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The physics of decision approach: a physics-based vision to manage supply chain resilience

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As instability becomes the norm, supply chain management is becoming increasingly complex and critical. As a result, supply chain managers must adapt to complex situations. Managing instability is a key expectation for these managers. One way to help them to manage this instability is to study resilience. Resilience is related to in the literature as the ability of a system to resist, adapt and recover from disruptions. Measuring and controlling supply chain resilience has therefore become a key issue for managers, especially in a context of instability. In 2013, the World Economic Forum [2013. *Global Risks 2013*. Davos, Switzerland: World Economic Forum] highlighted in its study, this priority for the surveyed companies to master this concept of resilience. To address this need, this paper presents an innovative approach to disruption and resilience management based on physics principles. It considers disruptions as forces that impact supply chain performance. These forces are created as a result of changes in the internal or external attributes of the supply chain. In this approach, supply chain performance is represented and visualised as a physical trajectory modelled in the framework of its performance indicators. Thus, disturbances are considered as forces that displace and deviate the supply chain's performance trajectory in its performance framework.

1. Introduction

In today's increasingly dynamic, uncertain and turbulent global environments, instability is becoming the norm (Benaben et al. 2021). From the Cambridge Dictionary, instability is defined as 'uncertainty caused by the possibility of a sudden change in the present situation'. Due to its complex networked nature which brings together various interdependent actors interconnected by their flow of money, goods and information, supply chains (SCs) are not immune to this instability (corresponding to the uncertainty of the environment in which they operate, as well as the uncertainty governing their processes) and are confronted with numerous events that threaten to disrupt their activities and jeopardise their performances. According to Knemeyer, Zinn, and Eroglu (2009), all actors in an SC network are susceptible to disruptive events and risks. SC risks can be categorised into two fundamentally different types: delays and disruptions (Sodhi and Tang 2012). Delays risks correspond to 'normal' and ordinary disturbances generated by the four categories of variability of an SC: supply, demand, production and management (Ptak and Smith 2019). SC disruptions are

unplanned and unanticipated events, with low frequency and high impacts on SC activities (Hosseini, Ivanov, and Dolgui 2019), by interrupting the flow of products and materials exchanged between its various actors (Craighead et al. 2007). These risks, which vary unpredictably in type, scale and nature, are difficult to identify, predict and estimate due to their intermittent and irregular nature (Hosseini, Ivanov, and Dolgui 2019). The severity of their impacts on SC activities and performance will depend on the duration and propagation speed of the risk (El Baz and Ruel 2021). In recent decades, the number of natural disasters and man-made threats has increased dramatically (Cheng, Elsayed, and Huang 2022), showing an increasing tendency towards uncertainty and therefore instability. This fact, coupled with the increasing complexity and uncertainty associated with modern global SCs, is driving researchers and practitioners to try to minimise the potentially harmful effects of disruption by increasing SC resilience (Münch and Hartmann 2022). Tan, Cai, and Zhang (2020) define SC resilience as 'the ability of a supply chain to both resist disruptions and recover its operational capability after disruptions'. Due

to the increase in disruptions impacting SCs, dealing with instability and managing these events has become a necessity for SC managers, making the study of resilience an extremely important topic (Chowdhury and Quaddus 2017). Despite this growing body of research since the early 2000s, when the concept of SC resilience was first defined, there is still a lack of consensus on how to conceptualise and measure SC resilience (Chowdhury and Quaddus 2017). Its development requires: (1) methods to define and measure it, (2) metrics to assess it, (3) new modelling and simulation techniques, (4) development of resilience engineering and (5) approaches for communication with stakeholders (Linkov et al. 2014). Empirical research on resilience assessment has been impacted by the lack of a valid (Chowdhury and Quaddus 2017) and replicable measurement model. Despite considerable efforts to characterise resilience, there is no generic metric to assess it for different systems impacted by different hazards (Cheng, Elsayed, and Huang 2022). According to Ponomarov and Holcomb (2009), the search for measures of SC resilience is an important stream of research that can provide essential knowledge for its management. Indeed, as mentioned in Dalziell and McManus (2004), 'that which isn't measured isn't managed'. The management of any system requires to process and know in real time the state of the system (Neely, Gregory, and Platts 1995). This state evolves as a function of the different efforts made to achieve objectives and other external and suffered variables. These objectives can be associated with performances to be achieved, and basically, there is a set of key performance indicators (KPIs) that represent the state of this system with respect to time and the identified objectives (Neely, Gregory, and Platts 1995). Risks can be viewed as events that, if they occur, will have an impact on the overall performance of the observed system. Essentially, they can change the values of its KPIs. When a risk is observed in the system's performance space in terms of KPIs and time, it will move the system away from its intended performance goals. Assessing the system performance in the face of disruptions is becoming a major concern for researchers and practitioners (Cheng, Elsayed, and Huang 2022), particularly for its ability to represent the 'real bottom line' of any organisation (Munoz and Dunbar 2015). In recent years, 'the notion of resilience has been proposed and popularised to characterise system performance deterioration and restoration due to different hazards and threats' (Cheng, Elsayed, and Huang 2022). However, resilience is a multi-dimensional performance concept, which cannot be measured by a single indicator and characterised with precision (Munoz and Dunbar 2015). In order to propose a measure of SC resilience that can capture its multidimensional aspect, this paper relies on the Physics

of Decision (PoD) approach, introduced in Benaben et al. (2021). This original physics-based approach considers the effect of events (e.g. occurred risks or decisions taken by managers) as forces that push or pull the system (an SC in the context of this article), thus influencing its trajectory in its performance space (a framework which aims to position the SC with respect to the dimensions of its KPIs). Indeed, the system is continuously moving in its performance space and these movements are due to the succession of events caused by risks or decisions taken by managers to limit their impacts. The benefits or damages of these events are considered as concrete deviations of the system's performance trajectory. The main objectives of this research work are first to define resilience, especially in the context of SCs according to the state of art about this concept; second, to analyse the proposed metrics to assess SC resilience; and third, to study the contributions of the PoD approach to evaluate SC resilience, in particular by modelling performance as a multi-dimensional trajectory. These objectives aim to answer the following research question: **how to evaluate the resilience of an SC with a physics-based approach?**

Accordingly, the remainder of this paper is organised as follows: Section 2 defines from the literature the concepts of resilience and resilience assessment. Section 3 describes PoD physics-based approach and its application to resilience management. Section 4 presents an application of PoD concepts to a fictitious SC use case. Finally, Section 5 concludes with the main takeaways of the article, limitations and next steps for the proposed resilience indicator.

2. Background about the concept of resilience and associated metrics

2.1. Definitions of resilience

Resilience is a multidisciplinary concept studied across different domains such as sociology, engineering, ecology and economy (Hosseini et al. 2019). It has its origins in the developmental theory of social psychology, in order to address questions related to ecological and social vulnerability, the politics and psychology of disaster recovery, and risk management in a context of increasing threats (Ponomarov and Holcomb 2009). Holling (1973) was the first to identify and define the concepts of resilience as the ability of a system to adapt and cope with change while still maintaining its original function and structure. Based on this definition, resilience has emerged as an important tool for managing SC risk and vulnerability (Ponomarov and Holcomb 2009; Adobor and McMullen 2018). In the SC domain, the concept of SC resilience emerged in the early 2000s, with the work

of Rice and Caniato (2003). Since, considerable effort has been devoted to quantifying and describing resilience from different perspectives (Cheng, Elsayed, and Huang 2022). Based on their review of the literature (113 papers analysed from 1975 to 2018), Clement et al. (2021) identify three types of resilience, as illustrated in Figure 1 and from definitions on the concept of SC resilience in Table 1. These three views of resilience (called respectively α , β and γ) differ mainly in the notion of zones of absorption and response, but also to the manner of returning to a stable state. Type α resilience, defines a system as resilient if it is able to absorb the disruption, i.e. despite a deterioration (not dramatic for the system) in its performance, the system then has the ability to return to its initial level of performance (the one before the disruption). This vision of resilience corresponds to that defined by Rice and Caniato (2003), as the ability 'to respond to an unexpected disturbance and then restore operations to normal'. Response implies the ability to react quickly to critical situations (Han, Chong, and Li 2020), which is an important variable that determines SC resilience. This resilience's property is found in the definitions of Brandon-Jones et al. (2014) and Hohenstein et al. (2015), who see resilience as the ability of an SC to recover quickly to a normal status, a normal state of performance. This ability to respond highlights a fundamental dimension of resilience: time. Type β resilience is close to type α resilience. The only difference is in

the expected performance after absorption of the disruption. For this type of resilience, the authors do not look for the system to return to its initial level of performance. They define a resilience zone, i.e. a zone of acceptable performance. The resilience of the system is then defined as the capacity of the system to return to this performance zone after having undergone a disturbance. This definition is close to the vision developed by Ivanov and Sokolov (2013), who define resilience as 'the ability to maintain and recover (adapt) planned execution, as well as to achieve planned (or adapted, yet still acceptable) performance', through this vision of maintaining the performance in a zone of acceptability corresponding to the resilience zone in Figure 1. For the last type of resilience, type γ resilience, the notion mainly is adaptation. A system is type γ resilient if, following a disturbance, it adapts and reaches a new level of stability, thus generating a transition from the initial state to a new stable state. According to Ambulkar, Blackhurst, and Grawe (2015), a resilient system is one that is able to adapt to disruption, especially by developing its capacity to reconfigure its resources, i.e. its ability to reconfigure, realign and reorganise its resources in response to changes in the external environment of the system. For Christopher and Peck (2004), through one of the most commonly cited definitions of SC resilience, the transition from the initial stable state to a new one after a disruption can only take place towards a state equivalent

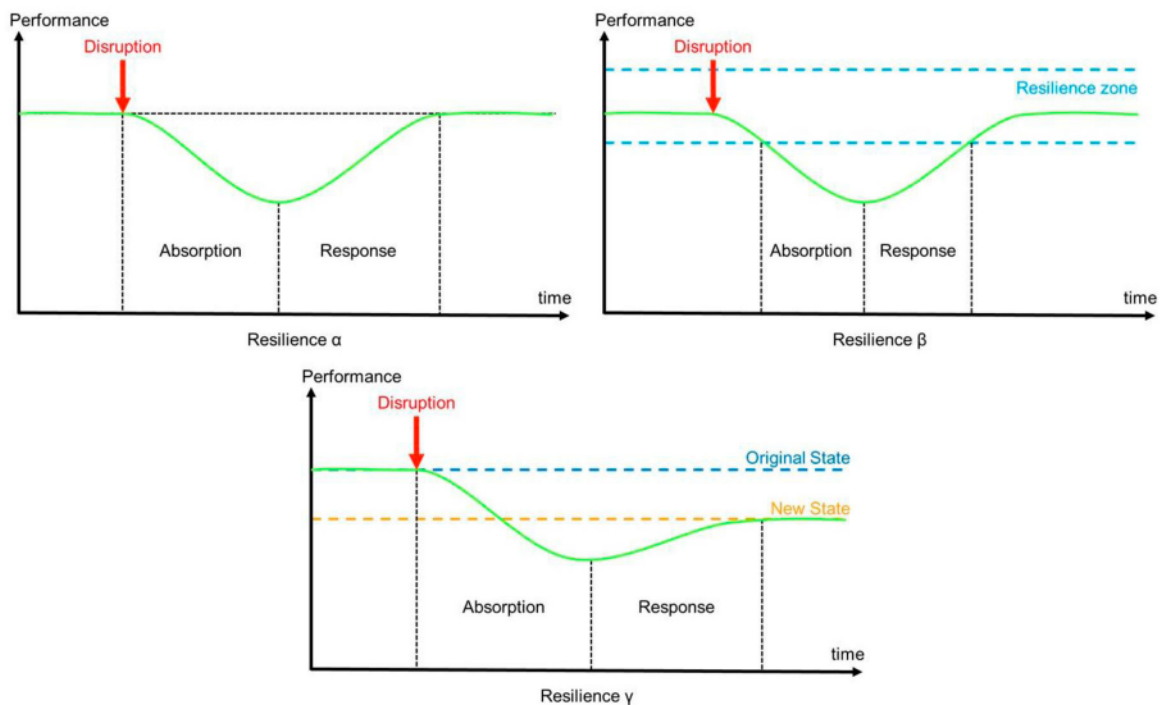


Figure 1. The three types of resilience α , β and γ , adapted from Clement et al. (2021).

Table 1. SC resilience definitions, according to their type.

Authors	Definitions	Type of resilience		
		α	β	γ
Rice and Caniato (2003)	'The ability to respond to an unexpected disturbance and then restore operations to normal.'	✓		
Christopher and Peck (2004)	'The ability of a system to return to its original state or move to a new, more desirable state after being disturbed.'			✓
Sheffi and Rice (2005)	'The firm's ability to absorb disruptions or enable the SC network to return to state conditions faster and thus has a positive impact on firm performance.'	✓		
Carvalho et al. (2012)	'Supply chain resilience is concerned with the system ability to return to its original state or to a new, more desirable state.'			✓
Ivanov and Sokolov (2013)	'The ability to maintain and recover (adapt) planned execution, as well as to achieve planned (or adapted, yet still acceptable) performance.'		✓	
Brandon-Jones et al. (2014)	'The ability of a supply chain to return to normal operating performance, within an acceptable period, after being disrupted.'	✓		
Ambulkar, Blackhurst, and Grawe (2015)	'Firm's resilience to supply chain disruptions is defined as the capability of the firm to be alert to, adapt to, and quickly respond to changes brought by a supply chain disruption.'			✓
Hohenstein et al. (2015)	'The ability of the supply chain networked to withstand disruptions and return to a normal status quickly.'	✓		
Tan, Cai, and Zhang (2020)	'The ability of a supply chain to both resist disruptions and recover its operational capability after disruptions.'	✓		

to the initial one or towards a more desirable state. A couple of years later, Carvalho et al. (2012) in their definition share this vision and thus add the notion of improvement and growth (also called antifragility, Taleb 2007 and 2012) to the definition of resilience. Growth goes beyond the recovery and return of the system to its original state, it aims to benefit from the system's response to the event to reach a new, more advantageous and desirable state (Hohenstein et al. 2015). Sheffi and Rice (2005), with their definition of resilience, see this notion of growth as a positive impact on the performance of the SC. More generally, resilience can be seen as the ability of an SC to adapt and reach a new level of stability after a disruption. This new state can be unfavourable for the performance of the SC, in this case, it is the concept of fragility.

In order to achieve the objectives defined by the previous definition, SCs have to consider several forms of

resilience (Adobor and McMullen 2018). Holling (1996) distinguishes two types of resilience: engineering and ecological, each with very distinct design and management objectives. Indeed, although they agree on the fact that following a disturbance, the system is pushed out of its state of equilibrium. They differ on the notion of stability, which Holling (1973) defines as the capacity of a system to return to a state of equilibrium after a temporary disturbance. Engineering resilience aims to focus on maintaining the efficiency of the system, focusing on 'stability near a stable steady state, where resistance to disturbance and speed of return to equilibrium are used to measure the property' (Holling 1996). Thus, with this view of resilience, the more resilient a system is, the faster it rebounds to a state of equilibrium. Ecological resilience, on the other hand, focuses on the continued existence of the system and 'emphasizes conditions far from any equilibrium steady-state, where instabilities can flip a system into another regime of behaviour, that is, to another stability domain' (Holling 1996). In other words, ecological resilience is measured as the amount of disturbance a system can withstand before changes in system structure and controls occur (Holling 1996). Thus, unlike engineering resilience, ecological resilience is not measured by the time a system needs to recover from a disturbance but by the intensity of the disturbance it is able to withstand (Adobor and McMullen 2018). Carpenter et al. (2001) define resilience as 'the magnitude of disturbance that can be tolerated before a socioecological system moves to a different region of state space controlled by a different set of processes', a definition very close to that of Holling (1996). Based on these definitions and concepts of resilience, Carpenter et al. (2001) highlight three other properties of resilience: (1) the amount of change the system can undergo (i.e. the amount of extrinsic force the system can withstand) while maintaining the same controls over structure and function, (2) the ability of the system to self-organise and (3) the ability to adapt and learn from perturbations.

Despite a lack of consensus on the definition of resilience, the set of definitions presented share common properties to the concept of resilience: (1) the term resilience assumes the realisation of a disruption, (2) it refers to the state of the system before, during and after, which in some definitions is seen as its performance level and (3) it aims at comparing and following the gap between these different states in order to evaluate the system's ability to absorb the disturbance. Thus, resilience is assessed by comparing the state of the system according to a specific performance parameter before and after a disturbance (Hosseini, Barker, and Ramirez-Marquez 2016).

2.2. Resilience assessment

Despite a wide range of definitions of SC resilience, few articles address the issue of measuring SC resilience and the need to create a quantitative framework to assess it (Spiegler, Naim, and Wikner 2012). Indeed, it is important for organisations to conduct an SC resilience assessment to understand the risk exposure of their SCs and evaluate resilience and risk mitigation strategies (Soni, Jain, and Kumar 2014). Without understanding and assessing the level of resilience of a system, it is difficult for managers to evaluate and manage the response and reaction of the SC following disruptions (Han, Chong, and Li 2020). As the management adage goes, 'you cannot manage what you cannot measure' (Munoz and Dunbar 2015). SC resilience management is not exempt from this rule. Managing SC resilience involves identifying SC states as an essential part of resilience analysis (Carvalho et al. 2012). One method of tracking the evolution of these states is to define and measure the various efforts undertaken to achieve the objectives of an SC. One of the most critical aspects of operations management is to make these objectives representable (Franceschini et al. 2006). This is usually done by translating the organisation's objectives into performance measures. Thus, these objectives can be associated with performances to be achieved, and basically, there is a set of KPIs that represent the state of this system with respect to time and the identified objectives represented as target values for these KPIs (Neely, Gregory, and Platts 1995). Due to its complexity, measuring the performance of an SC is not an easy task (Estampe et al. 2013). Performance measurement is the process of quantifying the efficiency and effectiveness of an operation (Neely, Gregory, and Platts 1995). In particular, it allows the identification and measurement of the gap between the current performance and the desired level of performance, the objectives (Mani et al. 2014). Performance measurement is therefore a fundamental managerial mechanism for informing decision-makers (Gunasekaran and Kobu 2007), both on the evolution of the gap and on the progress made in closing it. Over the past two decades, many studies have proposed conceptual or quantitative models to address SC performance evaluation (Lima-Junior and Cesar Ribeiro Carpinetti 2019). The developed conceptual models suggest a set of performance measures (Gunasekaran, Patel, and McGaughey 2004) that include financial and non-financial measures associated with different levels of decision-making: strategic, tactical and operational (Shepherd and Günter 2006). Shepherd and Günter (2006), through their analysis of the literature, have listed more than 130 performance indicators dedicated to SC performance assessment.

Despite all the indicators proposed in the literature, studies on resilience metrics remain scarce (Han, Chong, and Li 2020). However, appropriate performance metrics are needed to evaluate resilience (Sillanpää 2015), especially to understand and measure the level of resilience of an SC. Some studies measured the SC resilience by evaluating the impact of disturbances on stock level, service level, lead time and costs (Cabral, Grilo, and Cruz-Machado 2012). The studies are mainly focused on the classic performance triptych: *quality, delay and cost*. Han, Chong, and Li (2020) divide the performance metrics required to assess the resilience of an SC into eleven categories: *performance of maintaining customer satisfaction, efficiency of completing SC processes, efficiency of recovering to normality, performance of production and inventory, performance of relationship management, financial performance, performance of overseeing the SC situation, performance of discerning possible disruptions, damage of disruptions, efficiency of responding the disruptions and reconstruction of the SC*. Rajesh (2016) proposes to measure resilience according to five major indicators: *flexibility* (ability to manage changes quickly without undue effort and loss), *responsiveness* (speed of delivery of products), *quality, productivity* (related to customer satisfaction) and *accessibility* (network visibility and connections between network actors). Each of these major indicators is associated with several metrics to evaluate it (refer to Rajesh 2016 for more details about the proposed KPIs). These five major indicators are close to the performance attributes defined by the SCOR (Supply Chain Operations Reference) model. SCOR model is a process reference model that provides methodology, standard process definitions, metrics, diagnostic and benchmarking tools in order to improve SC performance and processes (Council 2017). SCOR defines five performance attributes (Council 2017): *reliability* (ability to achieve tasks as expected and focuses on predicting the result of a process), *responsiveness* (speed of completion of a task), *agility* (ability to respond to external disturbances), *costs* (SC running costs) and *assets* (ability to use assets efficiently). Performance attributes represent the strategic performance characteristics on which to align SC performance to meet the company's strategy. SCOR defines two types of performance attributes: customer (*reliability, responsiveness and agility*) and internal (*assets and costs*) focused attributes (Council 2017). According to their definitions, Rajesh's major indicators are very customer oriented, so they can be included in the attributes defined by SCOR: *flexibility* in *agility, responsiveness* in *responsiveness*, and *quality, productivity and accessibility* in *reliability*. Among SCOR attributes, *agility* describes the ability of an SC to respond to external disruptions, its capacity and speed of change (Council 2017). Because of

its description, it could represent a good way to evaluate SC resilience. For each performance attribute (*reliability, responsiveness, agility, costs and assets*), SCOR associates several KPIs. Rajaratnam and Sunmola (2021) propose a hierarchical performance measure framework based on 55 metrics proposed by SCOR in order to evaluate SC resilience.

From an engineering perspective, quantifying resilience involves measuring system performance over time, focusing on system performance during and after the disruption (Bruneau et al. 2003; Zobel et al. 2021). Most of the measures proposed in the literature are functions of one or more KPIs measured during these different phases (Cheng, Elsayed, and Huang 2022). Many approaches have been developed to measure the resilience of SCs as a time-dependent measure (without its consideration, the concept of resilience cannot be fully addressed). Generally, SC resilience is measured according to two main aspects: *the time of SC recovery* and *the performance loss due to a disruption* (Fattahi, Govindan, and Maihmi 2020). Lost performance is mostly defined as the difference between performance after a disruption and expected or baseline performance, i.e. optimal performance in the absence of disruption (Behzadi, O’Sullivan, and Olsen 2020). Both measures of resilience can be calculated from ratios of restored to lost performance, or from modelling several possible performance trajectories (Zobel et al. 2021), considering the effects of uncertainty related to recovery, which is a stochastic process, due to uncertainty about available resources and the severity of disruptions (Cheng, Elsayed, and Huang 2022). For example, Carvalho et al. (2012) propose to measure the recovery time (i.e. the time needed for the SC to return to a normal state after a disruption) by a ratio: the *lead time ratio*, a ratio between actual and promised lead time. This performance measure assesses the SC’s capability to fulfil the lead time agreed with their first-tier customers (Carvalho et al. 2012). In the case of resilience measurement through performance trajectory modelling, resilience triangle is the most recognised way of measuring system’s resilience (Tukamuhabwa et al. 2015). The measure provided by the resilience triangle is based on the fact that it is possible to measure the actual or potential performance of a system at any given time, and to represent it as a point or trajectory in the multidimensional space of its KPIs (Bruneau et al. 2003). It considers major concepts around resilience: performance level, loss estimation and recovery (Tukamuhabwa et al. 2015). Considering a time series response curve that represents the performance of the SC, Figure 2 illustrates the resilience triangle that models both the immediate effect of a sudden impact disaster and the response behaviour of the system. A possible static

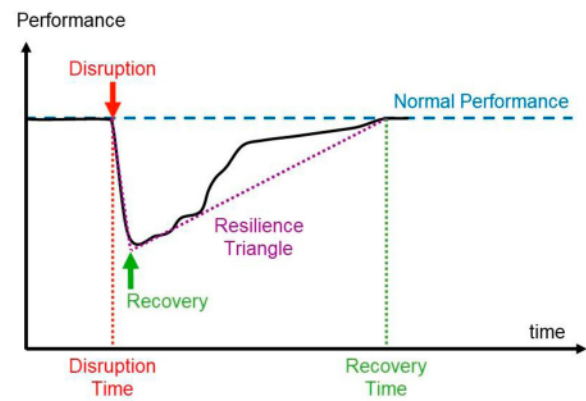


Figure 2. Resilience triangle.

measure of SC resilience is to calculate the area of this triangle (Adenso-Díaz, Mar-Ortiz, and Lozano 2018). Low values of the area of this triangle imply no significant consequences or rapid recovery. This tool can also be seen as a dynamic measure of resilience by comparing the evolution of the surface of this triangle following different events (Tukamuhabwa et al. 2015). Measuring the area under the curve to measure and compare the resilience of systems to disruptions is an approach which has been adopted by many disciplines (Macdonald et al. 2018). Since its inception by Bruneau et al. (2003), the resilience triangle concept has been applied and extended in many approaches. Its simplicity makes it a sound basis for developing new quantitative methods for assessing resilience (Zobel 2011).

No common agreement on a measurement model seems to have been reached in the literature, the assessment of SC resilience performance has been investigated structurally using the dimensions or phases of SC resilience. Most studies in the literature have focused more on the development of their own measurement models (Han, Chong, and Li 2020). The studies presented in this section focus mainly on an assessment of resilience with an engineering perspective. However, some authors such as Wieland (2021), propose to reinterpret the SC, by studying it as an organic system. This vision implies studying resilience according to its ecological vision and definition. Holling (1996) was the first one to outline the difference between engineering resilience and ecological resilience. Engineering resilience is focused on constancy, predictability and efficiency, while ecological resilience is focused on change, unpredictability and persistence (Wieland 2021). In other words, instead of measuring resilience as ‘resistance to disturbance’ or ‘speed of return’ to a stable performance state, as engineers would, ecologists measure resilience as the ‘magnitude of disturbance’ that the ecosystem can absorb (Wieland 2021). In his definition of resilience, Holling (1973) acknowledges the

importance of classical physics, from which he adapts terms (such as force, equilibrium, etc.) and draws on key intellectual antecedents to define the concepts associated with his vision of resilience. Work on defining the concepts of ecological resilience has drawn heavily on notions from physics (Ponomarov and Holcomb 2009), thus offering a study perspective of a physics-based approach as PoD.

3. Proposal: PoD approach

3.1. PoD: general ideas

Identifying the need for SC resilience requires defining the system (Linkov et al. 2014) and identifying the different system states, which is a ne ssential part of resilience analysis (Carvalho et al. 2012). System states describe the system's changing behaviours and situations across time (Ferreira and Otley 2009), instability being the main source of these changes. Identifying these state changes implies being able to characterise the system, in particular by being able to evaluate the different interactions between its parameters. This is at the heart of system diagnostics (Westphalen, Roth, and Brodrick 2003). Studying such links and their influence on system performance is required to control a system effectively and to be able to visualise and predict these state changes. The PoD approach uses an analogy with physical motion laws to study and predict the different states of a system. These state changes can be generated by different environmental or internal situations that an SC is confronted with. These environmental or internal situations are named *potentials* in the context of the PoD vision. The susceptibility of the system to these *potentials* generates *potentialities* (i.e. risks or opportunities with regard to the system). In the PoD approach, these *potentialities*, once activated by one or more triggering conditions, become *actuality* which can be seen and modelled as forces impacting SC performance (Benaben et al. 2019). Thus, performance is seen as a trajectory modelled in a multidimensional space characterised by KPIs (each KPI defining one dimension), risks and opportunities are seen as forces which, once triggered, craft the shape and dynamics of this performance trajectory.

As mentioned in Ponomarov and Holcomb (2009), SC resilience addresses several types of risks at several stages of the risk management process. Resilience is one of the critical elements in SC risk management, so it needs to be examined to determine how to incorporate it into a conceptual framework. To meet this need, the PoD approach proposes and is based on two modelling spaces: the description space (illustrated in Figure 3) and the

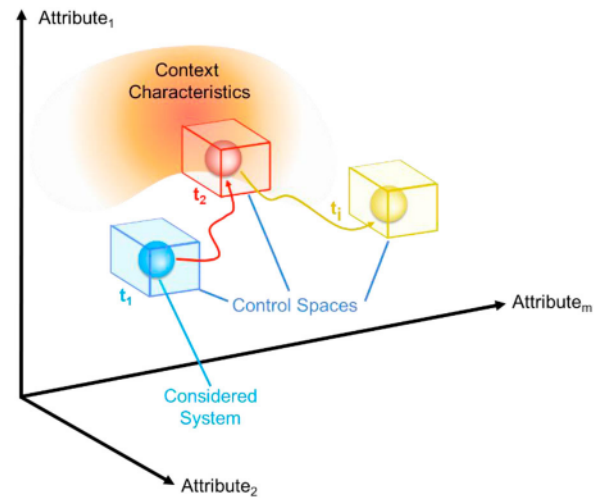


Figure 3. Description space.

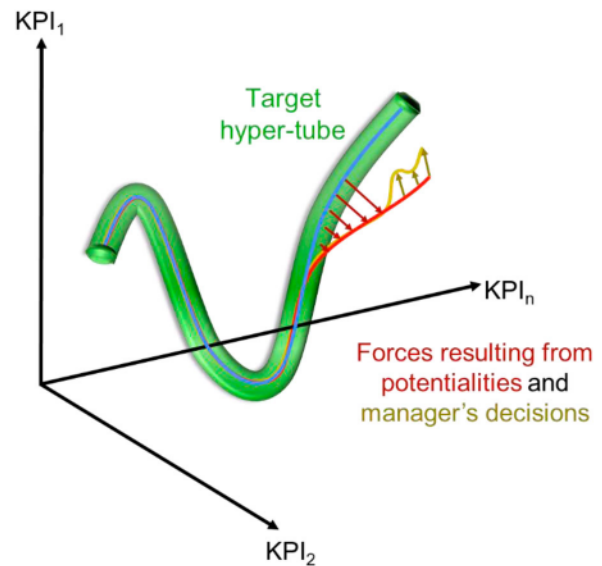


Figure 4. Performance space.

performance space (illustrated in Figure 4). The **description space** is a multidimensional space: each dimension is an attribute of the SC under study, or a parameter of its environment. In Figure 3, the SC is located within this description space as a blue sphere. Thus, it represents at each point in time the location of the SC with regards to dimensions describing its own attribute and its environment characteristics (e.g. customer demand, available capacity, raw material prices, production capacity, etc.). The degrees of freedom of each attribute defines the control space (colour parallelepipeds). This is a subspace in which the SC can move freely. This subspace allows us to consider the stochastic factors that can be associated with some attributes of the system (for example the forecast) but also the variations induced by the daily management

of the SCs. The context characteristics represent ‘risky’ areas in the description space (orange shape), where the SC is more sensitive to certain potentials and dangers that can impact it. The position of the SC in its description space evolves over time, following the realisation of potentialities modifying the attributes and parameters of the SC (red sphere), but also following the decisions taken by the managers (yellow sphere). Its position in this space models the different states of the SC.

The **performance space** is dedicated to the visualisation and management of the performance of an SC. It is a multidimensional space as well: each dimension is a KPI to be considered to assess overall SC performance. In the case of the study of SC resilience, its dimensions could be obtained from the KPIs identified in Section 2. The performance is visualised as a performance trajectory (colour trajectories of Figure 4) representing the changes of KPIs over time and the impacts of potentialities. These potentialities, by their nature, deviate positively (closer) or negatively (further) the performance trajectory of the system from its objectives. The objectives could take several forms (point of space to reach, hyper volume in which the SC should stay, hyper-surface representing a satisfaction trade-off between KPIs, etc.) and evolve in time (moving target). The performance objectives are modelled by a hyper-tube (green in Figure 4), which represents the supposed safe space for the performance trajectory to reach the objective (it could also represent the resilience zone of the system in which to maintain SC performance in the case of type β resilience). With this physics-based approach, potentialities are modelled by forces (colour vectors in Figure 4) that move the SC performance like an ‘object’ in its multidimensional KPI space (Cerabona et al. 2020). Each force reflects the intensity of the deviation from the performance trajectory, i.e. the potential impact of each potentiality.

This space is dedicated to support the manager in decision-making, including studying the best combinations of forces to select, to keep the system in the target hyper-tube. The first trajectory modelled in the performance space to apply the PoD approach is the *inertia trajectory* (blue trajectory). The *inertia trajectory* is seen as the trajectory if the system follows its ‘normal’ behaviour and is not disturbed (or at least undergoes the expected forces). Implicitly, it models the managers’ expectations in terms of performance, if everything goes as planned. Most of the time, the *inertia trajectory* can be seen as the target to be reached. It is used as a reference in the study of the scenarios presented in the potentialities study. Each deviation from this trajectory is seen as resulting from a force. The red trajectory (Figure 4) illustrates the notion of a *passive trajectory*. It is defined in the PoD approach as

the performance trajectory of a system following the realisation of an initially unexpected potentiality and that no corrective action has been implemented to minimise the impact of this potentiality on the system’s performance (Cerabona et al. 2021). This trajectory is obtained by varying the state of the system from t_1 to t_2 (the displacement between the blue and red spheres in the description space, in Figure 3). The yellow trajectory (Figure 4) illustrates the notion of an *active trajectory*. It is defined in the PoD approach as the performance trajectory of a system following the realisation of a corrective action that has been implemented to minimise the impact of this potentiality on the system’s performance. This trajectory is obtained by varying the state of the system from t_2 to t_1 (the displacement between the red and yellow spheres in the description space). The relationships between these two spaces are built by functions linking attributes to KPIs. However, depending on the type of system studied and its complexity, these functions can be more or less difficult to determine (Moradkhani et al. 2020). In the case where these relationships are too complex to determine (as for an SC for example), simulation models can be built and simulation experiments carried out, in order to model and estimate the dynamics existing between the attributes and the KPIs. Obviously, *inertia*, *passive* and *active trajectories* are all similar in nature (they represent the performance of a system facing actualities), but they differ from the sense given to these actualities (expected for *inertia*, expected and unexpected for *passive*, expected, unexpected and corrective for *active*).

3.2. PoD and resilience

The main contribution of this paper is to study how an approach like PoD can contribute to an SC, more resilient. As mentioned in the previous section, an essential part of the resilience analysis is the identification of system states. PoD, thanks to the two developed spaces, allows us to follow both the evolution of the system states over time with the *description space* and the impact of these state changes on the system performance with the *performance space*. The objective is to benefit from this performance framework to assess SC resilience and thus study the resilience from a kinetic point of view. Its geometrical definition remains to be defined. Christopher and Peck (2004) propose five key capabilities to increase SC resilience: (1) select strategies that leave as many options as possible, (2) re-examine the ‘efficiency vs. redundancy’ trade off, (3) develop collaborative working, (4) develop visibility and (5) improve SC velocity and acceleration. The last two capabilities are very interesting in the perspective of using the PoD approach to manage resilience in a kinetic manner. Adobor and

McMullen (2018) define visibility as the ability of managers to access an overview of the SC, and know its environment and key assets. All this information is included in the *description space*, which therefore aims to support the visibility. Improving the speed and acceleration of an SC requires defining and visualising the objectives to be reached, in particular by visualising, for example, the performance trajectory of an SC in a reference framework whose dimensions are its performance indicators. From a kinetics perspective, the following explains how to link the concept of performance management to kinetic and physics notations such as *displacement*, *velocity* and *acceleration*. *Displacement* (ΔKPI) measures changes in the value of a KPI. *Velocity* (v) is the derivative of this displacement over an interval δt : $\frac{dKPI}{dt}$. It thus represents the positive or negative growth of the KPI. *Acceleration* is the derivative of the velocity over an interval δt : $\frac{dv}{dt} = \frac{d^2KPI}{dt^2}$. The acceleration value reflects the strength or weakness of the fluctuation of a KPI in a positive or negative direction. Its direction is always the same as the net force acting on the system produced by the variation of its attributes (the changes in state due to a disturbance). In the proposed study, the calculated velocities and accelerations will be local velocities and accelerations, calculated as

$$\text{Velocity} = \left[\frac{x(t) - x(t - \delta t)}{\delta t} \right] = v_x(t) \quad (1)$$

$$\text{Acceleration} = \left[\frac{v_x(t) - v_x(t - \delta t)}{\delta t} \right] = a_x(t) \quad (2)$$

These notions of *displacement*, *velocity* and *acceleration* offer new perspectives in the study of the resilience of a system. The following points aim to explain how to interpret these concepts in the context of studying the resilience of a system.

- The *displacement* is equivalent to variations in the values of a KPI. It measures the gap between the initial performance of the system without any disturbance and the performance following a disturbance, in a type α or γ resilience view. For type β resilience, the displacement measures the gap between the objective performance area and the performance following a disturbance. The displacement thus makes it possible to measure the performance lost following a disruption. The notion of displacement is very close to the engineering vision of resilience which mainly refers to the area calculation method found in the literature (e.g. the resilience triangle presented in Section 2). The displacement provides a dynamic measure of resilience at each instant, whereas the area provides a measure of resilience over a range of time. Low values

of the displacement imply no significant consequences or rapid recovery.

- The *velocity* represents the growth of the system. The evolution of its sign (i.e. positive or negative growth) will make it possible to better apprehend and understand the internal dynamics of the system, in particular how the system organises itself to best absorb a disturbance (all the phases of alternating sign of the velocity).
- The *acceleration*, especially its norm, allows us to quantify the magnitude of disturbance a system can tolerate. From an ecological resilience perspective, Carpenter et al. (2001) define resilience as the magnitude of disturbance that can be tolerated by a system, i.e. the amount of extrinsic force the system can withstand. This definition, studied from a physical and kinetic point of view, allows us to define resilience as the intensity of the force (generated by a disturbance) that the system can absorb before moving. This resistance to movement is characterised by the mass of the system. By definition, physical mass is the resistance that a body of matter offers to a change in its velocity or position when a force is applied (the Encyclopaedia Britannica). Moreover, according to Newton's second law of motion, the intensity of a force is proportional to the mass of the system and the acceleration of the system produced by this net of force. The mass of a system as complex as an SC is difficult to evaluate. It is therefore necessary to quantify the ability of a system to resist a disturbance by measuring its *acceleration* after a disruption.

Thanks to its vision of system management by performance trajectory analysis and its analogies with physics (force, displacement, velocity and acceleration), the PoD approach makes it possible to link the two main visions of resilience existing in the literature: engineering and ecological. With this approach, it is possible to evaluate resilience according to these two visions. One important measure for engineering resilience is the performance loss due to a disruption, which can be measured by the concept of displacement and distance. Indeed, as illustrated in Figure 5, by analogy with the resilience triangle (illustrated in Figure 2), the idea is to approximate the resilience by the sum of the yellow distances, providing the means to estimate the area between the trajectories, in the case where the time intervals between each distance measurement are small enough according to the studied system and the considered KPIs (a one-time step in Figure 5). Three surfaces can be calculated: (1) the area between the *inertia trajectory* (for type α or γ resilience, respectively the closest border of the target zone for type β resilience) and the *passive trajectory*, measuring the

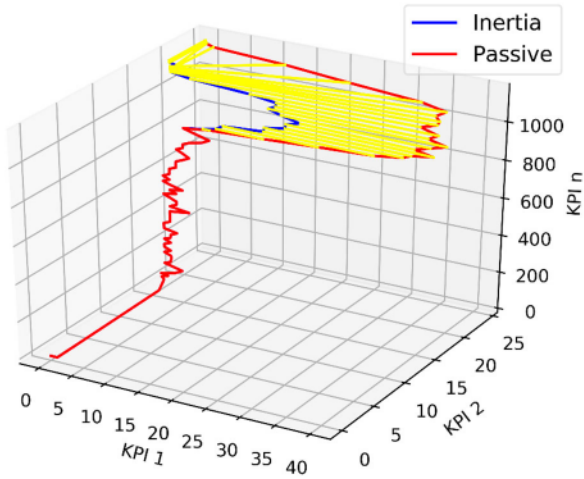


Figure 5. Distance at each time point between the inertia and passive trajectories.

degradation (used to measure the *natural resilience*), (2) the distance between the *inertia trajectory* (for type α or γ resilience, respectively the closest border of the target zone for type β resilience) and the *active trajectory*, measuring the *actual degradation* (used to measure the *corrected resilience*) and (3) the distance between the *active* and *passive trajectories*, measuring the *actual compensation* (used to measure the *gain in resilience*).

However, not being in dimension two, the measurement of the distances (2) and (3) is not quite accurate. These measurements imply to check point by point the value of the angle \widehat{IAP} between inertia (I), active (A) and passive (P) position at time t_i (illustrated in Figure 6). The closer the angle \widehat{IAP} is to 180° (the three points are on the same line) or strictly equal to 0° (the three points are combined), the more valid the measures are. It is then possible to say that the *actual degradation* (orange distance in Figure 6) is equal to the *measured degradation* (turquoise distance in Figure 6), the active position and the projected active position are thus merged. If this angle is too

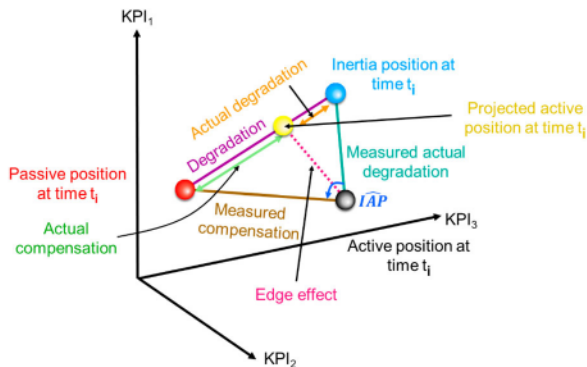


Figure 6. Illustration of distance concepts.

far from 180° , additional calculations will have to be carried out and a new distance will have to be considered, the *edge effect* (pink dotted line in Figure 6), which will have to be analysed in relation to the performance objectives of the system in order to know if its effects are positive or negative. The same reasoning can be applied to the *actual compensation* (green distance in Figure 6) and the *measured compensation* (brown distance in Figure 6). The ecological resilience, i.e. the magnitude of disturbance that a system can absorb, can be calculated thanks to the analogies with physics on which the PoD approach is based, as explained with the notions of acceleration and forces. This part will be discussed in the discussion section (Section 5).

4. Experiments and results

4.1. Studied supply chain: rich kids

To illustrate the contribution of the PoD approach to the development of SC resilience capabilities, the selected use-case concerns a worldwide SC network for electrical skateboards. This use-case has been created in 2019, the researchers who created this fictitious and illustrative use-case, decided to name it 'rich kids' because only rich kids could afford or rent this kind of 'vehicle'. Its network is composed of eight actual partners and three potential new partners (a new customer and two new suppliers). Figure 7 illustrates the studied network. Table 2 briefly describes the function of each actor in the network and their location.

In order to collect the material necessary to apply the PoD approach (for this case study, the management and measurement of the resilience of company A), a simulation model was built and developed on the AnyLogic© simulation software, combining discrete event and agent-based simulation. Besides its contribution to theory development (Davis, Eisenhardt, and Bingham 2007), simulation also provides a virtual laboratory in which it is possible to visualise the effects of potentialities and corrective actions on the behaviour of the SC (Falasca, Zobel, and Cook 2008), thanks to its ability to provide instantaneous information on the state of the system (Carvalho et al. 2012), including the evolution of its performance. These analyses are carried out from the study of sufficiently detailed scenarios, most often based in their construction on previous disturbance data, in order to identify and understand their causes and effects on the system (IAA 2013). This case study, although relatively simple, offers a large potential of evolution and complexification, especially for the study of a wide range of possible events and disturbances. In the proposed study, simulation is used to identify the performance gaps



Figure 7. Rich kids – SC network.

Table 2. Description of the Rich Kids network actors.

Company	Description	Location
A	builds electric skateboard that can be driven with an App.	Ga. USA
B	buys the electric part (engine and battery) from E and develop the App to sell both to A.	Fl. USA
C	builds synthetic wheels to sell to A.	Mexico
D	builds the board from synthetic and wood (bought from F) to sell to A.	France
E	builds engine and battery to sell to B.	China
F	provides woods to D.	Sweden
G	skateboard seller from a ski domain.	Canada
H	skateboard seller from a surf domain.	Ca. USA
I	skateboard seller from a ski domain (potential).	Italy
J	synthetic wheels supplier (potential).	Brazil
K	wood board supplier (potential).	Canada

between the actual and the desired state of the SC (Carvalho et al. 2012), when carrying out different scenarios (potentialities and corrective solutions). The collection of data related to these tests (the evolution of SC performance) was collected at regular time intervals during the simulation, following a standard procedure, which consists of running the simulation over a fixed period of time (in this study 365 days), in order to obtain time series of results to analyse (Macdonald et al. 2018). In this study, the time series of results obtained from so-called compare run simulations, in which AnyLogic© generates the random factors from identical seeds. These simulations

collect only the effects attributed to the experimental factors, thus removing the effects related to the stochastic factors, their cleaning is essential to obtain consistent and comparable results (Macdonald et al. 2018).

4.2. PoD: application to rich kids resilience management

In the perspective of the PoD approach, deviations from the SC *inertia trajectory* (SC's initial performance trajectory) are considered as potentialities (risks, opportunities resulting from inflicted events or manager's decisions) and so as forces. According to *passive* and *active trajectories* defined in Section 3, deviations are generated by variations in system attributes. These variations can be generated by two types of forces: *inflicted forces* that are imposed on the SC and modify attributes out of control of the managers (or hard to change), and *managed forces* that correspond to actions taken by decision-makers, i.e. variations on attributes over which the company's managers have decision-making power. Potentialities also have their own attributes called characteristics. For this case study, the characteristics retained are (1) the date of appearance of the potentiality, (2) its duration and (3) its impacts on the SC attributes.

Two potentialities will be studied in this illustrative example of the contributions of the PoD approach in managing SC resilience. The first potentiality (passive) will aim to stress the model with a *strike* at the board supplier D. This potentiality will be activated two months after the beginning of the simulation (the beginning of the year and the experiment lasting 365 days), will have a duration of four months and will reduce the production capacity of supplier D by 70%. The second potentiality will be a corrective action (active) implemented by the managers to reduce the impact of this strike on the performance of company A: The managers will activate the

opportunity to *double source* the supply of boards. A contract with supplier K will be concluded one month after the beginning of the previous potentiality and will last the whole simulation. The supplier will cover 30% of the board requirement. In order to be able to visualise the performance trajectories, three KPIs have been selected in this study: the *profit* (in hundreds of thousands of euros), the *inventory* of finished product and the *delay* (equivalent to the *lead time ratio* introduced by Carvalho et al. 2012). The *delay* indicator is calculated as the ratio between the sum of the waiting time to have the products in stock and the delivery time, all divided by the expected lead time agreed upon between company A and its customers.

As explained in Section 3, analysing and measuring SC resilience according to a kinetic vision is done in three steps: (1) *displacement* (the gap between the initial performance of the company A and the studied potentialities), (2) *velocity* and (3) *acceleration*. Figure 8 illustrates these three steps for the finished goods inventory KPI. In these figures, the orange area corresponds to the activation period of the disruption. The green line indicates the start date of the corrective potentiality. According to Figure 8, the effect of the disruption on finished goods inventory is not immediately felt. The first impacts appear 70 days after the start of the strike. At the onset of the disruption, company A had sufficient raw material inventories to continue operating properly. However,

once this stock was consumed, the impact of the disruption was brutal, as shown by the magnitude of the acceleration for this indicator. This disruption has a side effect and leads to a bullwhip effect (mainly due to the internal dynamics of the network and the accumulation of pending production orders) just after the recovery. The corrective potentiality delays the impact of the disruption on the finished product inventory by 43 days. However, it will not prevent the bullwhip effect, whose effects on supply performance appear more quickly, following a faster recovery.

Consistent with Section 3, the proposed resilience measure aims to extend the concept of resilience triangle with a multi-dimensional measure based on system performance trajectories. Figure 9 provides an overview of the three different trajectories modelled in its performance framework, in which dimensions are the three selected KPIs (profit, delay and finished good inventory). A first analysis (purely graphical) shows that following the strike (red passive trajectory), the performance of the SC is very degraded, particularly from a financial point of view. The action (black active trajectory) of double sourcing the raw material concerned allows to mitigate the financial impact and to return more quickly to normal at the level of delays and finished good inventory.

From these trajectories, a first measure of resilience is the sum of the *degradation* distances (purple horizontal line in Figure 6) at each time point (in this

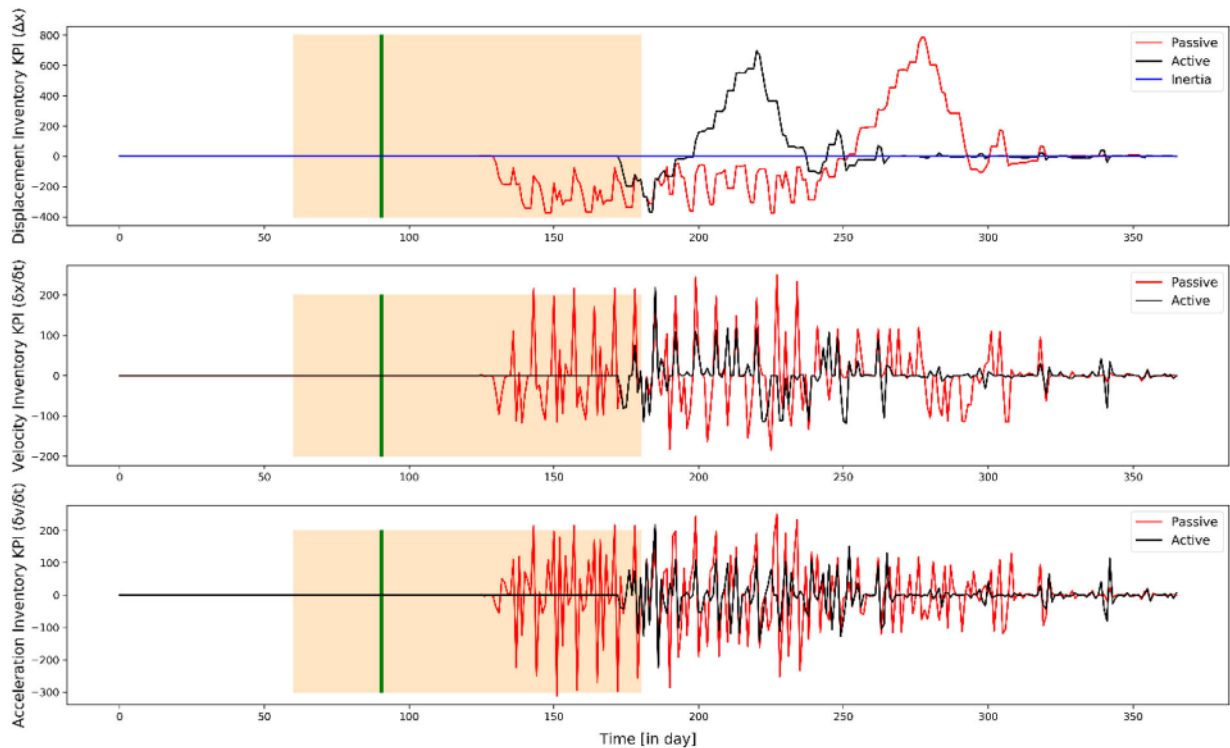


Figure 8. Distance, displacement, velocity and acceleration for the Inventory KPI.

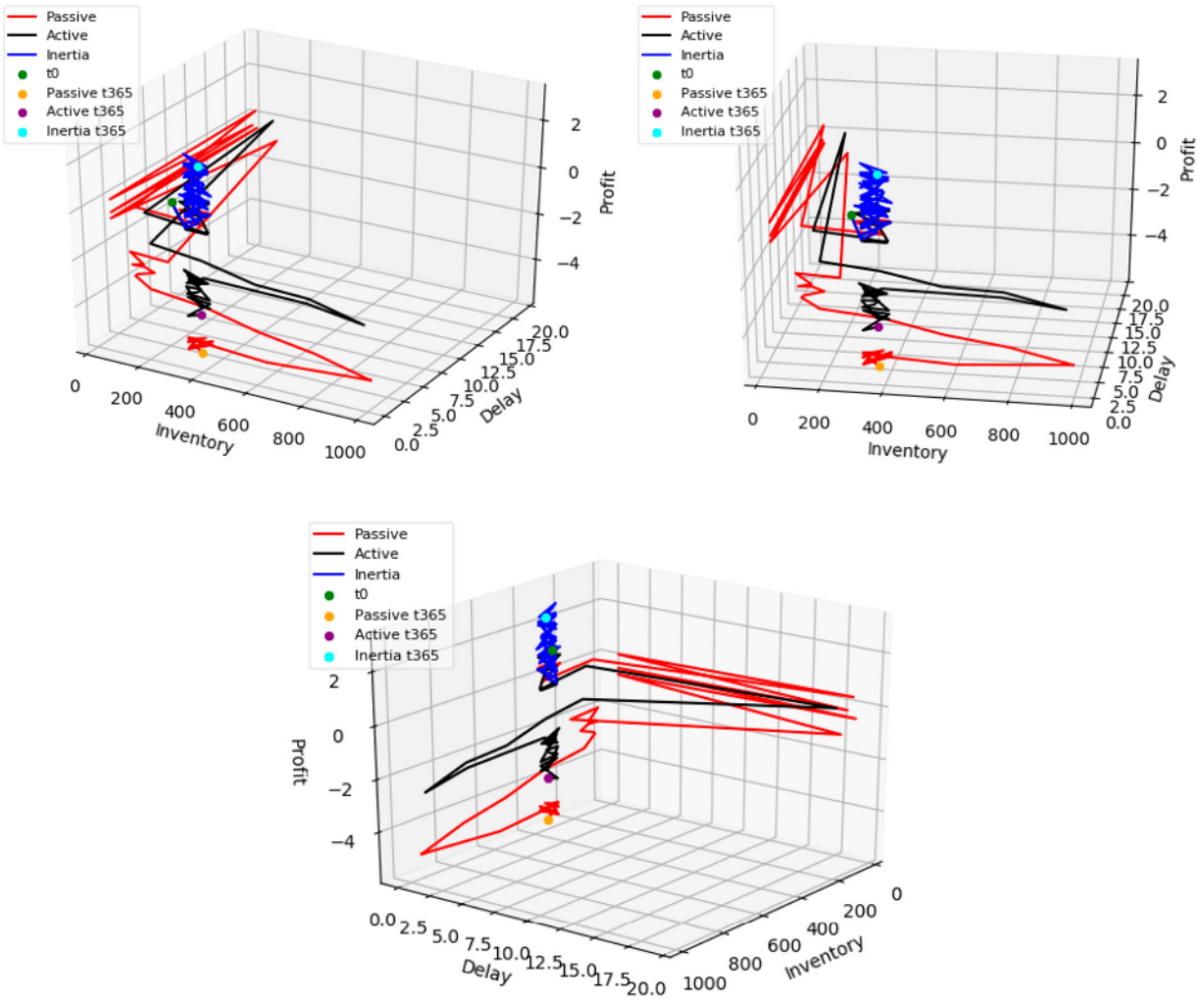


Figure 9. Rich kids 3D performance trajectories.

example, $\sum_{t=0}^{365} \sqrt{(\text{inertia}(t) - \text{passive}(t))^2}$, which corresponds to the *natural resilience* of the system. For the strike disruption, the *natural resilience* of rich kids SC is equal to 236.¹ The second measure of resilience is the sum of the *measured actual degradation* distances (turquoise distance in Figure 6) at each time point $\sum_{t=0}^{365} \sqrt{(\text{inertia}(t) - \text{active}(t))^2}$, which corresponds to the *corrected resilience* of the system. As mentioned in Section 3.2, not being in dimension two, the measurement of this distance is not quite accurate and implies to check point by point the value of the angle \widehat{IAP} between inertia (I), active (A) and passive (P) position at time t_i . For this illustrative example, 28% of the angles \widehat{IAP} are strictly equal to 0°, 59% are greater than 90° and 44% are greater than 130° (so only 13% are lower than 90°, while not being strictly equal to 0°). Thus, in this case, it is considered valid to approximate the actual degradation by the measured degradation. The *corrected resilience* of

rich kids SC is equal to 166, which is a 30% gain, showing that the selected counter measure has been significantly efficient.

If the majority of the angles \widehat{IAP} measured had been less than 90°, the *edge effect* would no longer have been negligible, the projection calculations would have become mandatory. For instance, this situation can be illustrated by the firefighter who, in order to increase his resilience to fire, wears a fireproof suit (active potentiality). However, this suit is heavy and cumbersome, which slows down his movements and his speed of movement (edge effect). In that case, the resilience can be calculated as the sum of the *actual degradation* distances (orange distance in Figure 6) at each time point $\sum_{t=0}^{365} \sqrt{(\text{inertia}(t) - \text{projected active}(t))^2}$ where the *projected active trajectory* is composed by the projections of all points of the *active trajectory* on the segments joining all *inertia positions* and *passive positions* at each moment of time. However, this absolutely implies simultaneously

measuring the *edge effect* as the sum of the distances between all points of the *active trajectory* and their corresponding projections on the segments joining all *inertia positions* and *passive positions* at each moment of time (pink dash line in Figure 6).

5. Conclusion, limitations and future works

5.1. Conclusion and limitations

This article illustrates some preliminary applications of the physics-based approach to supply chain resilience management, through first results, essentially conceptual, on a kinetic vision of resilience management. In this paper, by associating a simulation model to the presented decision framework, PoD, it is possible to predict the consequences of a disruption, an event, or a decision on a supply chain. This prediction is visually represented as a performance trajectory within the system's KPIs framework. Risks, opportunities and decisions are modelled from a 'what if' approach and their impacts on the supply chain are seen as deviations from the performance trajectory. Following that principle, this article shows how it is possible to benefit from this innovative approach to evaluate the resilience of a supply chain to disruptions. This resilience evaluation has been calculated as the surface between the expected trajectory (so-called 'inertia' or 'target' trajectory) and the perturbed trajectory (with or without corrective decisions and actions).

However, this vision is clearly strongly dependent on time and the duration on which the measure should be performed is hard to establish. This question of duration is also the main drawback and limitation of the resilience triangle from which this proposal is inspired. Theoretically, this duration should be defined according to the moment when the perturbed performance trajectory (*passive* or *active trajectories*) joins the reference performance trajectory (*inertia trajectory*). In the previous illustrative example of Section 4, the magnitude of the disruption (and/or the duration of the experiment, and/or the inefficiency of the countermeasure for the *active trajectory*) does not allow the *active trajectory* to actually join the *inertia trajectory*, which fundamentally shows no resilience. Nevertheless, the example still shows how the theoretical and abstract vision of the 'resilience triangle' can be extended and formally calculated thanks to the kinetic nature of the PoD paradigm. This question of duration is also the main drawback and limitation of the resilience triangle. With this view, this duration is therefore variable according to the system studied and the potentialities that impact it. However, according to Li et al. (2017), the lack of a bound for the measurement of

time, especially the recovery time (variable for each system and potentiality), means that the resilience triangle cannot be used to compare resilience between different systems. To overcome this problem and make the proposed measure comparable for any system, in the same way as the resilience measure proposed by Zobel (2011), a strict upper limit on recovery time should be defined, allowing a sufficiently long-time interval to be considered over which the loss of functionality can be determined. This value assumes of course that any system will return to its original state before this time limit (Li et al. 2017). This strict upper limit on recovery time offers the possibility of a standard measure for the time interval between each distance measurement (e.g. one thousandth of this time), thus allowing the surface between the different trajectories (expected and perturbed) to be approximated and compared for any system.

In addition to the temporal aspect of measuring resilience, its multidimensional nature also makes it difficult to assess (by multidimensional, we mean its measurement based on the evaluation over time of the impact of a potentiality on several KPIs). In order to facilitate the visualisation of performance trajectories, the performance space has been limited to three dimensions. Of course, for such a complex system, it is unlikely that decision-makers will limit themselves to observing three performance indicators. Actually, there might be dozens, hundreds or thousands of them. Although, 'some studies have addressed the multidimensional nature of resilience by aggregating the magnitude of deviation from equilibrium and the time to recovery of the performance profile to capture resilience' (Munoz and Dunbar 2015), notably through the use of the resilience triangle. Thus, the multidimensional nature of resilience tends to favour the use of an aggregate index over other forms of performance measurement (Munoz and Dunbar 2015). However, the use of an aggregation index does not allow for an accurate characterisation of resilience. It is in this case that the performance space will take all its importance, notably by its ability to be composed with as many dimensions as the number of KPIs. This capability allows us to assess distance between the expected trajectory and the perturbed trajectories, whatever the number of KPIs (even if it is not possible to visualise them beyond three dimensions).

5.2. Future works

However, being able to theoretically compute the overall performance of the observed system as a trajectory impacted by any event (positively or negatively) is clearly one great contribution of the PoD approach, it is mandatory to find a way to make these results handleable by decision-makers. Some first research works are currently

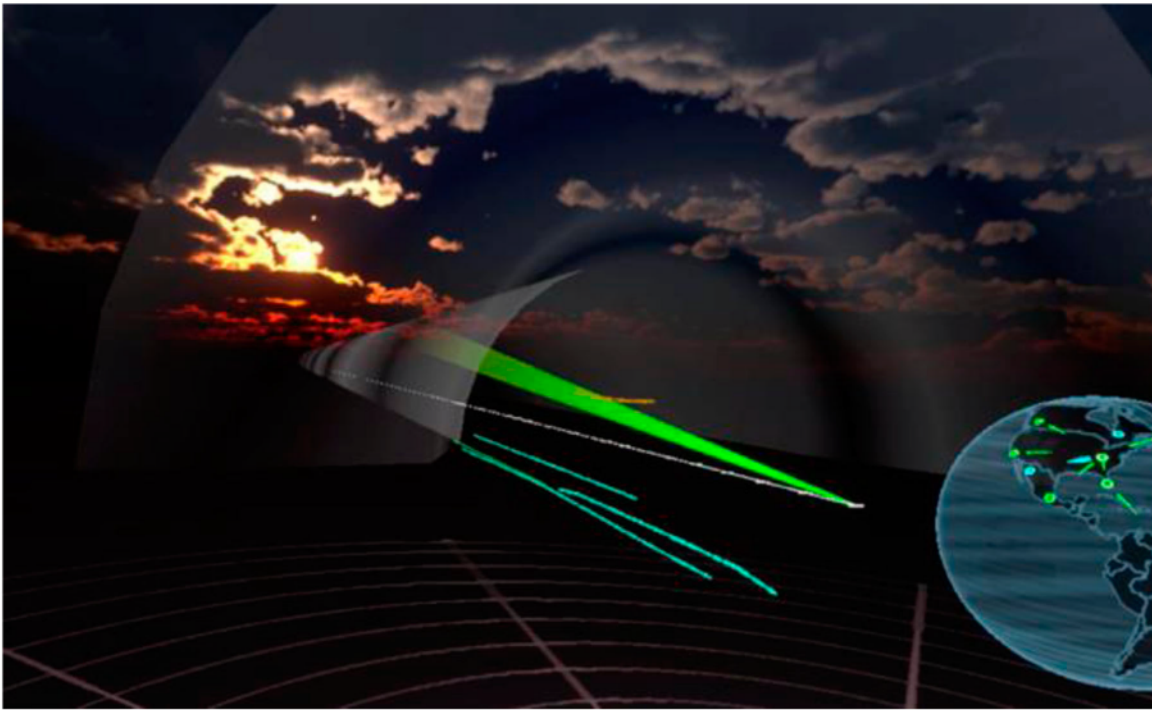


Figure 10. Immersive environment for PoD visualisation and interaction.

being conducted on the use of virtual and augmented realities (VR and AR) to immerse decision-makers in an abstract decision vision where they could visualise and feel the performance trajectories and interact efficiently with them (as shown in Figure 10).

In Figure 10, the ideal performance trajectory is represented by a perfectly straight white line (even though it has a more complicated trajectory in its original multi-dimensional space), while the actual performance trajectory is represented, relative to this white reference line, by a green line (which tends to be a cone to represent uncertainty). The coloured streams (blue, orange, etc.) represent events (risks or opportunities) that may occur and the grey vortex represents the target hyper tube. The world globe on the right presents the structure of the SC under consideration (so that the coloured events can be contextualised and better understood). This VR view could open the door to a new generation of immersive analytics exploiting theoretical contributions such as PoD and providing visualisation and interaction tools for decision-makers.

Besides, in addition to this immersive environment and the proposed resilience measure, the kinetics features of the PoD vision also allow us to consider a measure directly inspired by the notion of ecological resilience: resilience can be seen as the disruption that a system can face without becoming ineffective. More precisely, in the context of PoD, resilience can thus be seen as the perturbation force that an SC can take without becoming unable

to reach its expected target. As presented in Figure 4, the target hyper-tube can be considered as the sub-part of the space in which the performance trajectory should remain to be able to reach its performance objective. Considering these definitions, one can say that resilience could be defined as the set of forces that an SC can take without leaving the target hyper-tube (especially by activating counter forces). However, this hyper-tube is time dependent: the less effective the SC is, the more this hyper-tube will shrink and eventually disappear if the target cannot be reached anymore. To illustrate this idea, let us take the example of the writing of a 20-page document in 10 days, with a writing capacity of 5 pages per day. Initially, the target hyper-tube is quite wide: the writer can write 0, 1, 2, 3, 4 or 5 pages on the first day, the same on the second day, etc. and he may even decide to not write any page during the 16 first days. But obviously, when he reaches the 16th day, he only can write 5 pages per days on the 17th, 18th, 19th and 20th days. The hyper-tube did shrink to a line. And if the writer does not write 5 pages on each of these last days, there is no more solution and no more hyper-tube. This vision is on the one hand close to the notion of critical path, but on the other hand also close to the properties of some materials that are able to absorb shocks and impacts, to accumulate them to a certain level of accumulation at the end of which they break at the slightest shock.

With regards to the previous considerations and the PoD framework, SC resilience (by analogy with the

ecological resilience vision) can then be defined as the set of forces for which the SC is able to activate counterforce(s) which will allow its performance trajectory to remain within a doable target hyper-tube. The volume of the red hyper-cone presented in Figure 11 could thus be another measure of SC resilience: it corresponds to the space in which each force vector, representing one (or several) disruption(s) applied to the SC could be countered by managed forces (i.e. counter measures and decisions) maintaining the performance trajectory within a doable target hyper-tube. The SC cannot absorb an impact which force is outside of this volume. This new vision of resilience measurement implies: (1) being able to identify all the managed forces at each moment, (2) being able to measure their intensity and (3) being able to measure the global volume resultant of these forces. These points raise the question of the independence of the forces (which is at the heart of that approach) and therefore on the basis of which criteria is it possible to sum the forces?

The question of obtaining or estimating the forces is primordial for this approach. In this article, the forces are estimated by simulation. Simulation has been used to consider all the stochastic factors that can be associated with a disturbance: its date of appearance, its duration and its impacts on the system attributes. For instance, identifying the micro-impacts of natural disruptions such as hurricanes is not an easy task. Currently, there is no scientific method to accurately quantify and predict the long-term evolution and spatial distribution of hurricanes, nor their impacts on society's infrastructure (Linkov et al. 2014), such as an SC for example. Simulation allows to model the internal dynamics of a

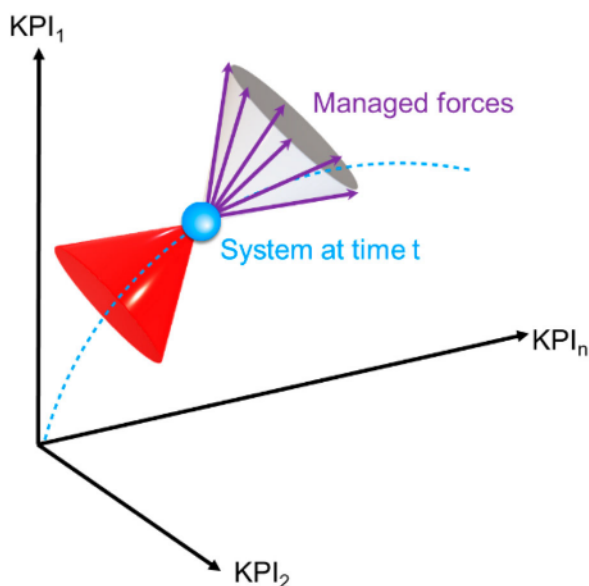


Figure 11. Resilience hyper-cone.

system (as a *black box*) at a granularity level which permits to observe the impact of a disruption while considering all micro-consequences. For example, it can be used to model the micro-consequences of the hurricane by picking randomly among the warehouses and roads of the impacted region according to a quasi-constant percentage and making them inoperative. This is why, simulation has also been used to link the *description space* and the *performance space*: Transforming micro-impacts to macro-impacts. The use of simulation as a link between these two spaces opens the door to a wider generalisation: studying the space of possibilities and the 'density' of the description and performance spaces in order to formalise the forces. In this context, density refers to the degree of ease or difficulty in reaching a point in the performance space. In a way, the study of the density of the performance space could show that some areas of the space are more or less accessible (depending on time of course) via the inflicted and managed forces. Conversely, some parts of this space could be inaccessible by any combination of the identified forces available (i.e. by any combination of the attributes of the system, any variation of the parameters of the associated digital model). This vision can be understood by analogy with the electronic density of the air which determines the course of a lightning bolt which travels the most advantageous path to strike the ground. The study of the density of the space, combined with the 'cone' vision of resilience introduced in the previously, could also allow us to determine the areas where the system is more or less resilient and ultimately the best combinations of forces to make the system resilient. To do this, it is necessary to make the simulation model sufficiently exhaustive and covering to extract, following sensitivity analyses, a generic formulation of the impact of an event on a type of system in the form of a force disturbing the performance trajectory. Of course, it would be possible to use other more formal tools (mathematical modelling, machine learning, etc.) to create the link between these two spaces and model the dynamics of a system. The use of neural networks could be another solution. However, this solution requires a large amount of training data, which means that the sensitivity analysis campaigns mentioned above must first be carried out. The big advantage over simulation is that once trained correctly, the neural network could (1) avoid having to formalise the force and (2) increase the range of possible scenarios covered.

Physics in addition to contributing to the question of forces, trajectory and movement, could also contribute to providing other measures of the resistance and absorption capacity of a system, in particular by the mechanics of the solid by studying the deformations of the solid following a disturbance, but also the ability of a system to

change its own attributes (i.e. its shape from the point of view of physics) to optimise (maximise or minimise) its susceptibility to a potentiality. Work on energy can also be carried out to determine the cost of maintaining a system in its resilience cone.

Note

1. It is important to notice that this value is for a duration of 10 months (the strike occurring 2 months after the beginning of the year and the experiment lasting 365 days). The time duration must be defined and discussed; else it is meaningless.

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Data availability statement

The data that support the application of the PoD approach to resilience assessment are only available from the corresponding author upon reasonable request.

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