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Physics of Decision: managing and preparing critical supply chains to supply disruptions

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Abstract: Today, supply chains face many uncertainties and making well-informed decisions requires performant decision support systems and methods. The purpose of this study is to apply a new perspective of decision support: the Physics of Decision (PoD). This approach considers risks or opportunities (potentialities) as physical forces and which are assessed regarding their intensity and contribution towards or as deviations of the system's performance trajectory compared to a target. Such an evaluation permits studying the effect of different mitigation actions to support the decision-making process and prioritize corrective measures. The approach is applied to an aerospace manufacturing case study facing a supply shortage, a high stake in this sector.

Keywords: Physics of Decision, Risk Management, Decision Support, Performance Management, Supply Chain

1. INTRODUCTION

In today's increasingly dynamic and uncertain global environments, instability is becoming the norm (Taleb 2007, Benaben et al. 2021). Historical data shows that disasters resulting from this instability have increased dramatically in recent years (Munich Re, www.munichre.com). Besides, surveys show that Supply Chains (SC)s are quite sensitive and vulnerable to disruptions (Sodhi and Tang 2012; BCI 2019). Indeed, COVID 19 pandemic is a good example of the SC chaos ensured (Fortune 2020). So today, SC risk managers are very interested in a decision-making support to identify disruption scenarios, fortify networks, monitor disruptions, and determine actions (Ivanov and Dolgui 2020), as it is key for organization to remain competitive (Bititci et al. 2012). However, such a system able to manage and aggregated multiple control variables and evaluating the impact on complex structures, such as SCs, on the performance has long represented a challenge in the field of performance management (Bititci et al. 2012). Going back to the basics, Simon (1955) proposed three essential steps for managing a system in an unstable environment: *intelligence, design* and *choice*. *Intelligence* provides a conceptual workspace for decision-makers to define and understand the system, *design* creates reference models to model potential consequences, and *choice* determines the mechanisms to select from the available options. None of the existing approaches dedicated to decision support can answer these three fundamental steps to support the decision-maker in the face of instability (Benaben et al. 2021).

Physics of Decision (PoD) as an innovative decision-support approach, based on physics motion laws, wishes to provide innovative decision-support tools in the context of instability and uncertainty (Moradkhani et al. 2022a), by answering Simon's three steps in a single approach. In the PoD approach (introduced in Benaben et al. 2020), the effect of potentialities is modelled by forces that push or pull a system like a SC in its performance framework (see Figure 1) by varying its Key Performance Indicators (KPIs). The PoD paradigm is intended to support decision-makers in day-to-day performance and risk management but it can also be applied during crisis management, as demonstrated in the following experiment.

This paper examines the performance of a SC, regarded as an aggregated network system, for which KPIs are measured. It is seen as a trajectory, representing its displacements as a result of events caused by potentialities. The consequences of these variations are observed through the deviation of the SC's performance trajectory in its performance framework. This approach aims to determine how decisions and the resulting events can be combined to assess their influence on SC performance. Decision makers are often overwhelmed by KPIs and lack visibility into potential disruptive events, making it difficult to make effective decisions. To cope with these the PoD paradigm seeks to provide decision makers with an intuitive decision and performance management system, with an immersive visualization of system performance in a 3D space and multiple KPIs around a targeted and predicted trajectories.

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The objectives of the paper are the following: (i) demonstrate the potential of PoD to deal with critical SCs with high demand volatility and environmental-related risks. Those are particularly sensitive to raw material supply shortages as of 2020 and provide to the digital revolution ongoing and (ii) apply the PoD approach based on a realistic case study (aerospace manufacturing environment) using simulation.

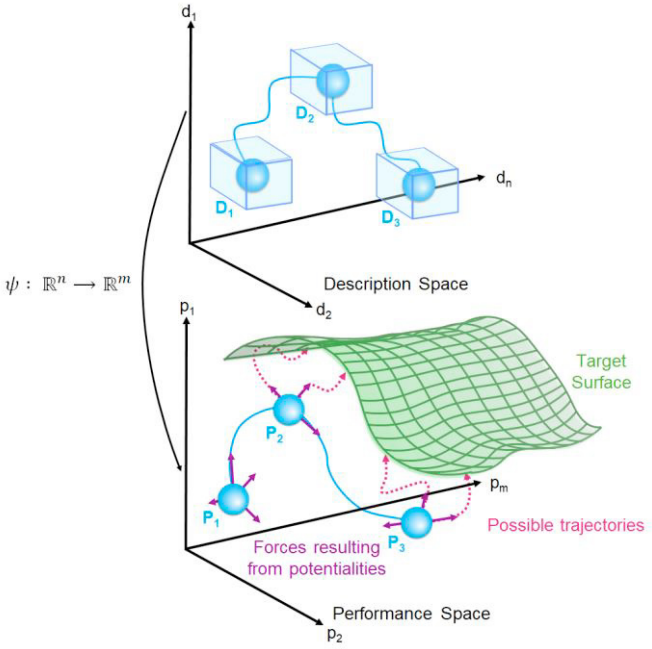

Figure 1. Representation of the PoD approach.

The remainder of this article is organized as follows: Section 2 presents the PoD paradigm and the underlying physics concepts. Section 3 presents an application of the PoD paradigm on a fictional but reality-inspired use-case. Finally, Section 4 concludes this article with some perspectives.

2. BACKGROUND AND RELATED WORKS

2.1 Physics of Decision foundations

The PoD approach is based on two complementary modeling spaces (illustrated in Figure 1): the *description space* and *performance space* (introduced in Benaben et al. 2021), which participate in the development of the different phases presented in Simon's framework. To support the *intelligence* phase, the *description space* is a multi-dimensional space dedicated to the study and description of the evolution of the SC attributes, which constitute the dimensions of this space (Benaben et al. 2021). The *performance space* addresses organizations' need to measure, monitor, and manage their performance across multiple dimensions (Nudurupati et al. 2011), by providing a dynamic multi-dimensional measurement and visualization space (each dimension being one of their KPIs) to support decision-making (Benaben et al. 2021). In this space, potentialities are modeled as forces, which once activated, will deviate the performance trajectory of the SC (monitoring and measuring the evolution of its performance), positively or negatively depending on their type. This concrete deviation of the performance trajectory reflects the intensity of the impact of each potentiality on the SC performance. Thus, with this physics-based approach, SC performance moves like an "object" in its performance space as a result of the different forces activated. This space is dedicated to the *choice* and decision-making stage, by studying the best combinations of forces, to join or stay in the target area with the least effort (possible trajectories in Figure 1). The target area (the shape of which remains to be studied and which could be, for example, a target surface, as in Figure 1) models the performance objectives of the SC, as well as their evolution after the occurrence of the potentialities and the decisions taken in return by the decision makers.

These two spaces are interconnected by different mathematical relationships of varying complexity (corresponding to the *design* phase in Simon's framework). In this study, only the input-output relations between these two spaces will be studied, *i.e.* how the variations of the value of the attributes (displacement in the description space) lead to impact on the KPIs (deviations of the different performance trajectories considered, seen and measured in the performance space). For a SC and its environment, composed of n attributes (d_1, d_2, …, d_n), the description space is therefore of n dimensions which can be defined as the space $\mathbb{R}^n$. SC performance is measured from m KPIs, (p_1, p_2, …, p_m), creating an m-dimensional performance space, defined as the space $\mathbb{R}^m$. These two spaces are linked by a function expressing the KPIs according to the attributes, defined by ψ: $\mathbb{R}^n \longrightarrow \mathbb{R}^m$. For each of its states *i*, SC can be modeled in its description space by the point $D_i = [d_{1,i}, d_{2,i}, \ldots, d_{n,i}]$. Thanks to the relation ψ, its corresponding performance P_i can be obtained as follows: $P_i = \psi(D_i)$ and $[p_{1,i}, p_{2,i}, \ldots, p_{m,i}] = [\psi_1(D_i), \psi_2(D_i), \ldots, \psi_m(D_i)]$.

With these equations and the degrees of freedom of each attribute (called control space, blue parallelepipeds in Figure 1), *i.e.* their constraints and variations related to the management of the system at each moment, it will be possible to adjust the shape of the target zone according to the capacities of the SC and time. For this study, the relations between the two spaces (being too complex to put into equation) will be built from a simulation model (presented in section 3), like a "black box" which will allow to estimate the relations between the attributes and the KPIs of the studied SC.

Figure 2 summarises the analogies between the PoD approach and Simon's framework.

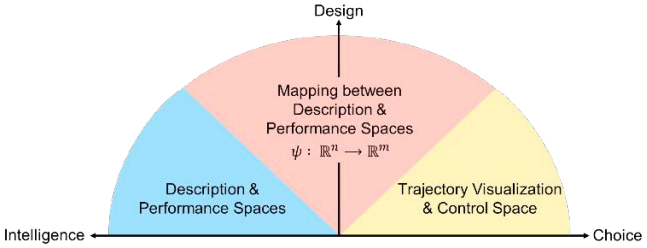

Figure 2. Positioning of the PoD framework in relation to Simon's framework.

2.2 Newton's second law

The principles of the PoD approach derive directly from classical physics, in order to assist the decision-maker in processing the complexities of the SC and to allow him to orient SC performance towards its objectives. For that

purpose, Newton's second law of motion will be used. This law claims that the magnitude of the net force is directly proportional to the acceleration of an object produced by this net force and the mass of the object. Three measures of kinetics will be of particular interest in the study of the movement of SC performance (its management): *displacement*, *velocity* and *acceleration*.

Displacement (ΔKPI) is the variation in the value of a KPI, which indicates where the SC is deviating from its optimal trajectory. This measure allows for quick corrective action to resolve the problem before it gets worse. It, therefore, offers an interesting opportunity for operational decisions, which are looking to get closer and closer to real-time performance measures.

Velocity is the variation of the displacement of a KPI over an interval δt: dKPI/dt. According to its sign, it shows the positive or negative growth of the KPI, and the progress or trend of the SC towards its performance objectives. To be fully effective and to provide a more accurate picture of SC dynamics, this measurement needs to be monitored over a longer period of time than displacement.

Acceleration is the variation of the velocity over an interval δt: $dv/dt=d^2KPI/dt^2$. The magnitude of the acceleration can reflect the strength or weakness of the fluctuation of a KPI, the sign of which reflects the nature of that fluctuation, *i.e.* whether it is moving towards (positive) or away from (negative) its targets. According to Newton's second law, the direction of its associated vector is always the same as the net force resulting from a potentiality (Moradkhani et al. 2022b).

In this study, the velocities and accelerations will be calculated locally, by the following formulas:

$$\text{Velocity} = [(x(t+\delta t) - x(t-\delta t))/2\delta t] = v_x(t) \quad (1)$$

$$\text{Acceleration} = [(v_x(t+\delta t) - v_x(t-\delta t))/2\delta t] = a_x(t) \quad (2)$$

3. EXPERIMENTS

This paper aims at demonstrating PoD's interest in piloting the performance of critical SCs. In this perspective, the assessment of the forces applied to an electronic card SC and different scenarios using simulation has been performed. The case study, method and results analysis are detailed in the following sections.

3.1 Studied SC

In this article, the considered SC is inspired by a real case study. It involves an electronic card manufacturer providing to a satellite assembling company. Today such a SC is regarded as critical as it contributes to the large demand for electronic components required by the digital revolution ongoing. However, it is today sensitive to "the electronic component crisis" affecting numerous industries worldwide that began in 2020, as a result of demand exceeding supply.

The model developed in the simulation, relying on the case study, embeds two production lines, one producing two relatively similar electronic cards, their specifications induce different production times on the same machine. Those, are sub-elements that once assembled on the second line become the final product sold to the client. This last is set with a stable demand of 5 products a month. Accordingly, but with some variably in quantity and frequency, the production planning of sub-elements is made. Triangular distributions have been used to reproduce the product launches based on real production order records obtained. Machine production times also follow a triangular distribution with minimum and maximum values gathered from the field. To ensure production, a pool of 40 human resources has been defined in the model. Operators are dispatched between 2x8 hours from 6 am to 11 pm with a fewer capacity during the afternoon. Due to the criticality of such components for a satellite to operate, numerous quality controls are performed along the production cycle and end with the choc test step. This last, not performed on-site, requires every batch has a sample to be sent to a specialized laboratory. If the sample passes the test, the batch is released and the delivery can then proceed. For the rest, regular gateways following a triangular distribution with a 98% of average compliance rate were set. Items failing the test are directed to an internal quality control process. There, time is spent to make a diagnostic and if repair is possible, depending on the amount of work, it is performed on-site (10%) or sent to a subcontractor (70%). Else, the item is sent to the disposal in 20% of cases. As for the supply of the set of components used for the assembly, a set of suppliers with a limited capacity ensure the deliveries. Supply orders are triggered when the stock reaches a threshold value defined as the average consumption of the item by the machines multiplied by the sum of the delivery, quality inspection lead times and the stock coverage value set in days. The quantity re-ordered is a fixed quantity equal to the threshold value.

3.2 Application of the Physics of Decision approach

The PoD approach proposes to study three different types of performance trajectories (Moradkhani et al. 2022a), illustrated in Figure 3. The *inertia trajectory* is obtained by measuring the SC performance caused by its natural behavior, *i.e.* the SC does not face any unanticipated disturbance (Moradkhani et al. 2022a). This trajectory is seen as a reference trajectory for the SC, even optimal in the absence of potentialities (it could be considered as the target at some point). Any deviation from this trajectory is considered as a potentiality and modeled by a force. The *passive trajectory* corresponds to the performance of the system facing a disruption without any specific reaction. It combined then the inertia of the SC with changes due to disturbances (of the SC itself or its environment). For the experiment, the perturbation is a supply shortage from the single supplier of electronic board occurring at the yearly beginning of the year 2020 (on day 762 of the simulation) and lasting for 30 weeks as an average delay as reported in media (finished on day 972).

The *active trajectory* corresponds to the performance of the system facing a disruption but adding some specific reaction. It combines the changes in performance measured by the passive trajectory with the changes in performance resulting from decisions made by managers to counter and reduce the consequences of these disturbances. To face the shortage of electronic boards, three different practices, usually performed

in the industry, have been studied. The first practice is to increase the item *safety stock* and gathers compensatory stock to mitigate shortage effects. For the experiment, the initial safety stock value was set to 5 days while 30 days (from the beginning to the end of the simulation). The second practice (activated following the disruption on day 762 until the end of the simulation), consists of sourcing from a "*broker*" (*i.e.* wholesaler) generally 6% more expensive than trading with the manufacturer and generally giving preference to the highest bidders. Finally, the last scenario includes *double sourcing* (activated following the disruption on day 762 until the end of the simulation), which represents one of the possible practices of supply risk reduction where an agreement is made with a second supplier to activate and ramp up its capacity to compensate the failing supplier when it happens.

To be able to visualize the different performance trajectories, the study is limited to the evaluation of the performance of this SC according to three business KPIs: the *turnover* calculated as the order monetary value with a discount in case of late delivery (0.001% of the order amount per day that cannot exceed a 10% reduction in total), the *Working Capital Requirement* (*WCR*) as the difference between the final product manufacturing price and the purchase costs, and the *production lead time* between the production order launching time and the end of the last step of the production process. The KPIs monitored in this use case were selected among the metrics mainly tracked in such a situation, after consultation with SC field experts. Although, it should be noted that many other KPIs are available and can be considered in a more global approach.

For the analysis to follow, 30 replications of each of the five studied scenarios (inertia, passive and three actives) have been simulated. KPIs values were recorded after 2 years of simulation ramp-up and for 900 days. In addition, to make the comparison of KPIs possible regarding the deviations and variations, all obtained KPI values for each scenario have been normalized, so that they are bounded between [0,1], using the following formula: $\mathrm{KPI}_{\mathrm{norm}} = \frac{\mathrm{KPI}-\mathrm{KPI}_{\mathrm{min}}}{\mathrm{KPI}_{\mathrm{max}}-\mathrm{KPI}_{\mathrm{min}}}$. According to this normalization formula and the definitions of the different KPIs, the target area was defined as the point in the performance space (0,1,0), *i.e.* seeking to maximize *turnover* and minimize *production lead time* and *WCR*.

It is important to take into consideration that the application of the PoD approach (generally and more particularly in this article) is not primarily intended to serve as an optimization approach, especially in obtaining the "best" active trajectories. By "best" active trajectories, we mean trajectories obtained by optimizing the characteristics of the active potentialities (the counter measures). The purpose of this paper is to apply the PoD approach for given potentialities with given characteristics for each specific time and thus benefit from the contributions of the PoD approach among these actions, which generates a force allowing to get as close as possible to the performance objectives. Of course, sensitivity analyzes could be performed in order to find the best combinations of the characteristics of the active potentialities, allowing to study the different zones of the description space (but also those of the performance space in view of the mathematical relations existing between these two spaces, refer to section 2 for more details), in order to determine the favorable and risky areas.

As it stands, the PoD approach relies on two strong assumptions (directly related by Newton's second law) to approximate a measure of forces applied to the SC: (i) considering the mass of the system as constant and (ii) considering the forces as summable. The constant mass hypothesis allows, according to Newton's second law ($\vec{F}_{net} = m\vec{a}$), to approximate the net force applied to the system studied by its global acceleration (modulo a constant factor). Based on this observation, all the following analyses will be derived from the analysis of the various accelerations measured (by equation 2, for a measurement performed every 30 days from t= 462).

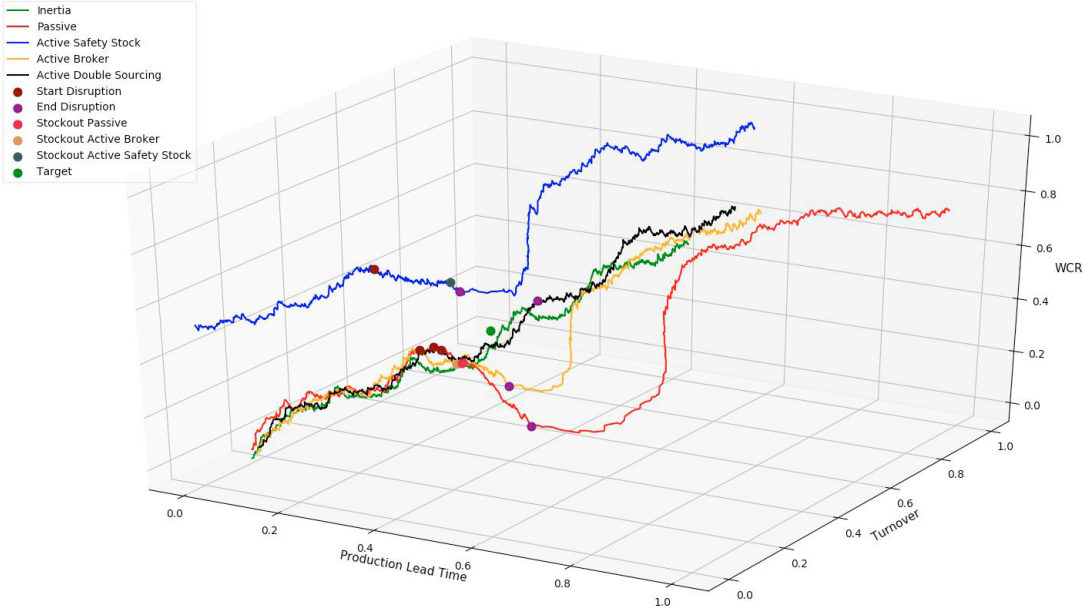

Figure 3. 3D performance trajectories.

4. ANALYSIS OF THE RESULTS

From the previous study, and from a motion perspective, the objective is to model the significant forces. These significant forces are (i) the *perturbation force* (the force due to the disruption) and (ii) the *compensation force* (the force due to the envisaged mitigation measures). These forces are to be modeled by approximating them as accelerations. First of all, there is the reference acceleration (the *inertia acceleration* representing the day-by-day acceleration of the inertia trajectory). Then, two different accelerations of interest representing the forces mentioned above: (i) the *disruption acceleration* obtained by calculating the day-by-day acceleration of the passive trajectory minus the inertia acceleration, and (ii) the *compensation acceleration* obtained by calculating the day-by-day acceleration of the active trajectory minus the passive trajectory. These accelerations are described in equations (3) and (4).

$$a_{disruption} = a_{passive} - a_{inertia} = \left(a_{disruption} + a_{inertia}\right) - a_{inertia} \quad (3)$$

$$a_{compensation} = a_{active} - a_{passive} = (a_{compensation} + a_{disruption} + a_{inertia}) - (a_{disruption} + a_{inertia}) \quad (4)$$

By using the previous equations, these accelerations have been calculated as 3D vectors within the performance space. To figure out the actual impact of each of these accelerations, two main elements must be considered: (i) the actual *intensity* of the force (approximated with the norm of the acceleration vector) and the *contribution* of the force (approximated with the scalar product of the acceleration vector with the vector connecting the current position of the performance and the target position). If the *intensity* is easy to understand, the *contribution* is less obvious. The idea to explain the *contribution* of the force is to try to find if the force is applied in the half space pulling the performance toward the target or in the other half space, pulling the performance away from the target. The sign of the scalar product will show if the angle between the force and the vector pointing to the target is lower than 90° (with a positive sign indicating that the force is an opportunity) or higher than 90° (with a negative sign indicating that the force is a risk). Finally, considering that the scalar product represents the product of the norms of both vectors with the cosine of their angle, by dividing it by the product of the norms, one can get that cosine. Finally, the product of the cosine by the actual norm of the force gives the *resultant force* on the direction of the target. This *resultant force* is thus the real impact of the force on the trajectory. Figure 4 shows these *resultant forces* for the four scenarios: one *disruption resultant force* (from the passive trajectory) and three *compensation resultant forces* (from the active trajectories). The grey dash lines represent the start and end of the perturbation. The purple dash line represents, for each scenario, the time when there is an actual shortage in stock. The analysis of the obtained values shows several aspects:

- First, the *perturbation resultant force* is very strong (maximum of -0.4) during the activity period of the perturbation, and then there is a natural compensation due to the availability of the supplier.
- Second, the *safety stock resultant force* is very strong in both directions (+0.4 and -0.3) generating oscillations.
- Third, the *broker resultant force* is less strong and less oscillating than the *safety force resultant force* but still follows the same pattern.
- Finally, the *double sourcing resultant force* is the less oscillating and the lowest in value (maximum of 0.1) while having the performance curve (see Figure 4) reaching almost the same end point as the inertia trajectory.

Finally, from Figure 3, it was already interesting to see how *double sourcing* and *broker* mitigation measures were visually the most interesting (but what about spaces of 4D, 5D, 10D and more). In Figure 4, this is even more obvious and general to higher dimensions spaces. This result from a single use case does not represent the proof of anything, however, it shows that the motion study of performance trajectory could be a way to support decision-making by (i) encapsulating multiple dimensions in one single performance space, and (ii) opening the door to motion metaphor to calculate the impact of measures on performances of observed SCs.

5. CONCLUSIONS AND PERSPECTIVES

There are mainly three essential takeaways to be considered from the previous study. The first one concerns how a SC is considered as a system: here, we consider the SC an aggregated system, a singularity within a physical space. The complexity of the reality of SCs as networks of flows and entities should be considered in future work. The second one concerns the general paradigm of performance visualization presented in the considered use case. The trajectory paradigm, as illustrated in Figure 4, opens the door to a multidimensional performance space (with potentially a very high number of KPIs) in which the performance trajectory could be formally assessed, modeled and anticipated (even if not visualized). The third one concerns the "physics inheritance" that this paradigm brings on the stage. Let us consider all the avenues that could be investigated: What about the density of the performance space (density representing the easiness or feasibility to reach one part of the performance space)? What about energy and power (potentially linked to the cost of actions)? What about equilibrium (representing the resilience or robustness of a SC)? What about solid motion instead of point motion (the shape and plasticity of the solid representing the ability of the SC to increase or decrease its sensibility to a force or even absorb it or amplify it)?

REFERENCES

BCI. (2019). SC resilience 10-year trend analysis. 2009–2018. Zurich Insurance Group, Business Continuity Institute.

Bekefi, T., Epstein, M.J., and Yuthas, K. (2008). Managing Opportunities and Risks. *Management Strategy Measurement*, The Society of Management Accountants of Canada, the American Institute of Certified Public Accountants and The Chartered Institute of Management Accountants.

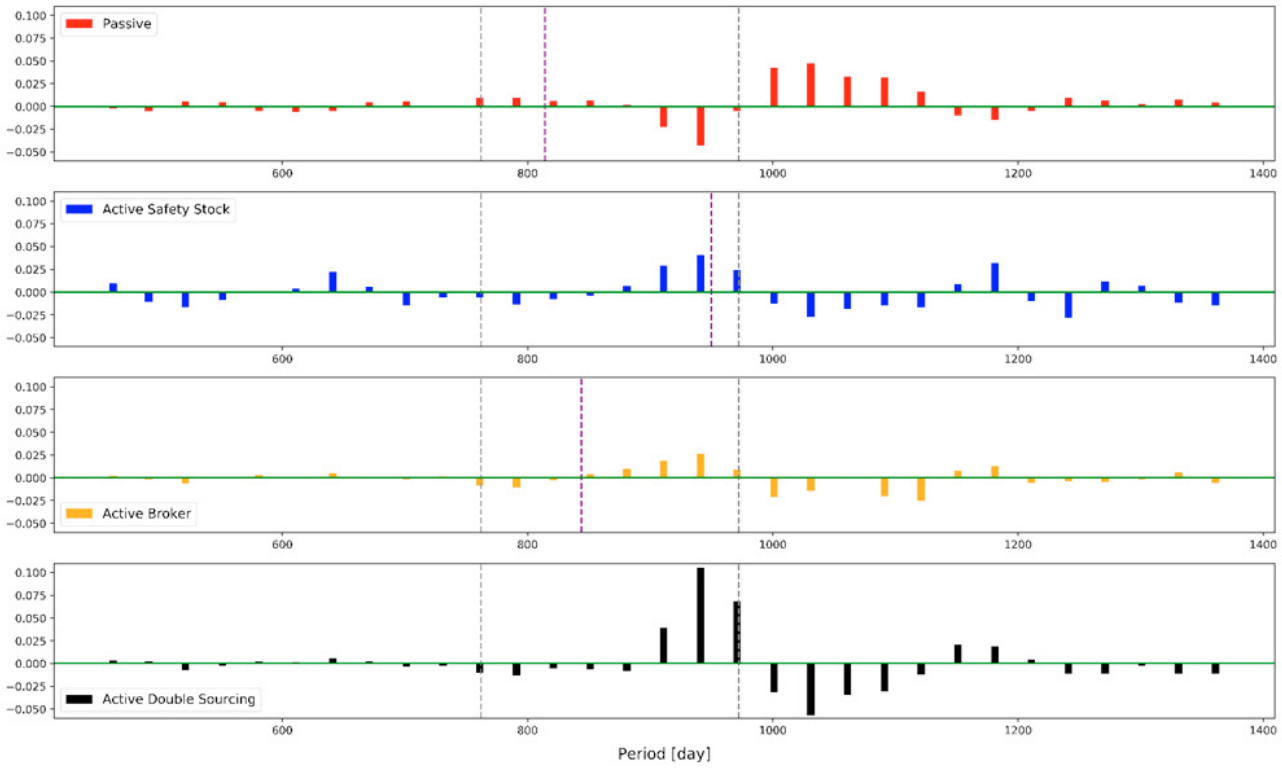

Figure 4. Acceleration intensity

Benaben, F., Faugere, L., Montreuil, B., Lauras, M., Moradkhani, N., Cerabona, T., Gou, J., and Mu, W. (2021). Instability is the norm! A physics-based theory to navigate among risks and opportunities. *Enterprise Information Systems*.

Benaben, F., Lauras, M., Montreuil, B., Faugère, L., Gou, J., and Mu, W. (2020). A physics-based theory to navigate across risks and opportunities in the performance space: Application to crisis management. 2187-2196. HICSS 2020 - 53rd Hawaii International Conference on System Sciences, United States.

Bititci, U., Garengo, P., Dörfler, V., and Nudurupati, S. (2012). Performance Measurement: Challenges for Tomorrow. *International Journal of Management Reviews*, 14 (3), 305-327.

Cerabona, T., Benaben, F., Montreuil, B., Barenji, A. V., and Nazzal, D. (2021). Physics of Decision: Application to Polling Place Risk Management. 1-12. 2021 Winter Simulation Conference (WSC), United States.

Fang, C., and Marle, F. (2012). A simulation-based risk network model for decision support in project risk management. *Decision Support Systems*, 52 (3), 635-641.

Fortune. (2020). https://fortune.com/2020/02/21/fortune-1000-coronavirus-china-supply-chain-impact/.

Ivanov, D., and Dolgui, A. (2020). A digital SC twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control,* 1-14.

Moradkhani, N., Benaben, F., Montreuil, B., Lauras, M., Jeany, J.,and Faugere, L. (2022a). Multi-criteria performance analysis based on physics of decision—application to covid-19 and future pandemics, *Transactions on Services Computing,* 523-533.IEEE, Greece.

Moradkhani, N., Benaben, F., Montreuil, B., Lauras, M., Le Duff, C., Jeany, J. (2022b) An Intelligent Decision Support System Inspired by Newton's Laws of Motion, *14th International KES Conference (KES-IDT-22)*, Greece.

Nudurupati, S.S., Bititci, U.S., Kumar, V., and Chan., F. T. S. (2011). State of the Art Literature Review on Performance Measurement. *Computers & Industrial Engineering,* 60 (2), 279-290.

Simon, H.A. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics*, 69(1), 99-118.

Sodhi, M.S., and Tang, C.S. (2012). *Managing SC Risk*. Springer, New York.

Taleb, N.N. (2007). *The Black Swan – The Impact of the Highly Improbable*. Random House, New York.

Yazdani, M., Zarate, P., Coulibaly, A., and Zavadskas, E.K., (2017). A group decision making support system in logistics and SC management. *Expert Systems with Applications*, 88, 376-392.