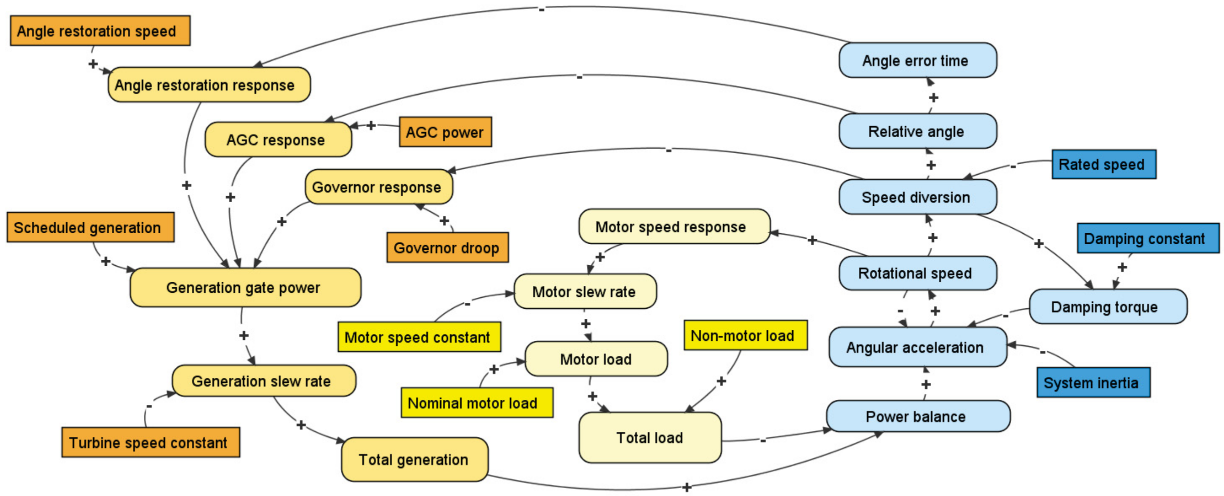


**Figure 6.** Causal loop diagram of power grid physics (blue), generation controls (orange), and load behavior (yellow).

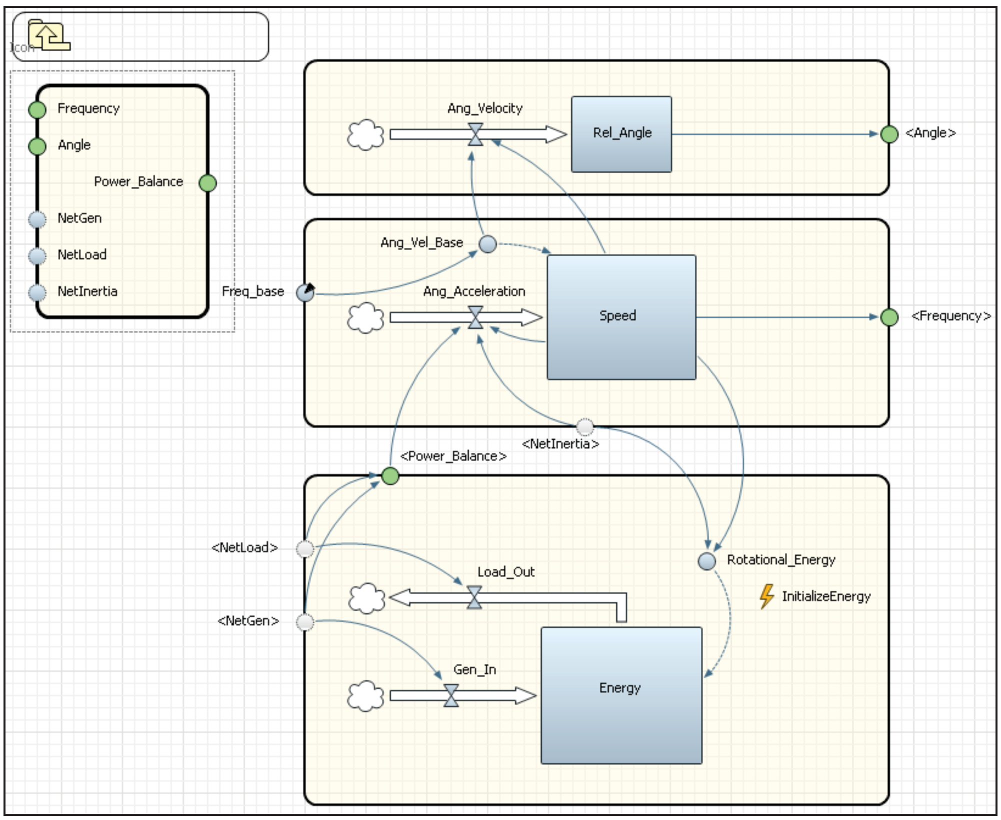


**Figure 7.** The dynamic energy balance of a power system is constructed using the system dynamics methodology. One feedback loop is apparent in this diagram, between angular acceleration and rotational speed.

## Agent-Based simulation of individual load behavior

To manage the complexity inherent in a multi-scale approach, MEGS utilizes an agent-based modeling methodology. As described by d'Inverno and Luck [10], the agent-based methodology offers an abstraction tool for systems with multiple interacting autonomous components. Using MEGS, the aggregated contribution of thousands to millions of individual load management devices can be accurately simulated in a fully customizable environment. Simulation experiments may also be constructed regarding the individual control settings of distributed devices. In MEGS, consumers and their load devices are the primary agents. Figure 9 illustrates the graphical design of the residential consumer agent. The types of loads common to residential consumers are explicitly simulated within this agent, such as electric water heaters for residential consumers. The residential consumer has agency because she is able to make autonomous decisions given data about the system. In most systems, these decisions slowly evolve based on the limited amount of data utilized by consumers (e.g. end-of-month billing data). As computerized autonomous load management technologies are added to the consumer's household, data availability and decision speed may be improved. This approach offers an unprecedented description of load behavior in response to both internal and external drivers. By using consumer agents, MEGS begins to examine the behaviors that cause load to exhibit particular patterns instead of merely empirically including these patterns.

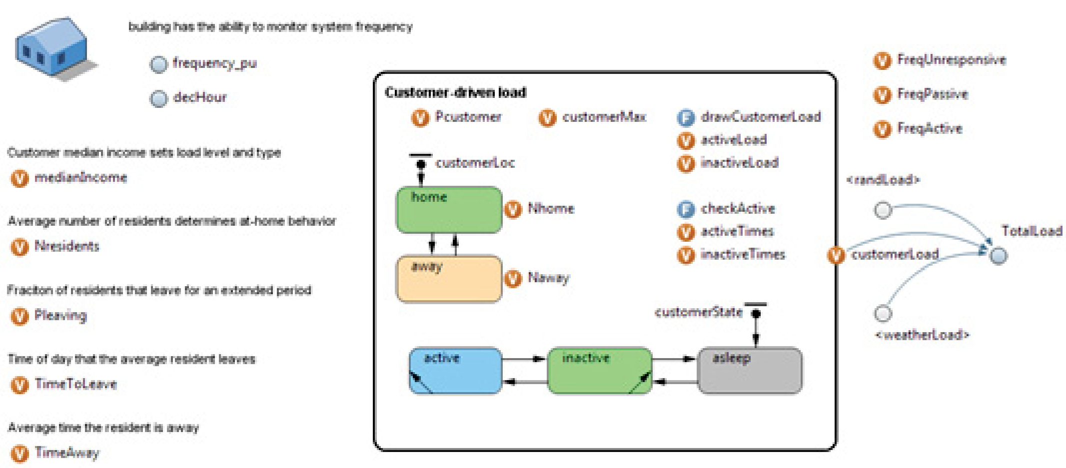


**Figure 8.** Agent-based construct for residential load behavior

## MEGS simulates multi-timescale phenomena

With MEGS, feedback loops can be explicitly included at multiple levels of abstraction. For example, figure 5 shows feedback loops at the coarsest level of granularity. The frequency of the power system affects the response of both generation and load, which returns to affect the frequency. At a finer level of granularity, figure 7 illustrates feedback between the rotational speed of generators and their acceleration. By including only the causal relationships that drive the behavior of interest and excluding extraneous detailed calculations, MEGS uses system dynamics to achieve speed and clarity.

MEGS currently simulates the dynamic power balance of a utility grid using the system dynamics methodology to numerically integrate the differential equations for system-wide frequency and angular displacement. The core differential equation to this dynamic is the swing equation, as described in detail by Kundur [11]. Because MEGS solves this equation along with control system logic and agent-based contributions very quickly, it is able to simulate system frequency at a 0.1 s resolution. Currently it is able to simulate a 24 hour period of frequency dynamics in less than 1 minute. These fast run speeds are critical to being able to reflect dynamics at multiple scales, because the finest scale will likely be the computationally-limiting factor. In addition to the swing equation, the types of dynamic behaviors currently included in MEGS are generator governor controls, centralized automatic generation controls, economic dispatch, generator scheduling, stochastically-sampled wind and solar generation, stochastically-sampled load, weather-driven load and consumer-driven load. MEGS achieves further computational efficiency by calculating dynamic changes in these behaviors at the appropriate time resolution. For example, diurnal dynamics are calculated at a 1 hour resolution and interpolated every time step instead of being directly calculated at each time step.

Several assumptions have been made to allow MEGS to have fast run speeds. The first and most scope-limiting assumption that MEGS makes is that the system is a very tight frequency island, meaning that differences in speed from generator to generator are much smaller than the change in system frequency due to exogenously-driven power imbalances. This also means that there is no tie-line coordination with external power systems, and therefore MEGS currently reflects dynamics on islanded systems only. The second major assumption of the current MEGS platform is that voltage issues do not significantly affect frequency during normal operations. Because MEGS is not meant to be a full electromagnetic transient simulator, this assumption has validity. Nonetheless, during significant power swings, generator excitation and reactive power flows can affect the flow of real power, and ultimately the system frequency.

**Simulating contributions of intermittent generation**

The accurate simulation of intermittent generation over multiple timescales will be critical to simulating the overall impact of increased renewable energy penetrations. Currently, MEGS simulates the contribution of power from wind plants and solar photovoltaic plants. A mean daily profile for each type of intermittent generator is imported, and stochastically sampled noise is added to this mean profile to simulate the aggregate unforecasted behavior. This noise may be sampled over multiple periods. For instance, in the case of solar generation, several high-frequency components of variability exist, and therefore short periods are used. In the case of wind, longer periods are acceptable. Daily profiles of wind and solar generation as simulated in MEGS are illustrated in figure 9.

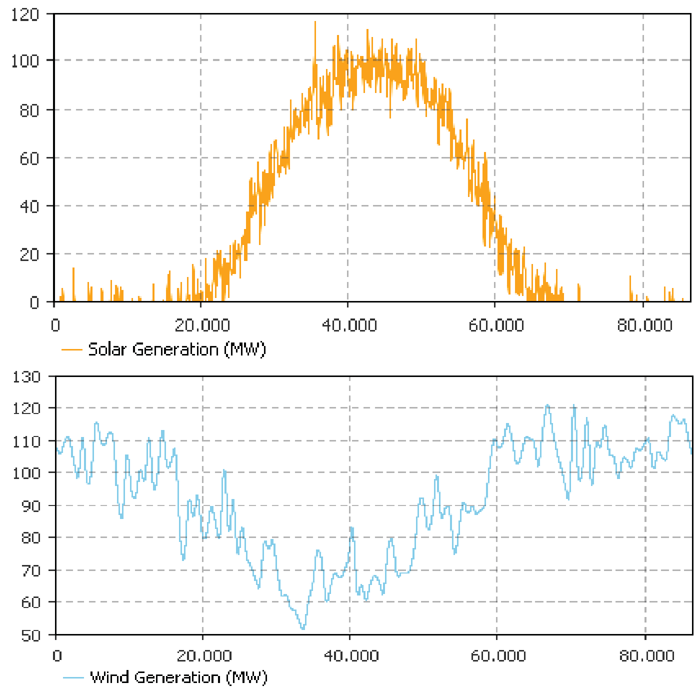


**Figure 9.** Daily generation profiles for (a) solar and (b) wind as simulated by MEGS with different components of stochasticity.

**Simulating economics and real-time dispatch**

To understand the difference between operational costs given multiple scenarios, in-depth economics are integrated into MEGS. Currently, MEGS incorporates a simplified economic dispatch algorithm into its calculation of dispatched generator unit commitments within the dispatched generation component. This algorithm assumes that generators have a discrete and constant cost relationship to one another, and therefore the economic priorities for operation are unchanging. This will be insufficient for simulating realistic operation once systems become large and generators exhibit non-linear cost behavior. To accurately simulate a dynamic economic dispatch, mixed integer programming techniques could be employed that solve for unit commitments given several constraints and objectives, such as cost minimization, reserve margins, and ancillary service contributions. Again, the tradeoff between speed and realism is weighed as additional calculations are incorporated.

**Simulating load behavior with load management**

The functionality of MEGS that has the highest impact on a prosumer paradigm shift is the realistic and fully-coupled simulation of load in response to grid conditions. Currently, MEGS simulates consumers as probabilistic agents, each having unique behavior in response to their own preferences and system variables such as frequency. Using this framework, consumer agents make autonomous decisions about when to increase or decrease load. In a scenario with no load management, these decisions are not based on grid conditions. Figure 10 illustrates results of a simulation in which consumers have no reactive response. Multiple agents combine to make the overall load profile to the utility. Each agent has preferences about, for example, when to wash dishes and take showers as illustrated by the timing of major household loads at the top of the diagram. As these decisions are aggregated, a realistic load profile is generated.

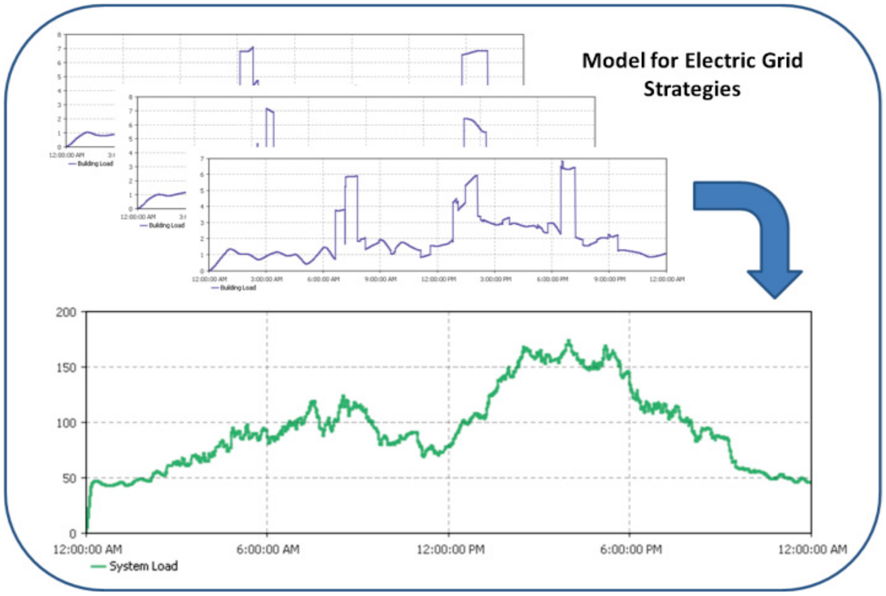


**Figure 10.** Multiple consumer agents contribute to the overall load profile.

*Model Validation and Preliminary Studies*

The MEGS model was compared to and validated against data from an electric utility that experienced a slow generation failure, triggering a frequency deviation event that lasted several minutes. Approximately 140 MW of generation was gradually lost over a period of five minutes. Available system data included generation, load, and frequency as functions of time. A simplified MEGS simulation was created to validate the model by disabling or removing all the control algorithms for generation and load management initially developed for MEGS. The recorded data were used to calculate apparent total system inertia and then to "tune" the model to the specific physical system properties by matching the general characteristics of the frequency data. Figure 11 shows the results of the tuned model compared to the actual frequency recorded during this event.

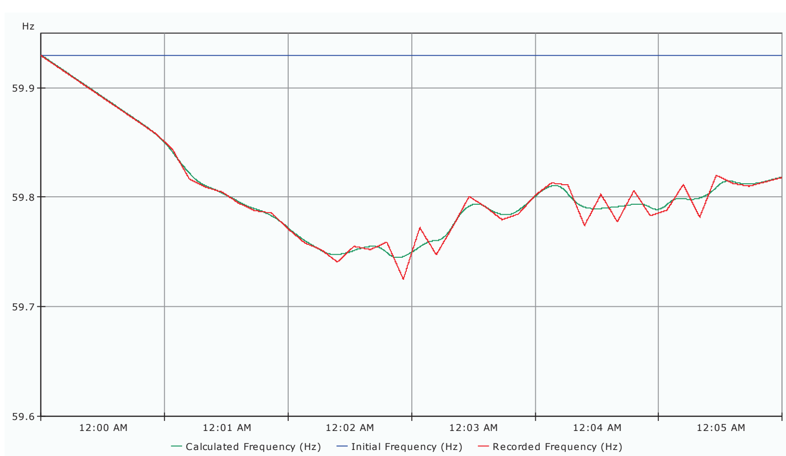


**Figure 11.** Frequency as a function of time for the simplified MEGS model compared to actual data.

The inertia-tuned frequency response of figure 11 gave us confidence in the model's ability to represent system frequency given power imbalances. Once the concept of frequency response to generation imbalance was studied, we tested an event on the larger Electric Reliability Council of Texas (ERCOT) system with an approximate 8% loss in generation. ERCOT is one of the Independent System Operators in North America Electric Reliability Corporation and provides power to nearly the entire state of Texas. This frequency event is shown in figure 12a, adapted from a study by Kirby et al. [12] which examined the relationship between frequency and power markets. While the study concluded that frequency deviations - some of which are due to higher renewable energy penetrations - do not pose a major reliability risk, they also show that the power trading market and scheduling algorithms have sizable room for economic improvement. After tuning the MEGS model using the generation control points (the dark orange squares in figure 7), we obtained figure 12b for the frequency response. The drop in frequency is similar to that for the observed ERCOT system, and the time to recover is approximately 9 minutes for the observed and simulated frequencies. The simulation does not vary load, but only drops the generation, which is likely the reason for our lack of sub-minute frequency variability. Also, the simulated frequency response asymptotically approaches a higher-than-nominal 60.01 Hz. The extra 0.01 Hz is seen because the simulated operators are trying to "make up" for the time spent below nominal frequency from a total energy sales accounting viewpoint.

a) b)

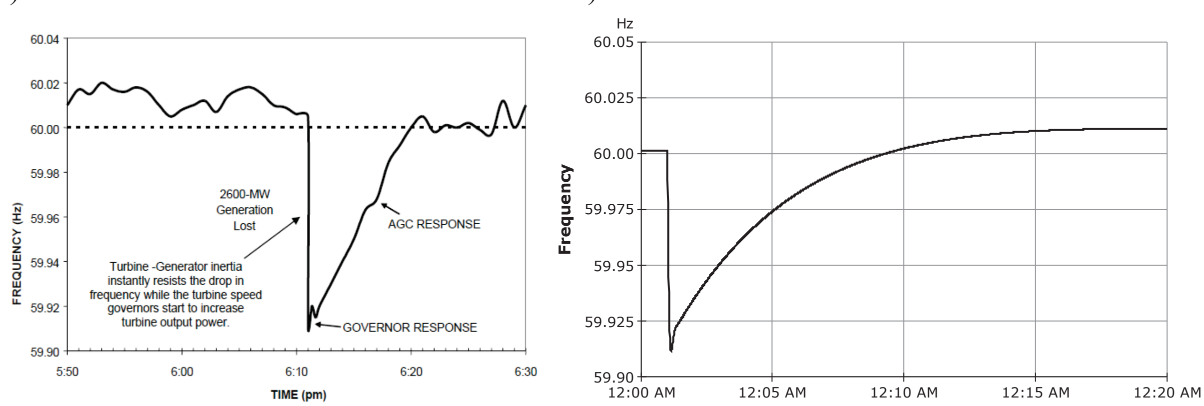


**Figure 12.** a) Frequency as a function of time for an actual loss-of-generation event in the ERCOT system [13]. b) Frequency simulated by MEGS to the same loss-of-generation event.

Once we developed confidence that MEGS models can simulate the frequency behavior of a large system such as ERCOT, we tested the benefit of responding to frequency variations using load management. With 300 MW of frequency-responsive load being controlled by a proportional-integrative-derivative controller, we obtained the frequency response depicted in figure 13. Notice that the frequency deviation is smaller but the recovery time is similar. The over-frequency make-up response is also lower in magnitude.

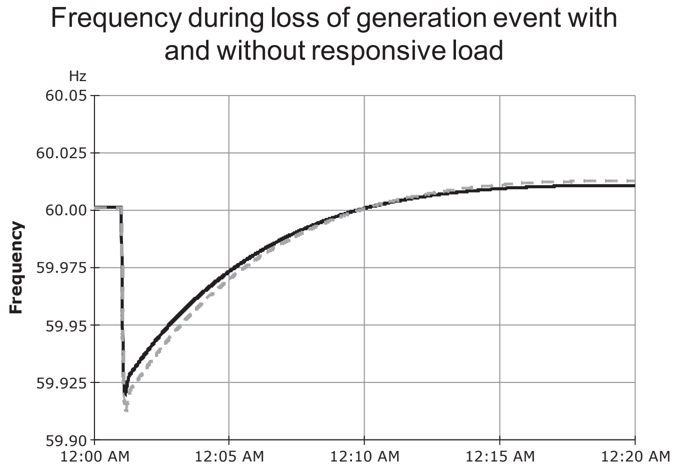


**Figure 13.** The response of the simulated ERCOT system to an 8% loss of generation is shown without a load management scheme in grey hashing, and with a load management scheme in solid black.

To investigate the improvement in economic operations and to begin to place a value on grid-responsive load, we added further economic calculations based on generator operation in MEGS. Shown in figure 14, the generators have an aggregated thermal efficiency curve, which controls the amount of fuel that they collectively need for a certain generation target. Generators are slightly more efficient at higher speeds, as indicated by the *effect of speed on efficiency*. Fuel prices were assumed to be near nominal natural gas prices in 2008, namely 6.8E-9 dollars per Joule [13]. Additionally, we assumed that generators operate less efficiently during ramping conditions such as those likely experienced in the first few seconds of an event. This behavior is reflected in the *Gen ramp cost* variable in figure 14, which itself is dependent on the rate of change of generation, named the *GEN SLEW RATE*. This kind of behavior can be equated to the efficiency lost during stop-and-go driving in a common automobile. We assumed ramping costs $20 for every MW/s ramp. Based on these assumptions, using the simulation of an 8% loss of generation on the ERCOT system, we simulated the operation cost during the event, which is illustrated in figure 15b. The simulated frequency-responsive load is shown in figure 15a. With only 300 MW of frequency-responsive load, which is approximately 1% of total load, the cost of operation is over 2% lower. The reason is threefold. First, load responds more quickly than generation to the event due to its low inertia and ability to employ derivative-based control. Second, this fast response limits the need for generators to ramp quickly because load is now the "first responder." Third, generators can operate at a higher efficiency during the event because the dropped load makes up nearly 10% of the initial generation imbalance and therefore the speed deviation is smaller during the event.

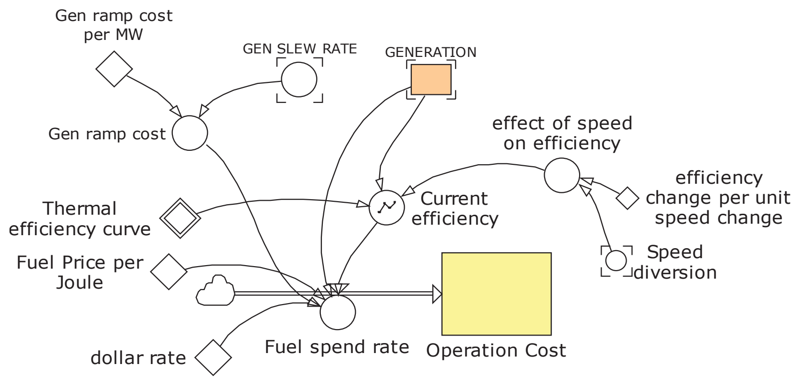


**Figure 14.** Stock and flow diagram of power system operation costs.

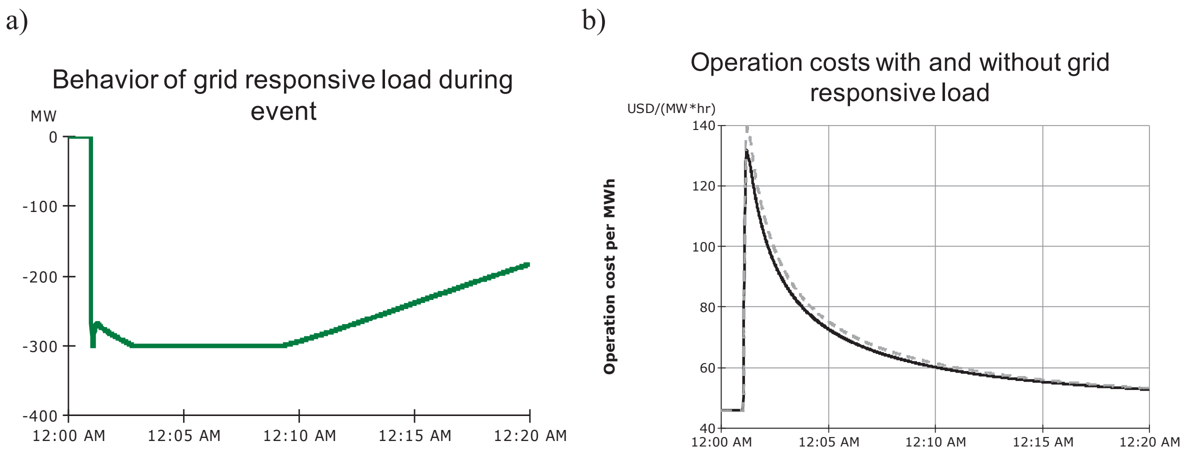


**Figure 15.** a) During the event, frequency-responsive load responds quickly and drops all of its capacity until the frequency recovers. b) Operation costs are lower with the frequency-responsive load online and remain lower for the entire simulation.

**Conclusions**

Application of system dynamics to study the control complexity of the United States electric power grid shows great promise for modeling and understanding the effects of renewable energy and smart-grid load management techniques and devices. We have constructed and demonstrated a model of a simplistic islanded power system to show and analyze the effects renewable generators including multiple levels control from the unit level to regional area control level. The beginnings of advanced load management techniques at the residential level have been introduced by treating households as agents with distinct personalities and properties from a behavioral viewpoint. This is especially important because combining the methods of agent-based and system dynamics modeling minimizes complexity, improves realism, and increases speed for power system dynamic frequency simulations.

The physics of the methodology has been validated by reproducing and studying two separate frequency excursions on real systems with the model encompassing the general behavior and characteristics of each event. The MEGS model was successfully tuned to replicate a small utility frequency excursion where 140 MW representing approximately 10% of the nominal generation was lost over a three minute time period with the subsequent system recovery as more generation combined with some load shed was used to stabilize the event.

On a larger system, the MEGS model was able to replicate the response characteristics of an excursion on the ERCOT system. Based on the response to this event, the ERCOT system appears good reliability characteristics and is capable of absorbing large amounts of variability from renewable generators. The beginning of economic analysis was introduced into the model to show how frequency excursions might impact the economic efficiency of the grid in the ERCOT system. As indicated by the spike in operating costs (figure 14b) when large MW/s ramping rates are required, increasing either the frequency or the magnitude of power variability may greatly increase the long-term cost of operation. We have shown that frequency-responsive load management can be nearly twice as effective at lowering the cost to respond to grid frequency perturbations as current operations are now using common generators. Therefore, the opportunity exists for utilities or power marketers to offer similar ancillary service incentives to the owners of grid-responsive load devices as they now offer to owners of generation. A number of new grid management strategies become available using these techniques. For example, even with a very large drop in generation, frequency-responsive load devices that provide valuable grid stabilization could return online within a few minutes of the event until generation stabilizes and recovers. However, if necessary, the loss of these devices for short periods of time can also be accounted and assessed for any loss of comfort or reliability to the smart device owner. These types of analyses can be readily incorporated into the system dynamics methodology developed and presented in this work.

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