Simulation Gaming to Study Design and Management Decision-Making in Flexible Engineering Systems

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Abstract—This paper reports on the development of a simulation gaming platform to study the dynamics of decision-making when multiple stakeholders are tasked to design and manage a flexible engineering system. Flexibility in design and management provides the “right, but not the obligation, to change a system in the face of uncertainty.” This approach shows clear lifecycle performance improvements for complex systems, as compared to standard design and management approaches. The process of enabling and managing flexibility involves many stakeholders at different levels of the decision-making process. Decisions at a higher level (e.g. system owner, client) impact the decision space available to other stakeholders down the line (e.g. system designers, operators), which affects the ability to respond to change. Managing different sources of flexibility in operations is challenging, especially when subjected to economic and/or legal constraints, information asymmetry, different uncertainty sources, and other agency problems between the stakeholders. The simulation gaming platform provides a way to devise, study, and evaluate the effectiveness of training and other uncertainty management techniques experimentally to help stakeholders better design and manage complex systems under uncertainty. Results of preliminary experiments are shown in the context of an urban emergency services system.

Keywords—complex systems; design and management; decision-making under uncertainty; flexibility in engineering design; real options analysis; serious gaming; uncertainty management

I. INTRODUCTION

The Blue Cross Blue Shield (BCBS) tower in Chicago is an example of a flexible engineering system designed to deal explicitly with uncertainty [1]. In the early 1990s, the company was facing an unstable market, and uncertain growth prospects. It was not clear how much office units would be needed for its new corporate headquarter to sustain its activities. The company designed the building initially for 27-stories, but carefully designed in the system the ability to accommodate later expansion to 54 stories. Realizing the need for more office space, the company exercised the flexibility a few years ago, and the second phase was completed in 2011. This is an example of a flexible phased capacity deployment strategy. Flexibility is a design and management paradigm that helps improve expected lifecycle performance of complex systems by reducing the impact of downside conditions (e.g. like an insurance policy, reducing possible losses), while providing contingencies to capitalize on upside opportunities (e.g. like a call stock option, providing higher payoffs, while limiting downsides). Standard approaches to design and management often focus on optimizing the system for deterministic projections (e.g. market, demand, technology, regulations), which ignores the effect of uncertainty on lifecycle performance, and potential value improvements stemming from flexibility. Expected lifecycle performance improvements ranging between 10% and 30% as compared to traditional approaches have been shown in many studies [2, 3].

This paper is motivated by the need to understand the conditions under which ideas of flexibility can be exploited most productively. The underlying assumption is that one can provide a more conducive environment and/or training to stakeholders involved, so as to exploit the benefits of flexibility as much as possible.

The main contribution of this paper is to report on the ongoing development of a computer-based simulation gaming platform that can be used to study different conditions and uncertainty management techniques in an experimental setting. The platform builds upon notions of serious gaming [4], real options analysis (ROA), and operations research. The idea is to recreate the conditions under which decisions are made to design and manage complex systems, so as to measure their impact under different conditions on lifecycle performance, and other project attributes.

The rest of the paper is organized as follows. Section II introduces related work and identifies the research gaps motivating this study. Section III presents the methodology and its application to preliminary experiments and results. Section IV follows with discussion and conclusions.

II. RELATED WORK

Flexibility in engineering design involves five phases: 1) standard/initial design, 2) uncertainty recognition, 3) concept generation and enabler identification, 4) design space exploration, and 5) process management [5]. In line with this study, phase 5 focuses on the conditions that are conducive of flexibility in design thinking, implementation, and management. To this day, not much work has been done in this area. Cardin et al. [6] studied the effects of different concept generation procedures to support creative flexibility.
generation in an experimental setting, relying on collaboration engineering techniques to stimulate creativity. More work is needed to understand the conditions that help decision-makers exploit these ideas most productively.

The ROA literature focuses on economic evaluation of flexibility. The techniques used include Monte Carlo simulations, decision analysis, and binomial lattice analysis. The community recognizes that standard design and management approaches underestimate the true economic performance of irreversible decisions in complex systems, because they ignore uncertainty, and the ability to adapt to changing conditions [2, 3]. This reality is captured in Equation (1), where $V$ captures the project net present value (NPV) based on standard discounted cash flow (DCF) analysis of assets in place. $F$ is the value stemming from flexibility:

$$V = NPV + F$$

Even though the work on real options recognizes that flexibility adds value to complex projects, more work is needed to understand how $F$ is impacted by multi-stakeholder interactions (e.g. a decision maker, a designer and an operator) interactions in a setting capturing real-world design and management cycles. Smit and Trigeorgis [7] showed how information asymmetry and suboptimal timing affect the value of a runway capacity expansion real option for two major European airports. Ferreira et al. [8] investigated the payoff structures for two mining companies and valued the flexibility to wait and defer an investment opportunity. These authors were among the first to suggest that context and stakeholder interactions can affect the value of flexibility $F$.

Even though many studies recognize the impact of stakeholder interactions on the value of flexibility, they rely heavily on theoretical economic models. Many assumptions may not hold in a real setting. For instance, it is not clear that all stakeholders act rationally, which is a fundamental tenet of game theory. It is not clear that stakeholders have the resources to exercise flexibility at the optimal time, in relation to the notion of a decision rule. Information asymmetry and other agency issues may be stronger/weaker depending on the context. Similarly, it may be unclear whether stakeholders understand the concepts and power of flexibility, and the underlying motivations for using in strategic decision-making.

Serious gaming is an area bringing relevant tools to study these issues more carefully. Ligtvoet and Herder [9] explain that serious games are “experience-focused, experimental, rule-based, interactive environments where participants learn by taking actions and by experiencing their effects through feedback mechanisms that are deliberately built into and around the game”. [4] Serious gaming techniques are useful in education and practice to understand the cognitive decision-making dynamics.

Serious gaming techniques can be used to understand agency and information asymmetries arising during the system lifecycle. Serious gaming differs, however, from game theory because it focuses on studying the dynamics of interactions, as opposed to the payoff structures, finding the Nash equilibrium, etc. The two methodologies can nevertheless be used complementarily to understand the best conditions from a theoretical standpoint, and testing such conditions in an applied setting. Different treatment conditions can be evaluated in a controlled environment (e.g. with or without information asymmetry), and/or relying on different uncertainty management techniques (e.g. lectures, visualization tools, etc.)

This study addresses the research gaps above by investigating these issues in a controlled experimental setting, and focusing on emergency medical services (EMS), because this area involves complex decision-making related to design and management. EMS systems provide a wide range of opportunities to study flexibility and uncertainty management, requiring adaptive decisions in daily operations (e.g. vehicle allocation) and longer-term strategic planning (e.g. station siting and capacity deployment). So far, much work has focused on optimizing daily operations to answer emergency calls [10]. Some efforts exist on strategic decision-making to determine the optimal siting configuration [11]. The analytical work typically models uncertainty, but some assumptions (e.g. on probability distributions) may not always capture reality. Most importantly, much of the work does not account for strategic level flexibility where decision-makers can site stations by exploiting various real option strategies, such as capacity expansion, staged capacity deployment, switching, abandonment, temporary closure, and/or a mix of the above.

III. EXPERIMENTAL METHODOLOGY

This section describes the proposed methodology applied for demonstration purposes to ongoing experimental work. All material used in experiments is available in Fu [12].

A. Step 1: Preliminary Setup

1) Design and Management Problem

The first step consists of describing the problem facing decision-makers. The engineering system of interest here is an urban EMS system providing ambulance services in Singapore. The goal is to determine siting configuration and ambulance allocation (referred here as the design) to optimize the main key performance indicators (KPI). Decision-makers must design and manage the system to maximize the fast response rate (i.e. percentage of calls handled within a certain time), percentage of lost calls, and operating cost, given a constrained budget. These KPIs are affected by multiple uncertainty sources, such as frequency of emergency calls during day and night, traffic conditions when incidents occur, demographics change, and construction of new population and industrial estates [13, 14]. Uncertainty sources are characterized by key parameters, like changing geographical incidents rate, travel times subject to random fluctuations, and variable patients’ condition.

The problem is devised to reflect the realities of the real-world problem, while being constrained enough to avoid shifting players’ focus on understanding the game mechanics, as opposed to making thoughtful decisions.

$$V = NPV + F$$

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Participants can decide where and what kind of station to deploy, and how many ambulances to allocate at each site. For instance, they may decide to deploy small stations that are cheaper and faster to build, but have lower capacity in each site (i.e. in terms of ambulance being assigned and operated from the site). Average response time may be affected if incident rates increase beyond capacity. Large stations may offer more capacity and lower cost per unit capacity, benefiting from economies of scale, but may require more time to build. If incident rates are lower, this may result in unused capacity in some areas, also affecting average response time. Flexible upgradable stations have the same capacity and time to build as small stations, but provide a capacity expansion real option, and can be upgraded to a large station at a later time. They represent a tradeoff between the two architectures enabling better adaptation to changing incident rates. A small additional expenditure may be required to provide such option compared to the cost of small capacity stations, and for exercising the flexibility.

In each round, decisions are made at two levels. A system designer decides of the types and locations of the stations given a constrained budget, whether to buy more ambulances, and/or upgrade a flexible station. A system operator decides how to allocate the ambulances at each site, depending on site allocations made by the system designer, and available budget. If the designer chooses a rigid deployment strategy of fire stations (e.g. deploying only large stations), the operator has to allocate available resources to respond best to uncertainties over the system lifecycle. This strategy may reduce overall costs by benefitting from economies of scale, but may suffer from a high upfront cost and perhaps low ambulance utilization rates. If the designer deploys flexible upgradeable fire stations, s/he will decide in subsequent rounds when to exercise the flexibility (e.g. build new stations, upgrade or demolish existing station, etc.), thereby also affecting the decision space available to the operator. As such, the problem captures path dependencies inherent to such complex system, where the sequence of irreversible decisions affects how the infrastructure is deployed and operated over time [15]. Choices available later on are limited by previous decisions and budget. The operator manages the system subject to previous decisions, those made by the designer, also constrained by the same budget.

Players are given an 8 x 8 gridded map of an area of the city, with each grid corresponding to a particular sector. They are given the deterministic short-term forecasted emergency calls intensity in each sector, but told that the rates will change over time. Information about current hospital locations, stations, and ambulances is given. Characteristics of the stations are given as small, large, and upgradeable. Construction and operating costs, together with capacities and construction time of each type are explained.

2) Participants

Eight participants from universities in Singapore were selected to participate in preliminary experiments for prototype demonstration: one third-year student, six final year students, and one research assistant, with five studying engineering, two science, and one computer science. There were six males, and two females. More data is currently being collected.

3) DOE setup

Four treatment conditions are evaluated with two participants each, consisting of two factors (or independent variables) with two levels each (TABLE I). Educational training (E) consists of an explicit training on flexibility (E = +1) by means of a short written document, or current training (E = –1). The short written document explains why uncertainty affects lifecycle performance, what are the benefits of flexibility, and provides generic examples of real option strategies. Participants are not told what to do or how to do it during the game. Rather, they are given conceptual training on uncertainty management and flexibility as a way to deal with uncertainty, with an eye on improving lifecycle performance. Current training assumes that participants play the game with their own background and experience, without explicit training on uncertainty and flexibility.

Factor F represents emergency call forecasting accuracy, which is set either to low (F = –1) or high (F = +1). Since forecasting is a widely used approach to deal with uncertainty, the motivation is to determine whether better forecasting can improve decision-making. Forecasts are created from a list of actual incidents. Forecast errors are introduced by applying a noise factor following a uniform distribution ~\( U(1 - e, 1 + e) \) with \( e = 0.1 \) and \( e = 0.4 \) for \( F = +1 \), and \( F = –1 \) respectively. For visualization purposes, participants are shown forecasts on the 8 x 8 color grid, with darker colors showing more likely forecast of incidents.

B. Step 2: Computer Model

A computer model is developed to assess quantitative lifecycle performance of the main system KPIs under different decision sequences. It is developed in close collaboration with a local EMS provider, who provided the original incident list, and from standard techniques in discrete event simulations (DES) and operations research [16]. The simulation focuses on dispatching ambulances to handle medical incidents that occur randomly. The Matlab® DES model generates stochastic medical incidents, also referred as demand for ambulances, or just demand for simplicity. The simulation is divided into two distinct sections: incident generation and incident handling. Incident generation is performed before the game starts. It produces a list of new incidents from the list of real incident data. Incident handling is performed during the game.

Notation

The following notation is used to describe the model:
$a_i$  Weight coefficient for score function $S_t$  

$C_t$  Operating cost for round $t$  

$d_i$  Proportion of incidents in day $i$ of a week, where $i = 1, 2, \ldots, 7$  

$h_j$  Proportion of incidents in two-hour block $j$ of a day, where $j = 1, 2, \ldots, 12$  

$I_{ij}$  Distribution of number of incident during two-hour block $j$ in day $i$, where $i = 1, 2, \ldots, 7$ and $j = 1, 2, \ldots, 12$  

$IAT_{ij}$  Distribution of inter-arrival time between two incidents during two-hour block $j$ in day $i$, where $i = 1, 2, \ldots, 7$ and $j = 1, 2, \ldots, 12$  

$L_t$  Rate of calls not responded, or incidents lost in round $t$  

$\lambda_{ij}$  Incident arrival rate per minute during two-hour block $j$ in day $i$, where $i = 1, 2, \ldots, 7$ and $j = 1, 2, \ldots, 12$  

$P_t$  Fast response rate in round $t$, or the rate of calls responded within eleven minutes (based on EMS provider’s KPI)  

$\text{rand}$  A randomly generated number between 0 to 1  

$S_t$  Score in round $t$  

$w$  Average number of incidents in a week

1) Incident Generation and Handling

Incident generation is illustrated in Figure 1. A week is divided into 84 two-hour blocks, and the expected number of incident for each two-hour block is shown in Equation (3):

$$E[I_{ij}] = wd_i h_j, \forall i, j$$  

(3)

Variables $d_i$ and $h_i$ are calculated from historical data, as done in Ong et al. [17]. The incident arrival is assumed to follow a Poisson process, with varying arrival rate throughout the week. The inter-arrival time $IAT_{ij}$ between two incidents during two-hour block $j$ in day $i$ follows an exponential distribution with mean $1/\lambda_{ij}$ as shown in Equation (4):

$$IAT_{ij} \sim \text{Exp}(\lambda_{ij})$$  

(4)

Variable $\lambda_{ij}$ is calculated using Equation (5):

$$\lambda_{ij} = E[I_{ij}]/120$$  

(5)

An instance of $IAT_{ij}$ is generated using Equation (6):

$$IAT_{ij} = -\ln \left(1 - \text{rand} \right) / \lambda_{ij}$$  

(6)

Indices $i$ and $j$ are calculated by checking the current time in the simulation. The generation continues until the last event generated exceeds the timeframe of the game.

In terms of incident handling, each incident generated is first randomly assigned to one of the grid elements on the map, according to its geographical distribution, as done by Ong et al. [14]. As incident distribution is by postal code, a mapping is done to convert into a distribution by grid. When an incident occurs, a nearby ambulance is dispatched from a nearby station to the incident location to attend to it. The ambulance will not be able to respond to other incidents until the first incident has been resolved.

In Equation (7), the response time rate for each incident, lost incident rate, and operating cost (normalized by the difference between the minimum and maximum operating cost constrained by resources, like fire stations, ambulance and available capital budget) are recorded for computation of score $S_t$ at the end of each round $t$. The weights $a_i$ are assigned based on close collaboration with the EMS provider (i.e. good fast response and lost call rates are more important than minimizing operating budget). They are $a_1 = 1$, $a_2 = -1$, and $a_3 = -1/500$ in this implementation to emphasize the EMS provider’s main KPIs, and to adjust to a similar scale. They could be determined more formally with techniques used in multi-attribute utility theory (e.g. interviews, scoring and analytic hierarchy process). They can be changed easily to represent different gameplay settings.

$$S_t = a_1 P_t + a_2 L_t + a_3 C_t$$  

(7)

C. Step 3: Simulation Game

A game scenario is developed where players can make decisions under different conditions, involving many rounds that represent the accelerated passage of time, in collaborative and/or sequential settings, depending on the characteristics of the problem. Although it is possible to separate the roles, in this study each participant played both roles of system designer and operator. The game is played for several rounds, each round corresponding to a certain time periods (e.g. 3-6 months). The stated objective is to

![Figure 1. Incident generation flow](image-url)
maximize total score, which captures tradeoffs in terms of EMS service quality, and operating cost.

Service quality is broken down into fast response to incident rate, and lost incident rate. As mentioned in Cummins et al. [18], the survival of out-of-hospital medical conditions depends heavily on response time, so that incidents responded fast will increase the score. Incidents not responded to at all impose a heavy penalty on the score. Although being an important performance indicator, service quality is not the only concern of the players. While providing a timely, quality service, the EMS provider also needs to keep its operating cost low. By incorporating operating cost into the score, the game forces the player to be efficient in using resources and carefully weighing the tradeoffs between service quality, and operating cost.

Decisions made by players aim to create realistic tradeoffs in EMS management and resource allocation, such as: 1) service quality against operating cost, 2) cost savings from centralizing capacity and associated economies of scale against wider coverage and shorter response distance, 3) deferring investment and use more information to make decision against early commitment of fund which provide greater utility of resources, and 4) greater flexibility against the cost of acquiring flexibility. There is no limit to the number of decisions players can make each round. Each decision, however, is associated to a capital cost deducted from the total budget.

The main graphical user interface (GUI) is shown in Figure 2. Participants right-click on any given grid cell to make strategic decisions (e.g. siting small or large station, upgrade, purchase new ambulance), and left click to make operational decisions (e.g. add more ambulances). On the bottom right, the GUI shows the available budget (150k), current score $S_i = 0$, the number of small, large, and upgradeable stations built (2, 2, and 0 respectively), the cost of building each station ($30k, $50k, $35k), the time taken to build in rounds (1, 2, 1), the capacity of each station in terms of ambulance (2, 4, 2), and the number of resources currently deployed (6 ambulances, 3 hospitals, capacity up to 12 ambulances). The bottom right shows alternative visualization tools, and gives access to other settings not discussed here for brevity.

D. Step 4: Data Collection

1) Sessions Structure

When used for research purposes, the games must be carefully arranged into different sessions to maximize signal-to-noise measurements. A pretest-postest structure is suggested to divide each experiment into two sessions [19]. This involves taking a measurement before and after a treatment is applied, to measure any within and between group variance differences. The moderator first welcomes participants, describes the design problem, and introduces the game context. All participants receive a text-based GUI training to get familiar with the game platform: how to view information, how to take different actions, and how to observe the results of different performance indicators. Participants play several rounds (e.g. 10) in session 1 (~25 minutes). Then follows a 5 minutes survey to collect demographics information, and user impressions via a questionnaire validated by Briggs et al. [20], based on standard Likert scale mechanisms (e.g. 1: very dissatisfied, 4: neutral 7: very satisfied). Participants play again for several rounds in session 2 for another 25 minutes under one of the treatments in TABLE I, then followed by another 5 minutes survey. A debrief explains the purpose of the study at the end of experiments.

2) Control conditions

Various strategies help mitigate the effects of nuisance variables (e.g. human factors, environment variables) likely to influence the experimental results. Participants without prior flexibility/real options training are selected to reduce potential bias. Participants are randomly assigned to different conditions...
treatments to dilute group bias due to human factors such as creativity levels, personality, collaboration skills, etc. The same content is presented in all activities (e.g. introductions to the design problem and game interface, training, lectures, etc.) to control for information variability. The same time is allocated to each session to account for the fact that participants get more familiar with the game over time.

3) Data

Raw data is collected via the computer engine, and online survey collection is done via LimeSurvey® for demographic information. The computer model records the impact of different design and management decisions made in each round based on relevant KPIs, and save to standard ASCII text format. Here the main performance metric is the sum of all scores $S_t$ at the end of each session.

E. Step 5: Analysis

This step involves response measurement and statistical analysis. The signal $\Delta y = y_2 - y_1$ is measured using a pretest-postest structure, or simply $y$ with only one session. The mean response for dependent variable $\Delta y$ is measured across different treatment groups, and expressed as a function of the main and interaction effects, as shown in Equation (8):

$$\Delta y(x_1, x_2, ..., x_n) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \sum_{j>i} \beta_{ij} x_i x_j + \epsilon$$  \hspace{1cm} (8)

Variable $\Delta y$ is the response of interest for independent variable $x_i \in [-1, +1]$ and $i, j = 1, 2, 3, ..., n$ assuming a two-level DOE setup, with $j > i$. $\beta_0$ approximates the mean response from the dataset, $\beta_i$ the main effect for factor $x_i$, and $\beta_{ij}$ the two-way first-order interaction effect between factors $x_i$ and $x_j$ (higher order interactions are not displayed, but can be measured). The term $\epsilon \sim N(0, \sigma^2)$ represents the experimental error compared to the group mean. Standard least-square minimization regression is used to test the null hypotheses of no main and interaction effects, stated formally as $H_0: \beta_i = \beta_{ij} = 0, \forall i, j > i$. The $p$-values are calculated using standard parametric tests.

Figure 3 shows the mean plots for $\Delta y = \Delta S$ under four treatment conditions. The lower curve shows mean results for high forecast accuracy ($F = +1$) and the upper curve shows results for low forecast accuracy ($F = -1$). The four points correspond to the mean score improvements under the four treatment conditions.

Only educational training ($E$) produced a main effect ($\beta_E = 33.25, p < 0.03$) on dependent variable $\Delta S$. There is not enough statistical evidence on the presence of a main effect for forecast accuracy ($F$) or the two-way interaction between educational training, and forecast accuracy ($\beta_F = -4.75, p < 0.66; \beta_{EF} = -0.75, p < 0.94$). The general linear model response is expressed in Equation (9):

$$\Delta S = 45.75 + 33.25E - 4.75F - 0.75EF$$  \hspace{1cm} (9)

For demonstration purposes, the preliminary results are interpreted below. Although more data is needed for better statistical support, the discussion below shows how one can interpret the above results.

The results show that explicit training can help participants make better decisions and improve the performance in the simulated EMS environment. This is consistent with the literature that designs with flexibility are generally better than designs without flexibility under uncertainties. Forecast accuracy does not produce any main effect, as shown by the narrow gap between the two curves in Figure 3. This may be because the 8 x 8 grid uncertainty visualization tool causes information overload, rendering the uncertainty visualization tool ineffective. There are 64 demand forecast values (one for each grid) and 64 demand history values for the participants to consider in each round.
in addition to other information such as the various KPIs. Therefore, improving forecast accuracy may not help much if participants cannot make full use of this information. This stimulates future work on how to best visualize uncertainty data and patterns.

Improving forecast accuracy does not affect actual demand pattern uncertainty over time. Even if forecasts are 100% accurate, participants only know what happens in the following round. How demand changes in the long run is therefore still as uncertain as if forecasts have low accuracy. For strategic decision-making, participants still need to handle the uncertainties in demand pattern changes when planning for the long term. It is exactly this type of uncertainties that make flexibility in design important. If forecasts were made for many rounds instead of one, improving forecast accuracy could produce different effects.

A point of interest is the considerable baseline score improvement of $\beta_0 = 45.75$ in Equation (9), most likely – but not only – attributable to the passage of time. Participants gain better understanding of the game after playing it in full in session 1. After one game of trial and error, they may obtain a better idea of the game mechanisms, the relative importance of different actions and the relative weightage of the components in the score, and hence may perform better. It is inevitable that there would be a learning effect under such setup.

The same incident list is used for both sessions (and for all participants) for the scores to be comparable. Hence, careful participants may roughly recall some demand patterns and how they may change. Randomized assignments to different treatment groups in combination to the pretest-posttest structure help mitigate this possible effect across the sample population.

IV. DISCUSSION

This paper reports on the development of an experimental platform based on simulation (or serious) games to study the impact of decision-making for complex systems operating under uncertainty, and exploiting ideas of flexibility. The main contributions are a systematic methodology to develop such platform, example application in the context of urban EMS, and preliminary experimental results in a university setting.

One may question the need for such experimental platform if it is possible to find an optimal design and management strategy through standard analytical techniques. This way, one can simply let the computer do all the decisions. Here, the simulation game can be considered in analogy to a flight simulator. While pilots are eventually called to operate a real system, they spend hours in the simulator before operating the real system, refining their decision-making skills. Even if an “optimal” strategy exists, pilots may be called to react differently to changing circumstances. This is what the simulation gaming environment enables to do. In addition, it enables to devise and evaluate in a controlled setting the environment and training techniques that are most conducive to successful decision-making.

The simulation gaming platform can be used to support decision-making in a real setting. It can be used to determine how well decision-makers do at implementing a recommended strategy. In that regard, it is possible that decision-makers do not trust computers to make strategic decisions in their stead, or may not fully grasp recommended techniques until they have tried them out. The platform can be used to support decision-making with any level of analytics required, providing some degree of artificial intelligence (AI) in decision support if needed. Some support can be provided via thorough analytics, or be left entirely to the user. The proper balance of AI support can be studied in an experimental setting by devising different treatments, and packaging them as uncertainty management techniques that can be taught effectively to leaders and decision-makers.

An important limitation of the current study is that only preliminary data and analysis can be shown at this stage. Participants at a major institution of higher learning are being recruited to further test the simulation gaming platform prototype, collect more data, and refine the results presented in Section III. Discussions are also ongoing with Singapore’s main EMS provider for use as a training platform in a real setting.

Because this study is among the first on this topic, it is difficult to claim for generalizability of the process to other engineering systems not related to emergency services. Applying the same process to develop more games in other contexts and environments sharing similar distributed properties (e.g. mobility on-demand transportation, smart power grids, etc.) will help further validate the methodology proposed and demonstrated above. While the issue of flexibility motivates the current study, a simulation gaming platform can be used to study design and management decision-making in a wider context. It can be used to study any kind of decision made under uncertainty, being operational, tactical, or strategic, and not just related to flexibility.

In terms of internal validity, many strategies are exploited to ensure that the main effects reported here (and in upcoming experiments) are valid. The control strategies described above are examples, in addition to the fact that the same performance model is used across all participants to assess results. Replications of the same treatment conditions help provide statistical support to the main effects reported here, but more are needed.

Although not considered here, the platform can also help measure value improvement or degradation stemming from multi-stakeholder interactions, by comparing the score obtained in each round with the best or ideal flexible design and management strategy. This strategy can be identified via a combination of real options analysis, stochastic/robust optimization, and statistical techniques.

An interesting facet of the simulation gaming platform is that it allows collection of decision-making data that is not otherwise readily accessible. It is possible to track every decision, and the impact of each decision in real time. This provides a very interesting dataset to test statistical analysis and inference techniques. This approach opens up a wider
range of research opportunities not only in systems design and real options analysis, but also in operations research, and data analytics.

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