Physics of Decision: Application to Polling Place Risk Management

Thibaut Cerabona, Frederick Benaben, Benoit Montreuil, Ali Vatankhah Barenji, Dima Nazzal

Proceedings of the 2021 Winter Simulation Conference
S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo and M. Loper, eds.

PHYSICS OF DECISION: APPLICATION TO POLLING PLACE RISK MANAGEMENT

Thibaut Cerabona
Frederick Benaben

Centre Génie Industriel

IMT Mines Albi
Campus Jarlard,
Albi, CT Cedex 09 81013, FRANCE

Benoit Montreuil
Ali Vatankhah Barenji
Dima Nazzal

H. Milton Stewart School of Industrial and Systems Engineering
Georgia Institute of Technology
755 Ferst Drive,
Atlanta, GA 30332, USA

ABSTRACT

Managing a system involves defining, assessing and trying to reach objectives. Objectives are often measured using Key Performance Indicators (KPIs). In the context of instability (crisis, global pandemic or just everyday uncertainty), managers have to adapt to multi-dimensional complex situations. This article introduces an innovative approach of risk and opportunity management to help managers in their decision-making processes. This approach enables managers to deal with the considered system's performance trajectory by viewing and assessing the impact of potentialities (risks and opportunities). Potentiality impacts are designed by forces, modifying the system's performance trajectory and its position within its multi-dimensional KPI framework. This approach is illustrated by an application to polling place risk management. This paper presents the results of simulations of a such place confronting pre-identified risks within a KPI framework.

1 INTRODUCTION

At the time of global uncertainty, managers and decision makers have to deal with instability, as the new norm (Taleb 2007). They have to adapt to more and more complex situations. Many tools are present in the literature to support them in their decisions and performance management. However as mentioned in Benaben et al. (2021), none of these tools provide decision makers at the same time with three essential points to manage a system in an unstable environment (inspired by the Simon's model of limited rationality, Simon 1955). The first point consists in providing the decision-makers with a conceptual workspace allowing to define and understand the system and its environment. The second point aims at designing reference models that allow to model, analyze and understand all the potential consequences generated by the identified changes. The last point consists in determining the mechanisms for choosing between the set of available options. This creates a gap between the needs and ambitions of managers to navigate through instability and the management tools at their disposal, dedicated to supporting decision making processes.

This article presents an innovative physics-based approach for risk and opportunity management. This approach aims to support managers in their decision making process. Managing a system involves defining and trying to achieve objectives, often evaluated by KPIs. Schematically, this is equivalent to wanting to control the trajectory of the considered system within its KPI framework. The evolution of KPI values is due to the realization of potentialities (risks and opportunities). In this approach, potentialities are designed by forces moving the system within its multi-dimensional performance framework.

The aim of this article is to present that physics-based approach and explore its value by applying

it to polling center risk management in the context of the 2020 presidential election in the USA. Polling centers play a major role in the current American voting system. They must ensure the efficiency, security and integrity of the elections. They have been present for so long in the voting systems, that their management seems to be granted and under controlled. However, the June 2020 primary in Georgia seems to show quite the opposite, with lines of up to five hours in some voting centers (Fowler 2020). Voting centers are in fact complex systems evolving in a risky environment, reinforced by the Covid-19 crisis.

This paper is organized according to the following structure: Section 2 provides an overview of existing scientific contributions in the fields of potentiality management and simulation. Section 3 describes our physics-based approach. Section 4 presents an application of that approach to polling place risk management. Finally, Section 5 concludes the paper with some perspectives.

2 BACKGROUND: POTENTIALITIES MANAGEMENT AND SIMULATION

During the last decades, many results and methods have been created by actors in the field of risk management, these contributions are considered as stable nowadays. The risk management process is one of such contribution. It is usually divided into four steps as described in Tummala and Schoenherr (2011): *risk identification, risk assessment, risk response strategies* and *risk monitoring*. The *risk identification* phase studies the system and its environment in order to detect and identify risks relevant to this system. The *risk assessment* phase evaluates the impact of identified risks on the system. The *risk response strategies* phase determines actions to limit and control the impact of a risk. The last phase, *risk monitoring*, oversees the state and evolution of identified risks.

Currently, many techniques and tools for risk management are available. White (1995), in her paper, provides an overview of the most well-known techniques: Failure Mode and Effects Analysis (Clifton 1990), Fault and Event Tree Analysis (Bell 1989), Hazard and Operability Study (Hambly and Hambly 1994), Cost Benefit Analysis (Lave 1986), Sensitivity Analysis (Covello 1987), Herzt-type simulation (Ho and Pike 1992) and Monte Carlo simulation (Merkhofer 1986).

Risk management techniques are much more developed than those for opportunity management. However as mentioned in Hillson (2002), current risk management techniques can be applied and expanded to opportunity management. The opportunity management process can thus be organized according to the same phases as the process used for risk management: *opportunity identification, opportunity assessment, opportunity response strategies* and *opportunity monitoring*. The risk and *opportunity identification* phases are identical. Techniques like force field analysis can be used in this phase. The force field analysis identifies both the influence of risks and opportunities in achieving objectives (Hillson 2002). For the risk assessment phase, Edwards and Bowen (2005) broke down a risk into two components: its impacts and its probability of occurrence. Thus, in the *opportunity assessment* phase, an opportunity could be seen in the same way, with the analysis and measurement of benefits instead of impacts. The *opportunity response strategies* phase identifies actions in order to control and take advantage of the benefits of the opportunity. The risk and *opportunity monitoring* phases are identical too, thus it is possible to use the same techniques.

In the Physics of Decision (POD) approach (presented in the next section based on materials from Benaben et al. 2021), risks and opportunities are treated in the same way and seen as the management of potentialities. This approach, introduced in Benaben et al. (2021), is based on physical laws and principles. It will be applied in this article to the risk management of voting centers. In order to collect the material and data necessary to apply and validate this approach, simulation models will be built. Indeed, as mentioned in Davis et al. (2007), simulation is a methodological approach increasingly used to develop theories (especially in the literature on strategy and organizations). Simulation is applied in many critical areas of engineering and allows issues to be addressed before they become problems (Müller and Pfahl 2008). Simulation models are virtual laboratories allowing to test hypotheses in front of identified problems and thus to experiment corrective strategies before realizing them in the real system, modeled and studied. They thus offer an excellent and powerful field of expertise for risk management. Process simulation allows to analyze the behavior of processes and to analyze the risks impacting the system under consideration. According to Neu et al. (2002), a simulation model is created to facilitate decision making and risk reduction through a better understanding of the processes and system being modeled. There are many modeling techniques (Müller and Pfahl 2008): (1) deterministic versus stochastic, (2) static versus dynamic, (3) continuous versus event-driven and (4) quantitative versus qualitative. The type of modeling techniques to use depends on the properties of the system to be modeled. The voting center model described in this article is based on the following techniques: stochastic, dynamic, event-driven and quantitative, in order to best adapt to its complexity (uncertain voter flow, variable process time, etc.), the voting process and its study context. IAA (2013) proposes risk analysis through the study of scenarios to test the resilience of a system to risks. This technique allows to evaluate the effect of risks simulated by scenarios that are detailed enough to identify and understand their causes and effects on the system. They are thus used to better understand the vulnerability of a system to certain risks. In the study proposed in this article, the same approach is used, especially by stressing the developed simulation model with different scenarios.

3 PROPOSAL: PHYSICS OF DECISION APPROACH

3.1 The causal, propagation and decision chains

In Zeng and Yen (2017), a risk is defined from three major concepts: (1) a danger generating the risk, (2) an event with a probability of occurrence of the risk and (3) consequences that are the expected results of the risk. Benaben et al. (2019) introduced a causal chain very close to these three concepts: potential (danger or favorability) – potentiality (risk or opportunity) – actuality (damage or benefit). That causal chain can be generalized by the blue chain described in Figure 1 (which describes the relationships between all the components). In the POD framework, the studied system deals with some of these four potentials:

- Environmental potentials (e.g. in 2019 as a result of fraud, the state legislature voted to change the equipment used by Georgia's voting centers, etc.),
- Charges: mandatory system costs (e.g. BMD costs, ballot printing costs, etc.),
- Innovations: actions dedicated to the improvement of the system (e.g. process improvement, new machine, etc.),
- Interactions: all the potentials created by the relationships between the system and its partners (e.g. information sharing between voters and volunteers operating in the voting centers, etc.).

Potentialities (risks or opportunities) appear as a result of the susceptibility of the system to some of these four types of potentials. They come to life when certain conditions activate them. Thus, these potentialities become forces that change the system's performance and leads to a movement within its performance space.

Moreover, actuality and potentiality can perturbate the current existing elements. Indeed, potentialities can change the considered system and its network, and make them more susceptible to new threats. For example, a city (system) located above the junction of two tectonic plates (potential), which makes it very susceptible to earthquakes (potentiality). These tectonic plates unfortunately every hundred years move and hit each other (condition), creating violent earthquakes that destroy a large part of the infrastructures of the city (actuality). It is easily conceivable that this earthquake has weakened all the buildings still standing, making them more susceptible to new potential, like hurricanes. Basically, the propagation chain illustrates the resulting dynamics of potentialities and actualities, especially the way they can modify, create or remove systems, potentials or conditions and thus create new causal chains. Propagation chain allows to take into account the notion of induced risk (red chain in Figure 1).

This vision of risk is in line with current risk modeling methods (Benaben et al. 2021). The concept of probability of occurrence of a potentiality is integrated in the probability of realization of a condition. The idea of actuality and movement allow to consider and represent the consequences of a potentiality. Thus, it is possible to assess their impacts on the system's performance, by comparing the difference between the current performance and predefined objectives. In order to minimize these gaps and achieve the objectives, managers have to make decisions that will lead to changes in the features (attributes) of the system, making it sensitive to new potentials (this is the green decision chain illustrated in Figure 1).

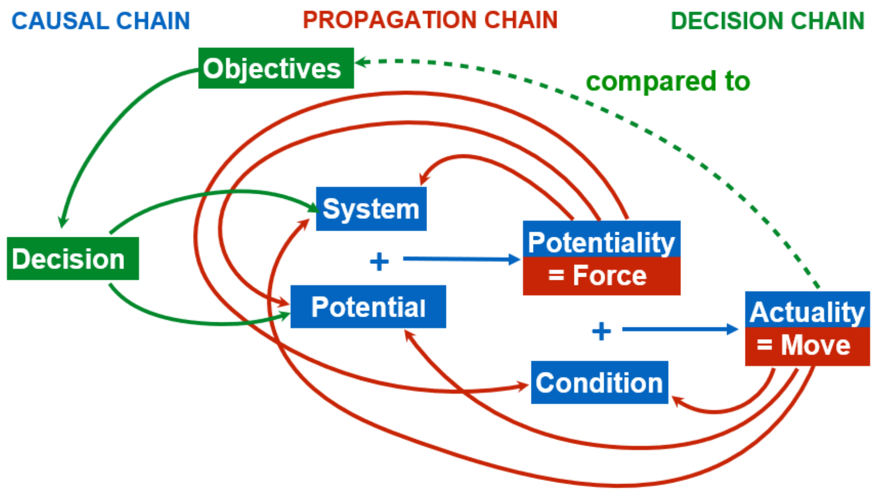

Figure 1: causal, propagation and decision chains (adapted from Benaben et al. 2021).

3.2 Description and Performance Frameworks

Based on these three chains, the POD approach requires two different modeling spaces: the description framework and the performance framework (described in Figure 2). The **Description Framework** describes the system (blue sphere) and its environment. The objective of this framework is to represent the nature of the modeled system, by positioning it within its significant attribute dimensions, that represent the characteristics and properties of this system. It is in this framework that the potentials described in section 3.1 come to life and are managed. The context characteristics is an area of this space where the system is more susceptible to these potentials (yellow shape). The value of attributes changes due to managers' decisions or potentialities. The control space is a continuously changing subspace of the description space in which the considered system can move freely (blue shape). It sets the constraints of liberty for each attribute.

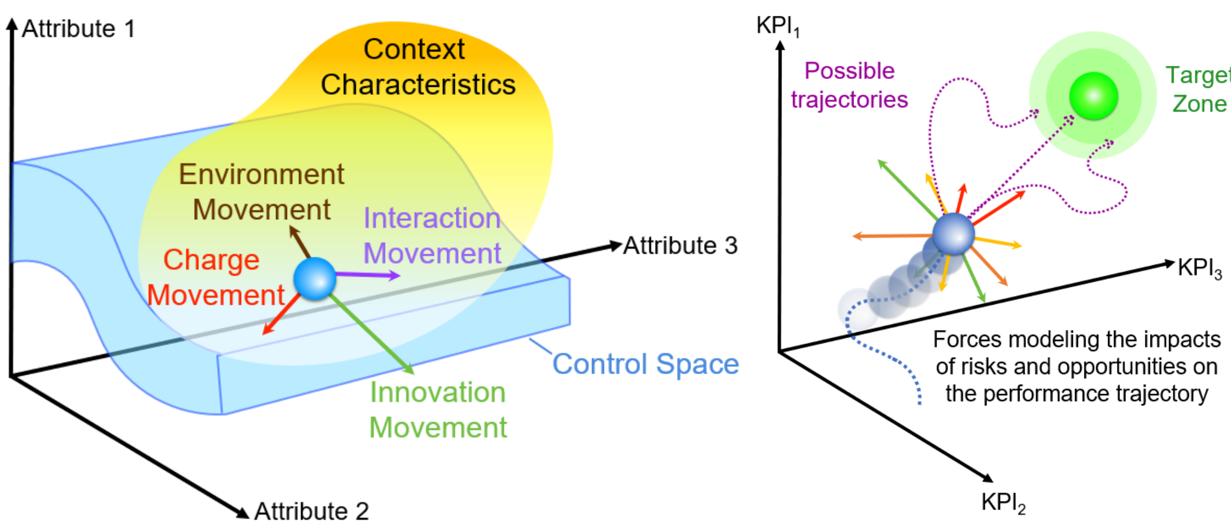

Figure 2: Description (left) and Performance (right) Frameworks.

The **Performance Framework** is dedicated to observe the performance of the considered system by viewing and merging the impact of modelled potentialities on system's performance. These potentialities, depending on their nature, create forces that move the system away from or towards its target values. Thus with that physics-based approach, potentialities are modeled by forces (color vectors) moving the considered system within its multi-dimensional KPI space (Cerabona et al. 2020). Each force mirrors and designs the potential impacts of each potentiality. As mentioned in Benaben et al. (2021), the major benefit of the performance space is the access to the system's performance trajectory, thus allowing to monitor and analyze the evolution of its performance (its position in this framework, represented by the blue sphere). Consequently as mentioned in Cerabona et al. (2020), this space will be used to support decision making, especially by studying the best combinations of forces to select to reach the target zone with the least effort. (it is the possible trajectories in Figure 2). The target zone models the system performance objectives and their evolution (green sphere). The shape of the target zone is still to be studied.

To link these two frameworks, functions from attributes to KPIs will be used and defined. However, depending on the type of system studied, these functions may be more or less complex to determine (Moradkhani et al. 2020). In the event that these relationships are too complicated to determine, simulation models will be built and simulation campaigns performed, in order to generate the necessary amount of data from which the unknown relations between the two frameworks could be estimated.

4 APPLICATION TO POLLING PLACE RISK MANAGEMENT

4.1 Study Framework

4.1.1 Problem Statement

Polling places play a key role in today's election systems. They must be the guarantors of the efficiency and integrity of the elections. They are omnipresent, making their management a matter of course. Yet, these are complex systems that evolve in a risky environment. It is possible to model them by complex discrete event systems (Allen 2011), whose complexity can be explained by uncertainties on the flow of voters, security constraints to which they are subject, etc. The analysis of polling station operations is therefore essential in order to manage them efficiently and achieve expected performance.

This section focuses primarily on an illustration of the approach presented in Section 3. The POD approach will be applied to measure the ability of voting centers to perform in a risky environment, such as equipment failures and cyber-attacks for example. In the case of a malware attack, the causal, propagation and decision chains could be organized as follows. Let us consider a voting center located in Atlanta (system), for example the McCamish Pavilion for all the studies conducted in this paper. This building is the basketball stadium inside the Georgia Institute of Technology campus. It was used as a voting center for the November 2020 presidential elections. Being located in Georgia, it uses BMDs (ballot marking devices) as equipment to allow voters to fill out their ballots. This machine, like any computer, is susceptible to attack by malicious persons (potentiality). Unfortunately, a lack of human resources (volunteers) to monitor voters (condition) allowed these people to infect several BMDs. In return, this potentiality will change the nature of this system, adding corrupted equipment, which when reused for other elections could corrupt other voting centers and allow other attacks. Aware of this danger, the managers of this voting center could decide to mobilize more volunteers or implement solutions such as tests to be carried out during low-traffic hours to verify the integrity of the equipment used.

4.1.2 Input Data

All the results introduced in this paper are part of the Safe and Secure Election Project, initiated and led by Georgia Tech professors. All the actors of this project were divided into several teams, making several contributions. These contributions serve as inputs to these works. The Facility Capacity and Layout Design

Team designed the McCamish voting center layout, shown in Figure 3. They optimized the arrangement, locations and number of available resources. Table 1 summarizes all the service parameters used for this study. As shown in Figure 3, this arrangement of resources was defined in order to respect the sanitary constraints related to Covid-19, to limit the crossing of voters' flows inside the polling place, to protect voter privacy, and election security. It is important to note that the results presented in the following sections are not intended to evaluate this layout but the susceptibility of this voting center to identified potentialities (disruption scenarios).

Figure 3: McCamish Pavilion Layout.

Table 1: Attributes' values.

Resource	**Number**	**Service Times (s: seconds, m: minutes)**
Primary Checking	1	Uniform (10,20) s
Check-in	5	Optimistic: Normal (2, 0.5^2) m Probable: Normal (3.5, 0.75^2) m Conservative: Normal (5, 1^2) m
BMD	12	Optimistic: Normal (7, 1.75^2) m Probable: Normal (8, 2^2) m Conservative: Normal (9, 2.25^2) m
Scanner	2	Uniform (20,40) s

The Scenario Forecasting Team estimated the used voter flow, for November 3rd, between 7:00 am and 9:00 pm. They are based on data from previous elections and estimates (based on multiple voter surveys in Georgia conducted over the few months prior to November 3rd) made for the 2020 elections. This team created also the different disruption scenarios, provided in the Table 2. Their impacts on the polling place's performance will be evaluated in the next section.

Table 2: Disruption scenarios.

Name	**Description**
DS1	Three BMDs down from the peak hour (from 5 pm to 9:30 pm)
DS2	Malware attack on all BMDs, changing 10% of Party A's votes to Party B's votes

4.1.3 Voting Process

In this study, the voting process (illustrated in Figure 4) is modeled from the time voters enter the polling location until they exit the place after voting. When they enter the McCamish Pavilion, to reach the area reserved for the elections, voters have to walk around the basketball court through the top of the bleachers (see Figure 3). The check-in process verifies voter eligibility, identity and registration using poll pads. At the end of this check-in process, voters receive their voting card. Voters needing help with administrative procedures can go to the helpdesks for assistance. It was estimated that 3% of voters needed help. Voters then proceed to one of the available BMDs to fill their ballot. Once the voting card is inserted, the ballot is filled out and printed, voters have two choices: review their ballot card and check the accuracy of the information on it, or go directly to the scanners, in order to scan and cast their ballot. Scanners interpret the ballots, store them and tally the votes. For the purpose of social behaviors of voters, the following elements have been considered as social sciences results in order to model the appropriate reaction of voters. According to the study described in Bernhard et al. (2020), only 40% of voters check their ballot. DeMillo et al. (2018) study shows that voters spend an average of 3.9 seconds reviewing their ballot cards. The error detection rate is set at 25.5% (DeMillo et al. 2018). After that, only 6.6% of voters who detected an error decided to report it and fill out a new ballot (Bernhard et al. 2020). The whole process has been modeled using AnyLogic© simulation software using the *Process Modeling Library*. Figure 4 shows the modeled voting process and gives an overview of its modeling in AnyLogic© simulation software.

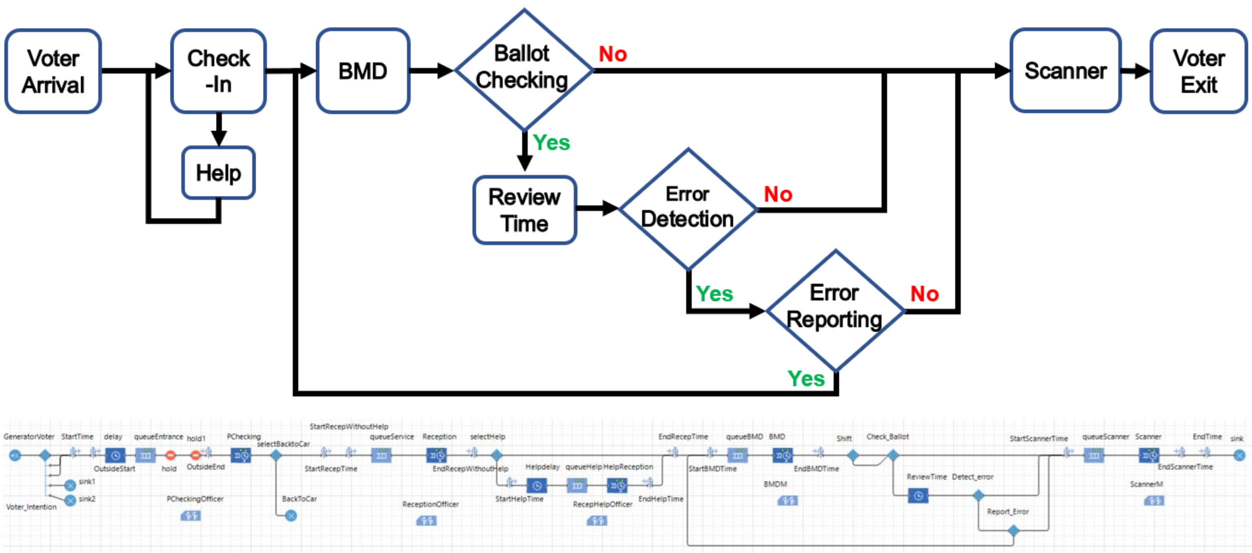

Figure 4: Voting Process.

4.2 Experiments and Results

4.2.1 Inertial trajectory

The experiments conducted in this section aim to study the impacts of predefined risks on the performances of the studied voting center. Its performances will be evaluated through the prism of various performance criteria such as efficiency, convenience and trust. From these criteria, several indicators will be retained to evaluate its performance, such as: voting time, number of waiting voters inside the voting area, number of completed votes, resource utilization or omniscient indicators to assess the confidence that can be placed in the voting process. These indicators will be the dimensions of the performance space defined in section 3. The description space will be composed of attributes characterizing the voters (e.g. speed, voting intention, etc.), the number of available resources and building capacity (e.g. queue size, number of voters allowed, etc.). Figure 5 provides an overview of the McCamish polling place description space. The first trajectory modeled in the performance space in order to apply the POD approach is the inertia trajectory. It is used as a reference trajectory in the study of the scenarios presented in section 4.1.2. As shown in Figure 5, in this study, three inertia trajectories are considered, one for each possible service time (changing the characteristics of the system and over which managers have no leverage because they cannot force voters to vote more or less quickly). Table 3 summarizes the results for these three possible inertial trajectories for the three different service time levels.

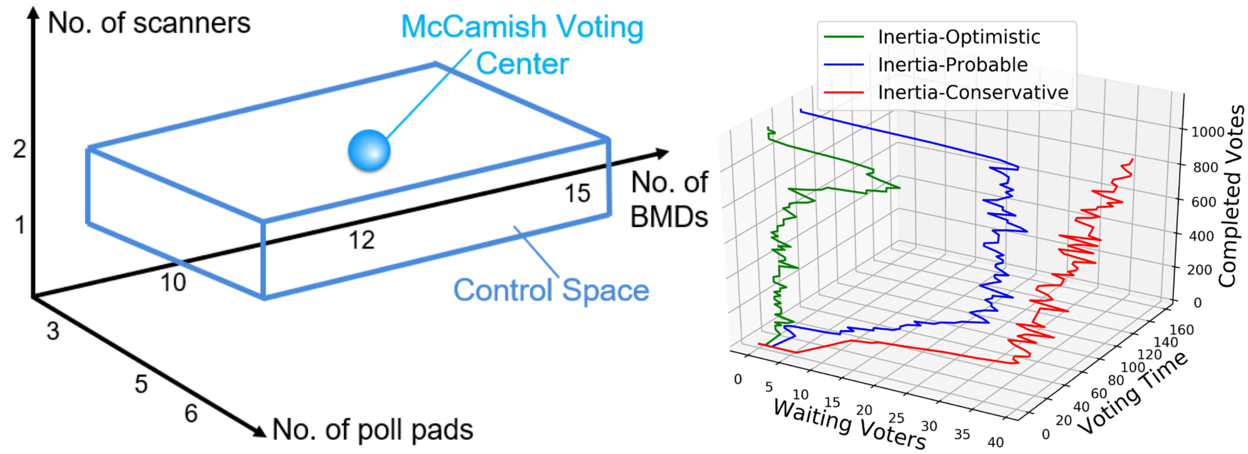

Figure 5: McCamish polling place description (left) and performance (right) spaces.

Table 3: Results for the three different service times.

KPI	**Service Time Levels**		
	Optimistic	Probable	Conservative
Average Voting Time (min)	16.95	32.84	83.49
Average Waiting Voters (n)	3.2	25.68	33.05
Completed Votes (n)	1 170	1 170	821
Check Utilization (%)	57.55	91.76	95.9
BMD Utilization (%)	72.28	81	66.79
Scanner Utilization (%)	32.62	30.16	21.71

The first results on the inertial performances of this polling location allow to highlight the strong impact of these three different service times on the performances of the McCamish polling place, but also their impact on the nature of bottleneck resources. This first analysis already shows that the number of available resources (especially the number of poll pads available) is not sufficient in the case where the time spent by voters on each resource is equivalent to the estimates made in the conservative case. This means that in this case, at the end of the simulation at 9:30 pm, 349 voters are waiting to vote.

4.2.2 Disruptive Scenarios

This section presents the results obtained when the McCamish polling place model was stressed by the two disruption scenarios introduced in section 4.1.2. DS1 stresses the system with the breakdown of three BMDs. DS2 stresses the system with a malware attack on all the BMDs of this voting center. This malware will change 10% of the votes for the Party A candidate, replacing them with ballots for the Party B candidate. The purpose of this disruption is to study the fragility of the current voting process and the machines used against cyber-attacks. Voting process modeling is a very powerful tool to study the impacts of the DS2 potentiality, as the model provides an omniscient view of voters' behaviors but also of their voting intentions. It is therefore possible to compare the gap between voting intentions and actual voting (this will be measured by the KPI called trust, that assesses the number of actual B votes over the number of expected B votes). For this study, 50% of the voters intend to vote for the A candidate, 45% for the B candidate and the remaining 5% for the other candidates. For the study of these two potentialities, the inertia trajectory selected will be the one with optimistic service times. From the POD approach, deviations from the considered inertia trajectory are seen as forces. Table 4 summarizes the impact of these disruptions on the performance of this polling location.

Table 4: Results Disruption Scenarios.

KPI	Inertia	DS1	DS2
Average Voting Time (min)	16.95	17.79	16.99
Average Waiting Voters (n)	3.2	8.15	3.34
Completed Votes (n)	1 170	1 170	1 170
Check Utilization (%)	57.55	57.47	58.62
BMD Utilization (%)	72.28	77.72	76.97
Scanner Utilization (%)	32.62	32.36	32.81
Trust	1	1	1.123

The performance spaces shown in Figure 6 offer insight into the evolution of performance to managers, providing a comparative picture of the performance of the undisturbed and disturbed polling location. The DS1 trajectory in Figure 6 (left performance space) allows to illustrate the notion of passive trajectory. In the POD approach, it is defined as the new trajectory of a system following the realization of a potentiality and that no corrective action has been implemented to reduce the impact of this potentiality on the system performance.

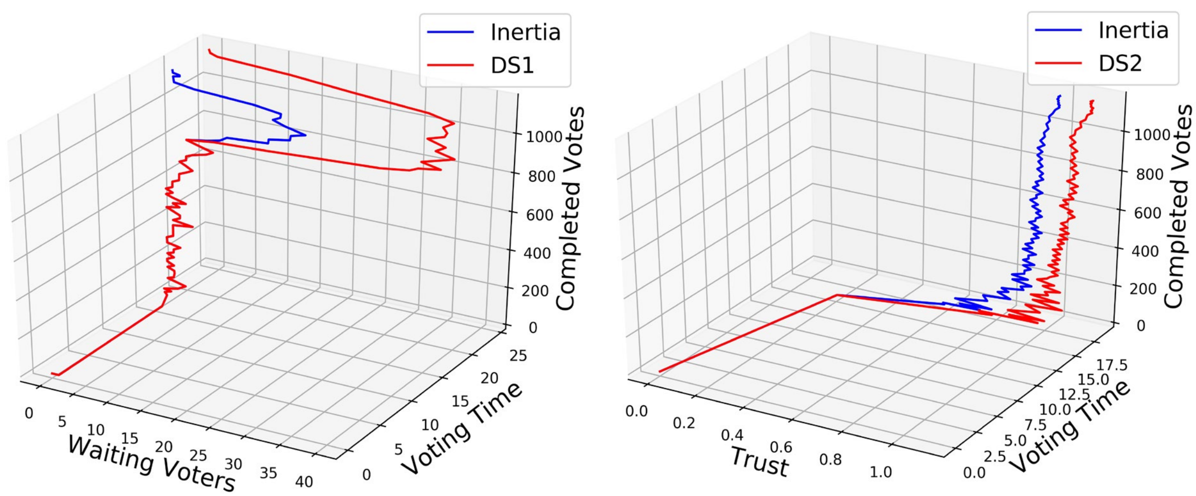

Figure 6: Inertia trajectory vs Potentiality trajectories.

It is important to note that the two performance frameworks shown in Figure 6 do not seek to provide the same information to decision makers. One of the objectives of this figure is to show the will to develop a tool able to adapt to the decisions that managers wish to take. With this approach, this means adapting the dimensions and KPIs to be observed to the decisions.

The results provided in Table 4 and the performance trajectories illustrated in Figure 6 show that the system in this configuration appears to be able to withstand the DS1 disturbance (at the end of the simulation all voters were able to vote). This disruption to 25% of the BMDs increased queue size by 154 % and increased the voting cycle time by 15% due to additional waiting.

On the other hand, the DS2 disruption perfectly illustrates the dire findings in Stark (2019) and Appel et al (2019), that there is no mechanism for election officials to detect that a BMD has been hacked, despite the fact that these acts of malfeasance can have significant impacts on election outcomes. The current process and the technology used is not ready to face cyber-attacks. Indeed, this attack has increased the number of votes for candidate B by 12.3%, thus completely changing election outcomes, without any action being taken to curb this attack. Thus the technology currently in use is *contestable*. According to Appel et al. (2019), a voting system is contestable, “if an undetected change or error in its software that causes a change or error in an election outcome can always produce public evidence that the outcome is untrustworthy”.

This study allows to illustrate the three essential points to navigate in an unstable environment described in the introduction section. (1) The description space and the trajectory of inertia illustrated by Figure 5 allow to describe and understand the system and its environment, from the point of view of its characteristics and attributes but also of its nominal performance. (2) The performance space allows to visualize the potential consequences of each potentiality, by observing the deviations between the inertial trajectory and the potentiality trajectories. (3) The third point, the selection of mechanisms between the different available options, will allow us to make the link between the purpose of the approach presented in this paper and the perspectives points presented in the following section. The aim of this approach is to provide an intuitive and immersive decision support tool, with which the managers from a "what if" reasoning will be able to analyze the impact (negative or positive) of the potentialities on their system, but also to visualize and analyze the effectiveness of the corrective actions implemented.

5 PERSPECTIVES AND CONCLUSION

This paper illustrates some preliminary applications of that physics-based approach to polling station risk management, through first results essentially focused on the visualization of performance trajectories. In this study, in order to facilitate the visualization of trajectories, the performance space has been limited to three dimensions. However, the goal of this new approach is to develop an immersive support tool, where it will be able to pilot trajectories of the systems within performance framework. Of course, this framework will surely consist of more than three dimensions (especially for complex system). Consequently, we have to find a visualization system that allows us to abstract ourselves from this problem. A solution could be to reduce the number of dimensions by considering as dimensions only the criteria to be studied, for example for this use-case: efficiency, convenience and trust. Thus, it would be necessary to define aggregation functions for the KPIs selected for each criterion.

The following points are a part of the roadmap to turn that approach into a workable practice. The first avenue consists of stressing the model with other scenarios that could impact the system, in particular scenarios modeling corrective actions (for instance, the pooling of resources between the different voting centers, the implementation of tests during low-traffic hours to verify the integrity of the equipment used, etc.) aimed at reducing the impact of the disruptions presented on voting center performance, so that the effectiveness of these corrective actions could be verified.

The second avenue is to conduct sensitivity analyses on all the attributes (model’s parameters) impacted by the scenarios studied in order to determine the range of impact of the associated potentialities and to formalize the forces generated.

The last avenue consists in studying whether the forces are independent and summable, in order to determine the best possible combinations of forces (best response strategies) to reach the target areas of the performance space while minimizing effort and costs.

In this article, the link between description and performance spaces has been made with simulation, but it could be possible to use other potentially more formal tools (mathematical modeling, machine learning, etc.). The use of simulation as a link between these two spaces opens the door to a wider generalization: for example, one could try to make simulations sufficiently exhaustive and covering the space of possibilities to extract, in the form of a force disrupting the performance trajectory, a generic formulation of the impact of an event on a type of system (e.g. the impact of a hurricane on a supply chain, etc.).

ACKNOWLEDGMENTS

The authors thank all Professors and Students of the Safe and Secure Election Project for their help and contributions used in this article. They particularly thank Dr. Richard DeMillo, principal investigator of this project, for the guidance and insights he provided.

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AUTHOR BIOGRAPHIES

THIBAUT CERABONA is a 2nd year PhD student in Industrial Engineering Center at IMT Mines Albi. His research interests include supply chain management, performance measurement, risk management, decision support and virtual reality. His email address is thibaut.cerabona@mines-albi.fr.

FREDERICK BENABEN is Full Professor in the Industrial Engineering Department of IMT Mines Albi (FRANCE) and Adjunct-Professor at Georgia Tech ISyE and Beijing JiaoTong University SEM. He earned his Ph.D. in Computer Sciences from University of Montpellier. He is the head of the research axis "Security and Crisis Management". He is Director of the IOMEGA-VR Lab (immersive technologies for security) and Co-Director of the international laboratory SIReN (Sentient Immersive Response Network), between IMT Mines Albi and Georgia Tech ISyE. He works on the use of data to model instable situation and exploit Artificial Intelligence to support decision making and security management. His email address is: frederick.benaben@mines-albi.fr.

BENOIT MONTREUIL is Professor in the H. Milton Stewart School of Industrial and Systems Engineering at Georgia Tech and the Coca-Cola Chair in Material Handling & Distribution. At Georgia Tech, he Director of Supply Chain & Logistics Institute, Director of the Physical Internet Center, and Co-Director of the international SIReN (Sentient Immersive Response Network) Laboratory. His main research interests focus on developing methodologies and technologies to model, optimize, transform and enable businesses, supply chains and value creation networks to enable them to thrive in a rapidly changing hyperconnected world. He has extensive research collaboration experience with industry, recently with Americold, Nissan, SF Express, The Home Depot, and UPS. He earned his Ph.D. in Industrial Engineering from Georgia Tech in 1982. His email address is benoit.montreuil@isye.gatech.edu.

VATANKHAH BARENJI ALI is a Research Scientist in the H. Milton Stewart School of Industrial and Systems Engineering at the Georgia Institute of Technology. Dr. Barenji's goal to demonstrate how Information and Communication Technologies (ICT) will enhance value creation along Supply Chain and Manufacturing. His email address is: abarenji3@gatech.edu.

DIMA NAZZAL is an academic faculty member and director of professional practice in the H. Milton Stewart School of Industrial and Systems Engineering at Georgia Tech. Her research focuses on modeling, design, and control of discrete event logistics systems, including healthcare delivery systems, manufacturing systems, and distribution systems. She earned her Ph.D. in Industrial Engineering from Georgia Tech in 2006. Her recent work has focused on election voting systems, higher education response to COVID-19, understanding and driving higher childhood vaccination rates in developing countries, modeling of collaborative robots in distribution systems; scheduling and dispatching policies in semiconductor manufacturing, and energy systems development. She has worked with companies, non-governmental organizations, and healthcare providers, including ExxonMobil, Emory University, Samsung, Gates Foundation, and Walt Disney World. Her email address is dima.nazzal@gatech.edu, and her website is https://www.isye.gatech.edu/users/dima-nazzal.