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Investigating the Impacts of Modeling Variables- A Case Study with Smart Grid Demand Response

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Abstract

When modeling and simulating a novel system to be designed, a modeler defines design variables, i.e., those parameters pertaining to the system to be realized, as well as modeling & simulation variables (M/SV), i.e., parameters regarding how the system (as an abstraction of reality) should be modeled and simulated. In this paper, the authors examine the influence of M/SV for a specific case of the conceptual design of a demand response (DR) program. DR is a proposed Smart Grid capability that can be implemented by a utility into an electricity distribution grid. M/SV considered include simulation time-step, number of electricity consumers, and seed variables used in modeling stochastic behavior. The influence of these variables on the ability of the DR simulation environment to produce accurate load curves and peaks is analyzed. For some M/SV, is shown that increased fidelity offers diminishing returns on greater computation time. Quantification of the influence of M/SV is used to support discussion and to identify important considerations when modeling large scale DR past the conceptual design stage.

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Keywords: Modeling & Simulation; Model Verification; Stochasticity; Agent-based Modeling; Time Step; Smart Grid

1. Background and Motivation

1.1. Virtual Modeling

When faced with engineering design problems, there are many different courses of action one may take. One common approach is to look at historical data for similar systems, which can be used for preliminary analysis. However, this approach cannot be applied for the design of a revolutionary system or system of systems (SoS). Another approach is to construct a model of the system, whether physical or virtual. [1] Physical testing can provide unique insights because of its ability to include the effects of uncertainties that may be associated with the environment. But physical testing can be costly or impractical for complex engineering problems. In these cases a virtual model, whether qualitative or quantitative, may be more useful in gaining insight into the problem. [2] These

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models can then be used in a simulation environment in order to gain insight into the behavior of the system, or SoS, of that particular engineering problem.

One should note that these two classifications of models used in a modeling and simulation (M&S) environment are not mutually exclusive, i.e., a qualitative model can be used to supplement part of a quantitative model, or the two model types could be used simultaneously. These M&S environments consider two main types of variables: design variables and modeling/simulation variables (M/SV). The authors classify design variables as related to physical parameters of the system or parameters of an algorithm that can be changed based on the needs of the designer. The M/SV do not directly relate to physical parameters under control of the designer, but are used to describe the degree to which the model approximates reality (e.g., a simulation utilizing a discretized time step does not mean that a system physically operates in a world of discrete time events, but that modeling the real-world continuity of space-time was not necessary to gain insight into the behavior or was impractical due to computational limitations). The choice of M/SV may relate to the fidelity of the model, which often varies depending on the current design phase of the system or SoS.

After requirements are set, the design of a system or SoS can be broken into three main phases: conceptual, preliminary, and detailed. One typically expects the fidelity required of a virtual model to increase through each successive phase of design. This makes intuitive sense for the design of a revolutionary system or SoS because as more knowledge is gained about the physical system or SoS, this knowledge is applied to the virtual model. For this paper, the authors focused on a virtual model that was being constructed during the beginning of conceptual phase of design. When dealing with this early phase of design, one does not need to have high fidelity models because the full impacts of the various design variables may not be understood or practical this early in the design. One may argue that in the early phases of design, a satisficing[b] [3] model should be sought because one may only want "the detail, depth of fidelity, and precision of the models [to] be sufficient only to clearly distinguish between the options." [4] For this reason, trade studies are sometimes performed on design variables while neglecting to explore the impacts of M/SV on the results of the simulation. In order to better understand the impact of choices made about M/SV, a case study was performed on the construction of a virtual model for the Smart Grid SoS.

1.2. Smart Grid

The fundamental mechanisms and infrastructure of the current United States energy grid were conceived over a century ago. It is rapidly reaching many physical and technological limits. [5] The next generation energy grid is often referred to as the Smart Grid, which increases information flow between grid systems, including two-way communication between the residential energy-consumer and the energy producer/distributor. Proposed Smart Grid capabilities include: Fault Isolation, Load Balancing, Distributed Generation/Storage, Demand Response (DR), etc. [5]. This paper focused on DR, which is a program generally designed to reduce peak loads, which are defined as maximum amount of power demanded during a day, by allowing the power generation/distribution companies to have some level of influence over a consumer's energy consumption [6]. The Smart Grid SoS is comprised of a combination of the systems, technologies, supply and distribution companies, and organizational and individual users of electricity. Some of the proposed residential programs for the Smart Grid depend on gaining sufficient participation from residential energy consumers, who, to some extent, independently and autonomously decide whether and when to adopt and use these technologies.

Implementing a successful DR program requires unique evaluation because it seeks to alter the current consumption of residential energy-consumers, while maintaining the current profitability of the energy producer/distributor. Proposed mechanisms for peak load reduction via DR include Direct-Load Control (DLC) or Variable-Rate Pricing [7]. In this paper, the authors focus on the use of DLC, which allows the energy producer/distributor to control specific appliances owned by the residential energy-consumer. This paper builds on previous work of building a SoS model for Smart Grid DR [8], where the authors constructed an M&S environment by leveraging both qualitative assessments and quantitative analysis. In this paper, the authors explore the impacts of the M/SV and how they can influence/impact the results from the Smart Grid DR M&S environment.

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[b] Satisficing is a portmanteau of 'satisfying' and 'sufficing' meaning that accuracy is at least enough to obtain a solution that is satisfactory.

2. Model Specifications

As previously stated, this paper examines the impact of M/SV during the early phases of conceptual design where lower fidelity models are often used to obtain a satisficing representation of reality, sufficient for early stage decision making. For the chosen DR study, the model is used to investigate the effects of controlling air conditioning loads, which created a tradeoff between reduction of peak loads and residential consumer thermal comfort. When constructing the model of the Smart Grid DR program, the model was intentionally constructed to utilize low fidelity approximations of physical phenomenon. [8] For example, all households were modeled using the same thermal coefficients of heat transfer. This means that the roofs, walls, and floor of the household only differ in their thickness, not their material properties. Before discussing more specifics of the model, one should understand the general flow/composition of the model. This model was built by leveraging qualitative assessments from subject matter experts and quantitative analysis from a stochastic, low fidelity, physics-based model. [8] The model underwent several steps of verification, which was defined as increasing the confidence of the results of the model [9], by iterating the results from the quantitative model with qualitative assessments. [8] This paper seeks to further increase the confidence in the model by examining specific details of the quantitative model.

The model used has elements of an agent-based model (ABM) and discrete event simulation (DES) to model a day of energy consumption by residential consumers; these two modeling techniques were combined in order to decrease the simulation run time. The M&S environment was constructed and executed using MATLAB R2010b. One should note that each household agent represents an entire family living in a household. This was done for two reasons. First, it decreased the number of agents, which resulted in a faster simulation run time. Secondly, and more importantly, it allowed for the use of Fanger's Comfort Equation (FCE) [10] to determine the thermal comfort of the household agent. This was an important need for accuracy of the model because the DLC DR scheme analyzed only focused on increasing the set temperature of households' thermostats. FCE utilizes a Predicted Mean Vote (PMV), which is the average comfort level of a group of people. PMV takes into a variety of factors, including: room temperature, humidity, air speed, clothing level, metabolic activity, etc. By utilizing a household's PMV with FCE, one can begin to quantify how residential agents are affected by and respond to changes in their thermostat settings. In order to simulate reality with the thermostat settings, the internal temperature of the house changes with the fluctuating external temperature. This external temperature was set to simulate a summer day with temperatures reaching 81^{o}F. To capture the effects of the external temperature, the internal temperature varied based on generic heat transfer equations for conduction and convection. [11] The general form used is shown in Equation 1 and Equation 2.

Conduction:

$$q \approx kA\frac{\Delta T}{\Delta x} \tag{1}$$

Where k is the coefficient of conduction, A is the surface is area, ΔT is the change in temperature across the surface, and Δx is the thickness of the material.

Convection:

$$q \approx \underline{h}A(T_s - T_\infty) \tag{2}$$

Where $\underline{h}$ is the average convection coefficient of the surface, A is the surface area, T_s is the temperature of the surface, and T_∞ is the ambient temperature of the room

These equations do not completely represent the real-world heat transfer of a residential home, but they do provide low fidelity approximations necessary to observe trends and general behavior of load profile and the effects of load control. Several other assumptions were used and are summarized in Table 1.

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Table 1. Summary of Major Model Assumptions

Parameter	Assumption
Residents' Schedules	Chosen from random distribution for heterogeneity amongst households and pre-determined before the simulation begins.
Appliances	Only Air Conditioning, Refrigerator, Freezer, Washer, Dryer, Lights, and Hot Water Heater were modelled.
Washer, Dryer, Freezer Defrost, Refrigerator Defrost, Lights	Usage was based on Department of Energy data. [12]
Hot Water Heater, Freezer Cooling, Refrigerator Cooling	Based on basic heat transfer equations, but not under control of the agents.
Air Conditioning	Under control of the agent or DR program, agent could set thermostat to a desired level based on PMV value (unless a DR event was occurring).
Comfort Levels of Agents	Each agent was assigned a threshold PMV value to determine if they became uncomfortable. This value was chosen from a random distribution.
PMV of Agents	Assumed values of clothing and metabolic activity were based on an agent's activity. Humidity was held constant and wind speed was set to zero.
DR events	Based on day-ahead predictions of when the peak load would occur. Agents have no control of their thermostats until DR event is over.

2.1. Variable Classification

There are many variables associated with this model. Listing all of the variables used in this simulation would be impractical, but Table 2 highlights a representative list of key variables and their classification as either a design variable or a M/SV.

Table 2. Key Design Variables and M/SV that can be varied in the M&S environment.

Type of Variable	Sub-type of Variable	Name of Variable/Parameter
Design Variable	Resident-related Variables	Number of residents/house, Wakeup time of residents, work time of residents, Return home time of residents, Bed time of residents, Thermal comfort threshold, Clothing level of residents, Metabolic activity level of residents
	Environment-related Variables	Size of household, Appliance usage schedule, External temperature, Internal temperature, Set (thermostat) temperature, Humidity, Coefficients of heat transfer for house, Appliances power consumption values, Size of appliances
	DR-related Variables	DR start time, DR end time, DR change in AC temperature
Modeling/Simulation Variable	N/A	Random seed (R_S), Number of agents (N_A), Time step (Δt)

3. Experiment Plan

It is important to elaborate on the M/SV shown in Table 2 because it is the basis for the experiments conducted in this paper. R_S is used to generate the value of the random numbers used in the M&S environment to set initial conditions or agent's schedule. N_A is considered an M/SV because one can gain insight into the behavior of a model without using a full-scale population of residential consumers. Δt refers to the discretization of time in the simulation environment and is important not only because of its impact on simulation run time, but because of the interactions with the discretized general approximations of the continuous model. When conducting experiments on the settings for these M/SV, changes were examined using two response metrics, total peak load and general shape of the power curve. These responses are used to gauge the impact on the general shape of the aggregate power curve and the magnitude of the rebound effect. All design variables were fixed for each and between each experiment.

The first experiment examined the impacts of the R_S on the outcome of the M&S environment. The only factor that changed between these simulation runs was the value of R_S. This experiment was conducted to determine how stochasticity affects the results from the M&S environment. The baseline for this experiment was the R_S set to a value of 1. It was hypothesized that changing the R_S will not only cause large variation in the peak load because of the stochastic nature of the initial conditions, but could also lead to false evaluation of a DR scheme.

The second experiment explored the effects of the N_A on the results of the simulation. This experiment was designed to determine how many agents were required to gain insight into the behavior of the model in response to a DR event, without excessive computational resources. This means that besides the two response metrics previously mentioned, this experiment also examined the simulation run time. The baseline for this experiment was 1,000 agents. It was hypothesized that changes in the N_A will have non-negligible impacts on simulation run times, but will not drastically affect the shape of the power curve after a given value of N_A, nor the value of the peak load because the values have been normalized. The loads were normalized due to difficulty finding details on specific appliances.

The third experiment focused on the Δt of the model, which not only impacts simulation run time, but also may affect the validity of the model assumptions. Due to the low fidelity nature of the model, some of the model relationships (e.g., load distribution of specific appliances) may no longer be accurate with rather large or rather small values of Δt. This experiment will also use simulation run time as metric when analyzing the results. The baseline for this experiment was fifteen-minute time intervals. It was hypothesized that changes in the value of Δt will drastically alter the shape of the power curve and simulation run time, but will not have a large impact on the peak load.

4. Results

Before examining the results of the three experiments described in the previous section, a baseline experiment was conducted. This experiment used the baseline values for the M/SV; the random seed was set to a value of 1 there were 1,000 agents, and the ΔT was set to 15 minutes. The DR variable for the change in the thermostat temperature was set to a value of approximately 4^{o}F to ensure the occurrence of a specific phenomenon. The results from this experiment can be seen in Figure 1.

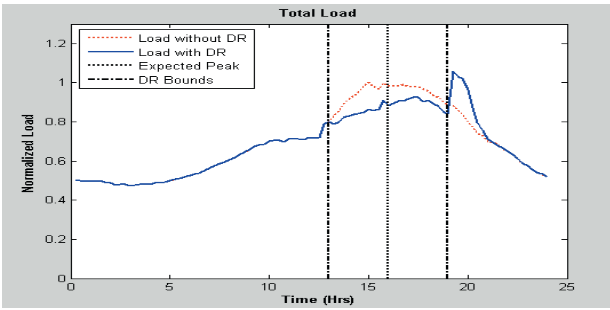

Figure 1. Results from the baseline run. It is important to note that rebound effect, which occurs around 20:00.

The results shown in Figure 1 exhibit an expected phenomenon commonly referred to as the rebound effect. This occurred because all agents are given control of their thermostats at the same time (when the DR event ends), and their air conditioning systems synchronize. This could increase the total power demanded higher than the original peak load. This was an important phenomenon that had no mitigating measures in this model. This was done in order to have an obvious shape pattern to use as a basis for comparison in the three experiments. The quantitative results of this experiment are presented in data tables presented for each of the three experiments as the baseline case for that experiment.

4.1. Experiment 1 – Random seed

This experiment was conducted using 100 different values of R_S, which were preprogrammed into MATLAB; the results from three selected cases are shown in Figure 2, and quantitative results are summarized in Table 3.

Table 3. Results from Experiment 1 showing variation in Normalized Peak Load.

R_S: 1		R_S: 15		R_S: 41	
Normalized Peak Load	**0.956**	Normalized Peak Load	0.947	Normalized Peak Load	1.056

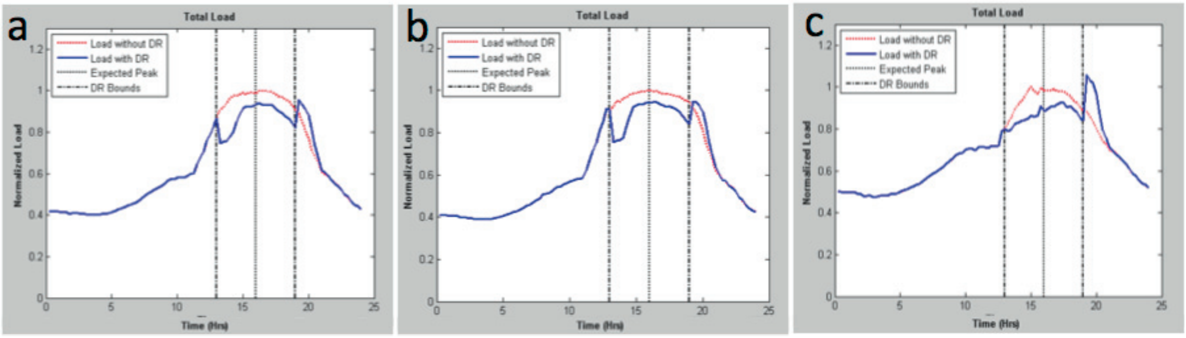

Figure 2. Results of 3 different values of R_S: a) 1 b) 15 c) 41.

The effects of the R_S are shown to have up to a 10% effect on the value of the peak load between simulation runs. This is a non-negligible value, especially considering a utility company that manages at least Gigawatts of power. The R_S also impacted the general shape of the model. The simulation run with a R_S 41 could easily be interpreted as a bad DR scheme because of the large rebound effect, but this may not be the case for R_S 1 and R_S 15. To further study this point, an analysis was conducted on the 100 different values of R_S; the results are presented in the form of a Cumulative Distribution Function, as seen in Figure 3. These results suggest that with all other variables the same, the effects of differing values of R_S result in a noticed rebound effect over 20% of the cases.

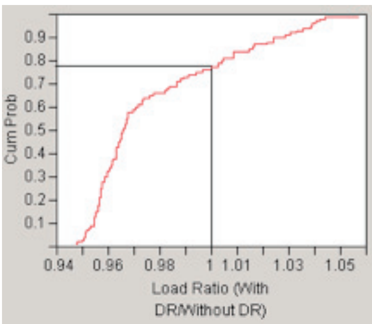

Figure 3. Cumulative Distribution Function of 100 different values of R_S. Load Ratio values greater than 1 mean that a rebound effect was noticeable.

However, the stochasticity associated with this SoS could imply that a thorough analysis would average the results, which would reduce the impacts of the variability in the results. This would mitigate the impacts of R_S on the response of the model. However, this also highlighted an important issue: a robust DR scheme should be able to handle a variety of situations (i.e., different values of R_S) within an expected range. This implies that examining the individual results of values for R_S could offer unique insight into the capabilities of a DR program.

4.2. Experiment 2 – Number of agents

This experiment was designed to explore the impacts of N_A. The results from three simulations are shown in Figure 4. Quantitative data on these simulations is summarized in Table 4

Table 4. Results from 3 simulation runs varying the value of N_A.

N_A: 100		**N_A: 1,000**		N_A: 10,000	
Simulation Run Time	4.34 Sec	**Simulation Run Time**	**13.54 Sec**	Simulation Run Time	1670 Sec
Normalized Peak Load	0.984	**Normalized Peak Load**	**0.956**	Normalized Peak Load	0.952

There was little variation in the value of the peak load for the different simulation runs, which was expected. But when examining the shape of the power curve, the peak load obviously occurs as a rebound effect in cases b and c, but not case a. As the N_A increased the shape of the power curve became more defined, which could impact the evaluation of a DR scheme. Another difference highlighted in this experiment was the simulation run time, which increased by an order of magnitude when going from 100 to 1,000 agents and by two orders of magnitude when going from 1,000 to 10,000 agents. Due to computational limitations an adequate estimate of the relationship between simulation run time and N_A could not be regressed from the data. When this experiment was conducted, it was observed that the simulation could not run on a single computer with more than 12,000 households (i.e., agents) because of memory limitations.

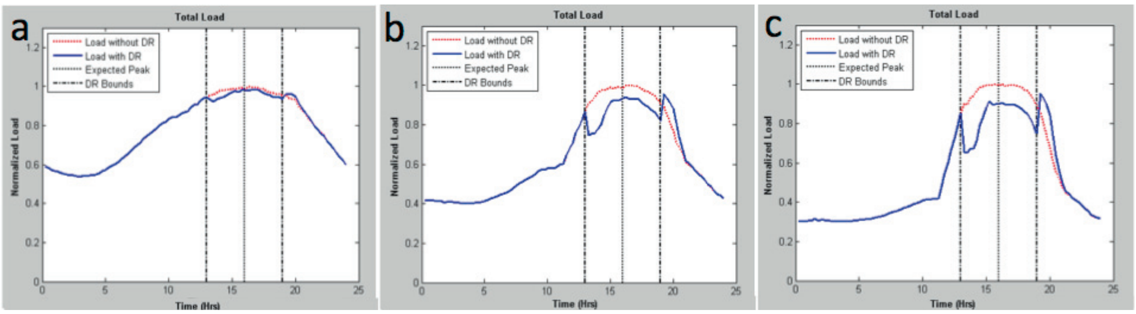

Figure 4. Results of 3 different values of N_A: a) 100 b) 1,000 c) 10,000.

4.3. Experiment 3 – Time step

Four different values of Δt were analyzed in this experiment: 1 hour, 30 minutes, 15 minutes, and 1 minute. This experiment tested the limits of the assumptions used to create this model. These assumptions include incorporating DES, and could show that the physics of the model might not have been accurately captured with very low or very high values of Δt. The results of this experiment are shown in Figure 5 and summarized in Table 5.

There was approximately a 4% variation between peak loads in these simulation runs, which was very large when one considers the Gigawatts of power potentially involved for a real grid. The simulation run time increased with lower values of time step, which was expected. The shapes of the power curves showed large variation, and the rebound effect was most apparent in the 15-minute Δt. However, the rebound effect could be noticed in the other simulations only if one knew to look for the rebound effect.

Table 5. Results from experiment varying the values of Δt.

Δt : 1 hour		Δt : 30 min		**Δt : 15 min**		Δt : 1 min	
Simulation Run Time	6.18 Sec	Simulation Run Time	8.65 Sec	**Simulation Run Time**	**13.54 Sec**	Simulation Run Time	160.7 Sec
Normalized Peak Value	0.979	Normalized Peak Value	0.961	**Normalized Peak Value**	**0.956**	Normalized Peak Value	0.937

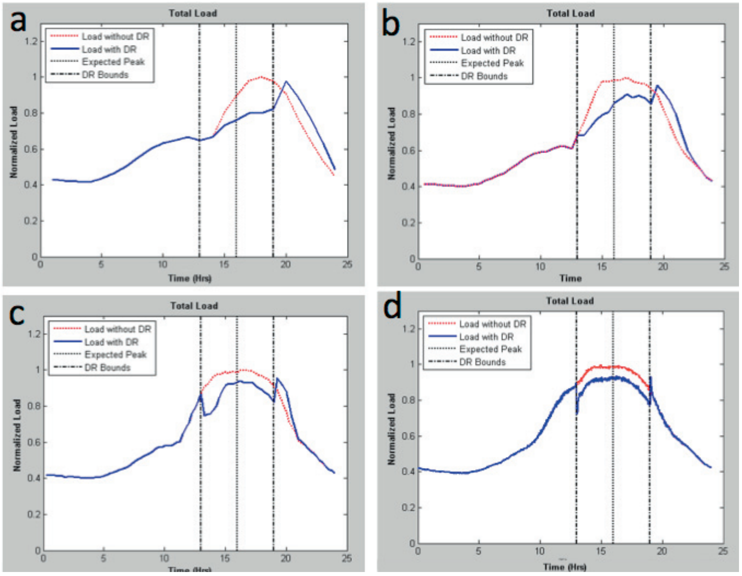

Figure 5. Results from experiment 3, with values of Δt set to: a) 1 hour b) 30 minutes c) 15 minutes d) 1 minute.

5. Discussion

Based on the results of this case study, M/SV can lead to large variability in the responses of a simulation and can lead to incorrect conclusions in the early phases of design. This could be seen in Experiment 1 when a noticeable rebound effect occurred in over 20% of the cases. It is not within the scope and intent of this paper for the authors to recommend specific actions to be taken for construction of any general model. However, some general advice can be offered when constructing an M&S environment to conduct virtual experiments. First, a modeler needs clear expectations on the purpose of a model in order to select M/SV settings that maximize accurate knowledge gained about the system's behavior (e.g., whether a DR scheme effectively reduces a peak and avoids a worse rebound) while minimizing computational resources required to simulate the model of that system (e.g., to enable scale up to a larger DR consumer base). This was highlighted by the results of the second experiment, where increasing N_A past 1000 did not greatly increase the knowledge gained, but did increase the simulation run time. Second, including a known behavior into the model (e.g., rebounds) and looking for its emergence in the results (as in Experiment 3) can be a useful way to quantify the effects of M/SV settings related to fidelity. This enabled the authors to quickly analyze the impacts of values chosen for M/SV for all of the experiments presented. Third, testing assumptions should encompass the entire M&S environment, i.e., since a model is an abstraction of reality it is necessary to tests the assumptions about the accuracy of the physics used in the abstraction. A final observation is that it may be easier to gain insight into the impacts of M/SV early in model development based on the presumption that quantifying the impacts of M/SV increases in difficulty as the complexity of the model increases.

This study leads to numerous research questions and future work. The effects of stochasticity are shown to have an effect on whether a noticeable rebound effect occurs that would be larger than the original non-DR peak load.

This motivates a study of the robustness of different DR designs or design parameters to stochastic factors that may exacerbate rebounds. One question is how to efficiently represent variability to support design for robustness. Another topic of interest is how to create a more rigorous process for determining what the appropriately satisficing M/SV settings might be and whether the benefits of such an activity would be worth its computational intensity, especially for conceptual design. Besides characterizing these research problems, this paper has described key aspects of the M&S platform needed for such research investigations in the context of DR.

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