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Simultaneous structural–operational control of supply chain dynamics and resilience

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Abstract

This study develops a resilience control model and computational algorithm for simultaneous structural–operational design of supply chain (SC) structural dynamics and recovery policy control. Our model integrates both structural recovery control in the SC as a whole and the corresponding functional recovery control at individual firms in the SC. Such a comprehensive combination is unique in literature and affords more realistic application to SC resilience control decisions. The focus of our study is to advance insights into feedback-driven understanding of resilience within open system control context. We construct a model that allows theorizing the notion of SC resilience within a disruption dynamics profile as a product of degradation and recovery control loops and examine the conditions for changes of disruption profile states. We show that the deviations from the resilient trajectory are associated with structural and performance degradation, and the recovery operations in structural adaptation yield the performance recovery. We contribute to existing works by comprehensively modelling structural dynamics and operational dynamics within an integrated feedback-driven framework to enable proactive SC resilience control. Our approach conceptualizes a new perspective as compared to the more common closed system view where SC resilience is treated from the performance equilibrium point of view. The proposed approach can help explain and improve the firms' operations in multiple ways. First, the combination of structural and functional dynamics can help revealing the latent supply–demand allocations which would be disrupted in case of particular changes in the SC design and suggest re-allocations of supply and demand Second, the model can be used to perform the dynamic analysis of SC disruption and recovery and to explain the reasons of SC performance degradation and restoration. This analysis can be further used to improve SC risk mitigation policies and recovery plans.

Keywords Supply chain resilience · Structural dynamics · Disruption · Recovery · Control

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1 Introduction

Resilience of the supply chain (SC) is its ability to sustain or restore functionality and performance following a significant change (e.g., a capacity disruption due to an explosion at a factory) in the system and environmental conditions (Gunasekaran et al. 2015; Tukamuhabwa et al. 2015; Jain et al. 2017; Dolgui et al. 2018, 2019; Ivanov 2018; Hosseini et al. 2019). While development of resilient SC designs is desirable and indeed critical to withstand the disruptions, exploiting the resilience capabilities to achieve the target performance outcomes through effective recovery is becoming increasingly important. Recent natural disasters and man-made catastrophes highlighted the high vulnerability of modern SCs, their disruption risk exposure and the importance of timely and effective recovery policy deployments (Tang 2006; Simchi-Levi et al. 2015; He et al. 2018; Ivanov 2018; Khojasteh 2018; Macdonald et al. 2018; Cavalcantea et al. 2019; Dolgui et al. 2019; Hosseini et al. 2019b).

There is a strong and growing literature on SC resilience that includes multiple perspectives of discrete optimization, simulation, and control research (Yadav et al. 2011; Spiegler et al. 2012, 2016; Ivanov and Sokolov 2013; Ivanov et al. 2014a, b; Hosseini et al. 2016; Chen et al. 2017; Reyes Levalle and Nof 2017; Sawik 2017; Altay et al. 2018; Pavlov et al. 2018). One difficulty in resilience control in dynamics are the changes in structural states (i.e., capacity disruptions) of SC elements which result in degradation and recovery of SC operational processes and performance and form open system context. Such scenarios are challenging by the resulting information feedbacks and can be difficult to model as a linear relationship in discrete optimization, but are convenient to describe using the continuous control paradigm (Ivanov et al. 2016b, 2018b). A growing body of empirical literature found positive associations that some of the SC resilience success is attributable to balancing vulnerability and recoverability capabilities (Blackhurst et al. 2011; Dubey et al. 2018). Though, little attention has been directed to the operationalization of those capabilities in quantitative studies even if such an integration has been highlighted in literature as an important precondition to comprehensively analyse the SC resilience (Christopher and Peck 2004; Wang 2008; Blackhurst et al. 2011; Govindan et al. 2016; Bode and Macdonald 2017; Ivanov and Rozhkov 2017; Elluru et al. 2017; Dubey et al. 2018; Hosseini et al. 2019a; Pavlov et al. 2019). Considerable ambiguity remains, however, as to how the performance degradation and recovery profiles can be modelled with consideration of multiple feedback loops. Such scenarios are challenging to model as a linear relationship in discrete optimization, but are convenient to describe using the continuous control paradigm.

The focus of our study is to advance insights into feedback-driven understanding of resilience within open system context. We theorize the notion of SC resilience within a disruption dynamics trajectory as a product of degradation and recovery control loops and examine the conditions for changes of disruption profile states. We show that the deviations from the resilient trajectory are associated with structural and performance degradation, and the recovery operations in structural adaptation yield the performance recovery.

In control terms, SC resilience is a trajectory that is manifested in several degradation and recovery states. The control of transitions between different stages in the disruption profile is feedback-driven according to the changes in state variables and SC performance. As such our approach takes a completely different perspective as compared to the more common closed system view where SC resilience is treated from the performance equilibrium point of view.

The feedback-driven disruption profiles usually includes a disruptive event, degradation, the recovery preparations, and the recovery stages. Notwithstanding the methodology used, the literature recognizes that while the degradation process follows the disruption and is widely out of control, the recovery process control needs to be investigated further and is of vital importance. One of the dominant themes in SC resilience literature, the disruption profile constituted in the work by Sheffi (2005) and further used or extended in numerous studies includes eight phases: preparation actions, the disruptive event, the first response, the initial impact, the full impact, the recovery preparations, and the recovery and long term impact. In control terms, this disruption profile can be presented as a trajectory that is comprised of several degradation and recovery states.

The transition between these states is accompanied by changes in SC structures, i.e., structural dynamics is encountered (Ivanov 2018). Recovery control is comprised of both structural and functional factors. Therefore, a problem of simultaneous structural–operational synthesis of SC recovery policies arises. More specifically, structural dynamics control implies the observation of structural constancy in the pre-disruption period, structural degradation changes in the post-disruption period, and control of structural changes in the recovery period towards the planned output performance such as annual sales, market share, or customer service level.

Our study makes substantive contributions. First, recent research by Ho et al. (2015), Rangel et al. (2015), Ivanov et al. (2017b), Sawik (2017), Reyes Levalle and Nof (2017), Blackhurst et al. (2018), Yoon et al. (2018), Namdar et al. (2018) and Tan et al. (2019) point to examining the impacts of different structural variations on SC performance. This literature build on the theoretical perspective that differences in the structural states can be explicitly observed between the system state at the moment when adjustment recovery decisions are starting to be prepared on the basis of feedback information and the system state at the moment of decision implementation. In other words, delayed feedbacks occur due to system inertia. The recovery decisions are then implemented in the SC which is structurally and functionally different from the SC that has been observed after the disruption and considered for reconfiguration decision planning. As such, the need for proactive control models arises for SC reconfiguration. Simultaneous control of both structural transformations and the related recovery policies seeks to bring the discussion forward, providing some ideas and rigorous technical elaborations on how to think and act in relation to these challenges. The literature analysed, at the structural level, targets semantic network analysis in order to identify the underlying interdependencies between network graph forms and SC robustness, flexibility, adaptability, and resilience (Basole and Bellamy 2014; Lücker and Seifert 2017; Giannoccaro et al. 2018; Lücker et al. 2018). Left ignored, however, was the integration of degradation and recovery profiles in a dynamic, information feedback driven framework—a distinctive contribution made by our study.

Second, the literature analysis shows that complex networks have become more vulnerable to severe disruptions which change SC structures and are involved with SC structural dynamics. Ivanov et al. (2010) developed a general notion of SC network dynamics control at the structural level. Spiegler et al. (2012, 2016) analyzed SC resilience using extended feedback control at the production-inventory parametric level. An attempt to integrate structural and functional levels was undertaken by Ivanov et al. (2018a). They analyzed SC resilience as a result of the schedule optimization of a recovery control policy under sever perturbations with interval disturbance data and the help of attainable sets. Schedule optimization for the recovery control policy was performed with the help of optimal program control where schedules were presented as optimal control trajectories in line with studies by Khmelnitsky et al. (1997), Ivanov and Sokolov (2012) and Ivanov et al. (2016b, c). For resilience analysis, a comparison of different optimal control trajectories outputs under disruptions with disruption-free outputs was used. None of these studies, though, formally and rigorously described the structural dynamics control in the SC in the open system context with a comprehensive consideration of both disruptions and recovery. Such a combination is explicitly considered in our study and unique in literature. It mimics the complexity of business reality affording more realistic applications to making strategic SC resilience management decisions.

Our study introduces a new resilience control model and computational algorithm for simultaneous structural–operational design of SC structural dynamics and recovery policy control that integrates both structural recovery control in the SC as a whole and the corresponding functional recovery control at individual firms in the SC. Such a comprehensive combination is unique in literature and affords more realistic application to SC resilience control decisions. The focus of our study is to advance insights into feedback-driven understanding of resilience within open system control context. We construct a model that allows the resilience to be explicitly considered within a disruption dynamics profile as a product of degradation and recovery control loops. We contribute to existing works by comprehensively modelling structural dynamics and operational dynamics within an integrated feedback-driven framework to enable proactive SC resilience control. In control terms, SC resilience is a trajectory that is manifested in several degradation and recovery states. The control of transitions between different stages in the disruption profile is feedback-driven according to the changes in state variables and SC performance.

Our approach conceptualizes is a new perspective as compared to the more common closed system view where SC resilience is treated from the performance equilibrium point of view. The findings suggest that our model can be of value for solving the problems of simultaneous structural–operational synthesis with consideration of intermittent processes and SC recovery control. Our model can also help manage resilience in situations when structural dynamics and functional dynamics need to be analysed within an integrated framework to enable proactive SC resilience control. For example, Nissan was able to efficiently recover from severe disruptions in their SC caused by earthquake and tsunami in Japan in 2011 because they predicted different disruption scenarios and were able to quickly deploy the reconfiguration paths (Schmidt and Simchi-Levi 2013). PepsiCo is using a combination of structural and functional resilience instruments (e.g., facility backups and supplier flexibility, respectively) (Banker 2016). In case of structural changes, those companies are able to modify the functions of their suppliers by re-allocating supply and demand.

The remainder of this study is designed as follows. Section 2 is devoted to literature analysis. In Sect. 3, the structural dynamics control framework for SC resilience is presented. Section 4 develops generalized models of structural dynamics control and optimal recovery policy scheduling. Subsequently, a computational algorithm is presented in Sect. 5. Section 6 concludes the paper by summarizing the most important results of this study and outlining future research issues.

2 Literature review

Disruptions and the resulting ripple effect cause SC structural changes, also referred to as SC structural dynamics (Ivanov et al. 2010; Ivanov 2018). Structural SC properties have a crucial impact on the ripple effect and SC robustness and resilience (Xia et al. 2004; Nair and Vidal 2011; Kamalahmadi and Mellat-Parast 2016; Tang et al. 2016; Chen et al. 2017).

With regards to the structural perspective, Mizgier et al. (2013, 2015), Sokolov et al. (2016) and Mizgier (2017) revealed that the model outputs in terms of performance impact of SC disruption cannot be completely explained by direct effect and should rather be considered in terms of disruption propagations and the resulting chains of indirect effects. This finding was further explained in the study by Chen et al. (2017) and Macdonald et al. (2018), which demonstrated the impact of indirect effects and disruption propagations on SC performance using the Bayesian method and discrete-event simulation, respectively. The findings of works in this area show that SC robustness and resilience should not merely be based on a straightforward disruption magnitude analysis, but rather seek trajectories of how different disruption scenarios influence the severity of network degradation (Pavlov et al. 2019). To this end, the direct effect of the weakest link on SC performance does not always represent the worst-case scenario, and it must be considered a multiple dimension which is subject to the entire range of disruption propagation and the resulting indirect effects of the chain of capacity reductions.

Moreover, the ripple effect in the SC occurs, which describes disruption propagation downstream in the SC and the resulting changes in the SC structures (Liberatore et al. 2012; Ivanov et al. 2014a, b; Sokolov et al. 2016; Levner and Ptuskin 2018; Pavlov et al. 2018). At the same time, structural changes inevitably pertain to functional changes in SC operational policies. This implies the state changes of SC structural elements (e.g., supplier, factories, warehouses) subject to production, inventory, and transportation control policies. Recent control literature has mostly addressed structural and functional aspects of SC resilience as isolated from each other.

With regards to the functional perspective, control theory methodologies have been applied to SC disruption analysis. Ivanov et al. (2016a, 2017a) considered speed and time of recovery and developed a hybrid control-based model blended with linear programming in order to analyze different recovery policies with regards to performance impact. They showed the impact of transportation and warehouse capacity on SC service levels and costs.

The studies by Spiegler et al. (2012, 2016) underlined that non-negativity nonlinearity can cause limit cycles, which are oscillations intrinsic to nonlinear production and the inventory control system itself and not imposed by demand. Another finding is that nonlinearity in the shipment system has no impact on the order rate and work-in-process inventory. Nonlinearity in the shipment system is frequency-dependent, and not only high demand levels, but also medium–low frequency demands can cause higher backlogs. Spiegler et al. (2016) applied nonlinear control theory to investigate the underlying dynamics and resilience of a grocery SC. The authors presented a control loop for the distribution center system.

Ivanov et al. (2013, b) modeled SC structural dynamics using intervals of structural constancy during which the SC structures did not change. The transitions between intervals of structural constancy were fixed and driven by some fixed disruption scenarios. Mathematical optimization was used to optimize the material flow reconfiguration in multi-stage, multi-product SCs. Pavlov et al. (2018) considered SC structural dynamics and reconfiguration simultaneously with a resiliency analysis. They used a hybrid fuzzy-probabilistic approach and described SC networks as structural genomes. The results allowed the comparison of different SC structures in terms of resilience to disruption propagation and consideration of recovery. It also allowed for the identification of groups of critical suppliers whose failure would interrupt the SC operation. However, SC structural dynamics in these studies was considered as a given input without explicit control modeling. Ivanov et al. (2018a) developed a control model for SC resilience analysis with consideration of recovery dynamics. They used attainable sets to quantify the SC resilience as a product of deviation from the planned performance by means of interval control policy variations. This analysis was restricted to the functional and parametrical dynamics and has not included the incorporation of the structural dynamics level.

The present study furthers the research by extending the problem statement from an operational scheduling model to the structural control level and incorporating SC structural and functional synthesis dynamics under disruptions and recovery. For the first time, SC structural and functional synthesis dynamics are presented in an integrated model complex with consideration of disruptions and recovery. Distinctively and principally, our study takes a dynamic perspective on SC resilience control while avoiding two major inconveniences, namely information feedbacks and state changes in SC design. Such a perspective appears to be more relevant in a practical decision environment, relative to the inherent feedbacks in SC resilience control. Utilizing the outcomes of this research could support the design of resilient supply networks with observing and controlling a large number of feedbacks: critical events with degradation risks can be identified and efficient recovery policies can be developed.

3 Structural dynamics framework for supply chain resilience control

Consider the SC structural dynamics in Sheffi's (2005) framework (Fig. 1).

Recall that SC resilience represents the system's ability to sustain or restore functionality and performance after disturbances. Let us introduce some definitions that explain our concept of SC resilience analysis in terms of structural dynamics control.

Functional state is a generalized characteristic of SC elements (i.e., suppliers, customers, warehouses, and retailers) with regards to their ability to operate according to planned performance; without loss of generality, three functional states will be considered (cf. Fig. 1), i.e., planned operation, partially disrupted operation, and disrupted operation.

SC state is a generalized characteristic of the SC as a whole. It depicts both the functional states of SC elements and the states of the relations (connections) between them. Analo-

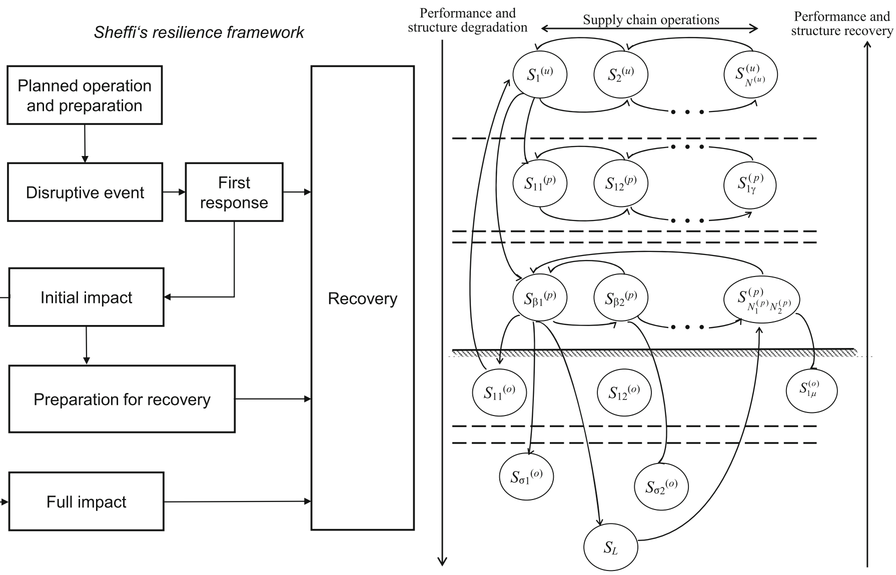

Fig. 1 SC structural dynamics and resilience profile

gously to functional states, we consider planned operation, partially disrupted operation, and disrupted operation SC states.

Structural state is the entirety of SC states in different structures.

SC structural dynamics control is the process of SC transition between different structural states when it is impacted by different disturbances.

The structural states (cf. Fig. 1) can be classified as planned control states $S^{(u)} = \left\{S_{\alpha}^{(u)}\right\}$, $\alpha = 1, \ldots, N^{(u)}$, partially disrupted states $S^{(p)} = \left\{S_{\beta\gamma}^{(p)}\right\}$, $\beta = 1, \ldots, N_1^{(p)}$, $\gamma = 1, \ldots, N_2^{(p)}$ with β-level of operation capability and γ-level of degradation, and disrupted states $S^{(o)} = \left\{S_{\delta\mu}^{(o)}\right\}$, $\delta = 1, \ldots, N_1^{(0)}$, $\mu = 1, \ldots, N_2^{(o)}$ subject to δ-disruption type and μ-losses. For example, S_L is the full degradation state where all SC elements are disrupted and degradation level is at its maximum.

According to Ivanov (2018, p. 56), state transitions can be classified into four categories:

D—transitions caused by SC disruptions leading to a decrease in capability and/or performance,

H—transitions caused by disruption propagation through the SC, i.e., by the ripple effect, and

B—transitions caused by SC recovery.

In Fig. 1, D—transitions follow the degradation arrow, H—transitions follow the disruption arrow, and B—transitions follow the recovery arrow.

Assume that, due to structural dynamics, the SC can take the shape of one of the structures $G = \left\{ G_\chi, \chi \in W\right\}$ from the set of alternative SC structures, where W is a set of alternative structure numbers. The dynamic alternative multi-graph (1) is used to describe structural dynamics in line with (Ivanov et al. 2010)

$$G_\chi^t = \left\langle X_\chi^t, F_\chi^t, Z_\chi^t \right\rangle, \tag{1}$$

where the subscript χ characterizes the SC structure alternative; the time point t belongs to a given set T; $X_\chi^t = \{x_{\langle\chi\rangle}^t, \chi \in L_\chi\}$ is a set of elements of the structure G_χ^t (the set of dynamic alternative multi-graph nodes, e.g., suppliers) at the time point t; $F_\chi^t = \{f_{\langle\chi,l,l'\rangle}^t, l, l' \in L_\chi\}$ is the set of arcs of the dynamic alternative multi-graph; G_χ^t represents available transportation channels at time t; and $Z_\chi^t = \{z_{\langle\chi,l,l'\rangle}^t, l, l' \in L_\chi\}$ is a set of SC node and arc parameters such as capacity and inventory.

For example, in the case of six possible SC structures, a SC state can be defined as the inclusion (Eq. 2).

$$S_\delta \subseteq X_1^t \times X_2^t \times X_3^t \times X_4^t \times X_5^t \times X_6^t,\ \delta = 1, \ldots, K_\sigma. \tag{2}$$

Now we obtain the set of the structural states (Eq. 3):

$$S = \{S_\delta\} = \{S_1, \ldots, S_{K_\sigma}\}. \tag{3}$$

Allowable transitions from one structural state to another, i.e., structural dynamics, can be expressed by maps, as shown in Eq. (4):

$$\Pi_{\langle\delta,\delta'\rangle}^t \colon S_\delta \to S_{\delta'}. \tag{4}$$

We assume that each structural state at time $t \in T$ is defined by a composition (Eq. 3). Now, the *problem* of SC structural dynamics control can be considered as the selection of structural states $S_\delta^* \in \{S_1, S_2, \ldots, S_{K_\sigma}\}$ and transition sequences using composition $\Pi_{\langle\delta_1,\delta_2\rangle}^{t_1} \circ$

$\Pi^{t_2}_{\langle\delta_2,\delta_3\rangle} \circ \cdots \circ \Pi^{T_f}_{\langle\delta',\delta\rangle}$ under the optimization of some performance criteria, e.g., annual sales or customer service levels.

4 Mathematical models

According to the framework defined in Sect. 3, three levels of resilient SC control need to be analyzed, i.e.,

- Structural dynamics control states with regards to the transition of the δ-SC structural state,
- Structural state control with regards to the SC in the particular χ-structure,
- Functional dynamics control with regards to dynamics control of the *i*-structural element in the SC (e.g., suppliers, factories, warehouses), and
- Operational dynamics control level with regards to scheduling and routing control for dynamics in customer order fulfillment, processing and transportation channel utilization, and material supply and consumption dynamics (i.e., inventory dynamics).

This section presents mathematical models for the first three aforementioned levels. The fourth level, i.e., the operational control level, is also integrated into the framework presented in the unified methodological principles of optimal control. Because of the limited length of this paper, we restrict ourselves to the first three levels, and refer interested readers to the studies (Ivanov and Sokolov 2012; Ivanov et al. 2014c, 2016b, c, d).

The formalization of SC structural dynamics control will be performed by the dynamic interpretation of operations execution in the SC. Three types of operations will be considered:

- Structural operations, i.e., reconfiguration or recovery operations for transition between structural states,
- SC operations, i.e., operations for running the processes at the SC level, and
- Functional operations, i.e., operations for running the processes at the SC element level.

4.1 Structural state dynamics control (model $M_c^{(1)}$)

Consider the following notations:

$x^{(c,1)}_{\delta\eta_1}(t)$ is a variable characterizing the execution of the operation $D^{(c,1)}_{\delta\eta_1}$ that describes the SC structural operation in the state S_δ at η_1 control cycle;

$\tilde{x}^{(c,1)}_{\delta}(t)$ is a variable characterizing the execution of the operation $\tilde{D}^{(c,1)}_{\delta}$ that describes the structural transition (e.g., recovery) from current state $S_{\delta'}$ to the required state S_δ (in some cases, $\delta' = \delta$);

$\tilde{\tilde{x}}^{(c,1)}_{\delta\eta_1}(t)$ is an auxiliary variable that quantifies the duration of the time interval after completing the operations $D^{(c,1)}_{\delta\eta_1}$;

$\tilde{h}^{(c,1)}_{\delta'\delta}(t)$ is a given constant that quantifies the transition time from current state $S_{\delta'}$ to the required state S_δ;

$u^{(c,1)}_{\delta\eta_1}(t)$ is a binary control variable that equals 1 if the operation $D^{(c,1)}_{\delta\eta_1}$ needs to be fulfilled, and 0 otherwise;

$\tilde{\tilde{u}}^{(c,1)}_{\delta\eta_1}$ is an auxiliary control variable that equals 1 at the moment of operation $D^{(c,1)}_{\delta\eta_1}$ completion, and 0 otherwise;

$\tilde{u}^{(c,1)}_{\delta}(t)$ is a binary control variable that equals 1 if the transition from current state $S_{\delta'}$ to the required state S_δ needs to be executed, and equals 0 otherwise.

$a_{\delta}^{(c,1)}$ is the given duration of the structural state S_{δ}.

Structural dynamics control model

$$\dot{x}_{\delta\eta_1}^{(c,1)} = u_{\delta\eta_1}^{(c,1)}; \quad \dot{\tilde{x}}_{\delta}^{(c,1)} = \sum_{\delta'=1}^{K_\Delta} \frac{\tilde{h}_{\delta'\delta}^{(c,1)} - \tilde{x}_{\delta}^{(c,1)}}{\tilde{x}_{\delta'}^{(c,1)}} \tilde{u}_{\delta'}^{(c,1)}; \quad \dot{\tilde{\tilde{x}}}_{\delta\eta_1}^{(c,1)}$$
$$= \tilde{\tilde{u}}_{\delta\eta_1}^{(c,1)} \quad \delta = 1, \ldots, \mathrm{K}_\Delta; \quad \eta_1 = 1, \ldots, \text{Œ}_1. \tag{5}$$

Constraints

$$\sum_{\delta=1}^{K_\Delta} \left(u_{\delta\eta_1}^{(c,1)}(t) + \tilde{u}_{\delta}^{(c,2)} \right) \leq 1, \quad \forall \eta_1; \quad u_{\delta\eta_1}^{(c,1)}(t) \in \{0, 1\}; \quad \tilde{u}_{\delta}^{(c,1)}(t), \ \tilde{\tilde{u}}_{\delta\eta_1}^{(c,1)}(t) \in \{0, 1\}; \tag{6}$$

$$\sum_{\eta_1=1}^{\text{Œ}_1} u_{\delta\eta_1}^{(c,1)} \cdot \tilde{x}_{\delta}^{(c,1)} = 0, \quad u_{\delta\eta_1}^{(c,1)} \left(a_{\delta(\eta_1-1)}^{(c,1)} - x_{\delta(\eta_1-1)}^{(c,1)}(t) \right) = 0; \tag{7}$$

$$\tilde{u}_{\delta}^{(c,1)} \left[\sum_{\chi' \in \Gamma_{\delta 1}^{(2)}} \sum_{\omega' \in \Gamma_{\delta 2}^{(2)}} \tilde{x}_{\chi'\omega'}^{(c,2)} + \prod_{\chi'' \in \Gamma_{\delta 3}^{(2)}} \prod_{\omega'' \in \Gamma_{\delta 4}^{(2)}} \tilde{x}_{\chi''\omega''}^{(c,2)} \right] = 0; \tag{8}$$

$$\tilde{\tilde{u}}_{\delta\eta_1}^{(c,1)} \left(a_{\delta\eta_1}^{(c,1)} - x_{\delta\eta_1}^{(c,1)}(t) \right) = 0. \tag{9}$$

Boundary conditions

$$t = T_0\colon \ x_{\delta\eta_1}^{(c,1)}(T_0) = \tilde{\tilde{x}}_{\delta\eta_1}^{(c,1)}(T_0) = 0; \quad \tilde{x}_{\delta\eta_1}^{(c,1)}(T_0) \in \mathrm{R}^1; \tag{10}$$

$$t = T_f\colon \ x_{\delta\eta_1}^{(c,1)}(T_f) \in \mathrm{R}^1; \quad \tilde{x}_{\delta\eta_1}^{(c,1)}(T_f) \in \mathrm{R}^1; \quad \tilde{\tilde{x}}_{\delta\eta_1}^{(c,1)}(T_f) \in \mathrm{R}^1. \tag{11}$$

Functionals

$$J_{1\delta}^{(c,1)} = \sum_{\eta_1=1}^{\text{Œ}_1} x_{\delta\eta_1}^{(c,1)}(T_f); \tag{12}$$

$$J_2^{(c,1)} = \sum_{\eta_1=1}^{\text{Œ}_1} \sum_{\delta=1}^{K_\delta} \left(a_{\delta}^{(c,1)} - x_{\delta\eta_1}^{(c,1)}(T_f) \right)^2; \tag{13}$$

$$J_{3\delta}^{(c,1)} = \sum_{\delta=1}^{K_\delta} \int_{T_0}^{T_f} \tilde{u}_{\delta}^{(c,1)}(\tau) d\tau; \tag{14}$$

Equation (5) describes the dynamics of SC structure degradation and recovery. In particular, it shows the durations of different structural states (cf. Fig. 1) and the transitions between the structural states. The introduction of Eq. (5) is a distinctive feature of the model reported in this paper as compared to other control models for SC resilience (Spiegler et al. 2012; Ivanov and Sokolov 2013; Reyes Levalle and Nof 2017; Ivanov et al. 2018a). Constraints (6)–(9) determine the sequence of the control inputs. $\Gamma_{\delta 1}^{(2)}, \Gamma_{\delta 3}^{(2)}, \Gamma_{\delta 2}^{(2)}, \Gamma_{\delta 4}^{(2)}$ in Eq. (8) are the sets of structure and structural state numbers. This equation connects the structural state dynamics control (model $M_c^{(1)}$) and structural state control (model $M_c^{(2)}$). Equation (12) allows the estimation of the total duration of the SC in S_δ. The Mayer's functional (13) estimates total losses from violating the given duration of the structural state. Equation (14) allows the estimation of the total duration of the transitions between the states. Equations (12)–(14) can be used by decision-makers to form multi-objective functions according to individual preferences.

4.2 Structural state control (model $M_c^{(2)}$)

Consider the following notations:

$x_{\chi\omega\eta_2}^{(c,2)}(t)$ is a variable characterizing the execution of operation $D_{\chi\omega\eta_2}^{(c,2)}$ that describes the structure G_χ's behavior in the state $S_{\chi\omega}$ at the η_2 control cycle; ω is the running number index of the structural states;

$\tilde{x}_{\chi\omega}^{(c,2)}(t)$ is a variable characterizing the execution of operation $\tilde{D}_{\chi\omega}^{(c,2)}$ that describes the structure G_χ's transition process from the current state $S_{\chi\omega'}$ into the desired state $S_{\chi\omega}$;

$\tilde{\tilde{x}}_{\chi\omega\eta_2}^{(c,2)}(t)$ is an auxiliary variable that quantifies the duration of the time interval after completion of operation $D_{\chi\omega\eta_2}^{(c,2)}$;

$\tilde{h}_{\omega'\omega\chi}^{(c,2)}$ is a given constant that quantifies the transition time of the structure G_χ from the current state $S_{\chi\omega'}$ into the desired state $S_{\chi\omega}$;

$u_{\chi\omega\eta_2}^{(c,2)}(t)$ is a binary control variable that equals 1 if the operation $D_{\chi\omega}^{(c,2)}$ needs to be executed, and equals 0 otherwise;

$\tilde{\tilde{u}}_{\chi\omega\eta_2}^{(c,2)}(t)$ is an auxiliary control variable that equals 1 at the moment of operation $D_{\chi\omega\eta_2}^{(c,2)}$ completion, and 0 otherwise;

$\tilde{u}_{\chi\omega}^{(c,2)}(t)$ is a binary control variable that equals 1 if the transition of the structure G_χ from current state $S_{\chi\omega'}$ to the required state $S_{\chi\omega}$ needs to be executed, and equals 0 otherwise.

Structural state control model

$$\dot{x}_{\chi\omega\eta_2}^{(c,2)} = u_{\delta\omega\eta_2}^{(c,2)};\quad \dot{\tilde{x}}_{\chi\omega}^{(c,2)} = \sum_{\omega'=1}^{K_\Omega} \frac{\tilde{h}_{\omega'\omega\chi}^{(c,2)} - \tilde{x}_{\chi\omega}^{(c,2)}}{\tilde{x}_{\chi\omega'}^{(c,2)}} \tilde{u}_{\chi\omega'}^{(c,2)};\quad \dot{\tilde{\tilde{x}}}_{\chi\omega\eta_2}^{(c,2)} = \tilde{\tilde{u}}_{\chi\omega\eta_2}^{(c,2)};\qquad \chi = 1,\ldots,K_c; \omega = 1,\ldots,K_\Omega; \eta_2 = 1,\ldots,Œ_2. \tag{15}$$

Constraints

$$\sum_{\omega=1}^{K_\Omega}\left(u_{\chi\omega\eta_2}^{(c,2)}(t) + \tilde{u}_{\chi\omega'}^{(c,2)}\right) \le 1,\quad \forall\chi,\forall\eta_2;\quad u_{\chi\omega\eta_2}^{(c,2)}(t) \in \{0,1\};\quad \tilde{u}_{\chi\omega}^{(c,2)}(t), \tilde{\tilde{u}}_{\chi\omega\eta_2}^{(c,2)}(t) \in \{0,1\}; \tag{16}$$

$$\sum_{\eta_2=1}^{Œ_2} u_{\chi\omega\eta_2}^{(c,2)} \cdot \tilde{x}_{\chi\omega}^{(c,2)} = 0,\quad u_{\chi\omega\eta_2}^{(c,2)}\left(a_{\chi\omega(\eta_2-1)}^{(c,2)} - x_{\chi\omega(\eta_2-1)}^{(c,2)}(t)\right) = 0; \tag{17}$$

$$\tilde{u}_{\chi\omega}^{(c,2)}\left[\sum_{i'\in\Gamma_{\chi\omega1}^{(3)}}\sum_{w'\in\Gamma_{\chi\omega2}^{(3)}}\sum_{f'\in\Gamma_{\chi\omega3}^{(3)}} \tilde{x}_{i'w'f'}^{(c,3)} + \prod_{i'\in\Gamma_{\chi\omega4}^{(3)}}\prod_{w''\in\Gamma_{\chi\omega5}^{(3)}}\prod_{f''\in\Gamma_{\chi\omega6}^{(3)}} \tilde{x}_{i''w''f''}^{(c,3)}\right] = 0; \tag{18}$$

$$\tilde{\tilde{u}}_{\chi\omega\eta_2}^{(c,2)}\left(a_{\chi\omega\eta_2}^{(c,2)} - x_{\chi\omega\eta_2}^{(c,2)}\right) = 0. \tag{19}$$

Boundary conditions

$$t = T_0:\ x_{\chi\omega\eta_2}^{(c,2)}(T_0) = \tilde{\tilde{x}}_{\chi\omega\eta_2}^{(c,2)}(T_0) = 0;\quad \tilde{x}_{\chi\omega}^{(c,2)}(T_0) \in \mathsf{R}^1; \tag{20}$$

$$t = T_f:\ x_{\chi\omega\eta_2}^{(c,2)}(T_f) \in \mathsf{R}^1;\quad \tilde{x}_{\chi\omega\eta_2}^{(c,2)}(T_f) \in \mathsf{R}^1;\quad \tilde{\tilde{x}}_{\chi\omega\eta_2}^{(c,2)}(T_f) \in \mathsf{R}^1. \tag{21}$$

Functionals

$$J_{1\chi\omega}^{(c,2)} = \sum_{\eta_2=1}^{Œ_2} x_{\chi\omega\eta_2}^{(c,2)}(T_f); \tag{22}$$

$$J_{2\chi\omega}^{(c,2)} = \sum_{\eta_2=1}^{Œ_2} \tilde{\tilde{u}}_{\chi\omega\eta_2}^{(c,2)}; \tag{23}$$

$$J_{3\chi}^{(c,2)} = \int_{T_0}^{T_f} \sum_{\omega=1}^{K_\Omega} \tilde{u}_{\chi\omega}^{(c,2)}(\tau)d\tau; \tag{24}$$

$$J_{4\omega\eta_2}^{(c,2)} = \sum_{\chi=1}^{K_c} \tilde{\tilde{u}}_{\chi\omega\eta_2}^{(c,2)}(t); \tag{25}$$

$$J_{5\omega\eta_2}^{(c,2)} = \tilde{\tilde{u}}_{\chi\omega\eta_2}^{(c,2)}(t). \tag{26}$$

Constraints (16)–(19) determine the sequence of the control inputs. In Eq. (18), $\Gamma_{\chi\omega1}^{(3)}, \Gamma_{\chi\omega4}^{(3)}$; $\Gamma_{\chi\omega2}^{(3)}, \Gamma_{\chi\omega5}^{(3)}$; $\Gamma_{\chi\omega3}^{(3)}\Gamma_{\chi\omega6}^{(3)}$ are the sets of running numbers of SC elements, SC element functional states, and the places of SC elements in the SC structure, respectively. This equation connects the structural state control (model $M_c^{(2)}$) and functional state control model (model $M_c^{(3)}$). Functional (22) allows the estimation of the total duration of the SC structure G_χ in the structural state $S_{\chi\omega}$. With the help of Eq. (23), how many times the structure G_χ was in the state $S_{\chi\omega}$. can be computed. Equation (24) allows the estimation of the total time during which the structure G_χ was in transition between the structural states. Functional (25) allows the counting of the number of structures G_χ in the state S_ω ($\delta = \omega$) at the η_2 control cycle. Equation (26) allows observation of when the structure G_χ is in which state, if $S_{\chi\omega}$, then $J_{\delta\chi\omega\eta_2}^{(c,2)} = 1$, and if another then $J_{\delta\chi\omega\eta_2}^{(c,2)} = 0$. Equations (22)–(26) can be used by decision-makers to form the multi-objective functions according to the individual preferences.

4.3 Functional state control model (model $M_c^{(3)}$)

Consider the following notations:

$x_{iwf\eta_3}^{(c,3)}(t)$ is a variable characterizing the execution of operation $D_{iwf\eta_3}^{(c,3)}$ which describes the operation dynamics at SC elements B_i in the functional state S_{iwf} at the η_3 control cycle; (w', w are the running numbers of SC elements B_i states; f', f are the places of the SC elements in the said states.

$\tilde{x}_{iwf}^{(c,3)}$ is a variable characterizing the execution of operation $\tilde{D}_{iwf}^{(c,3)}$ that describes the transition of SC element B_i from the current state $S_{iw'f'}$ into the desired state S_{iwf};

$\tilde{\tilde{x}}_{iwf\eta_3}^{(c,3)}(t)$ is an auxiliary variable that quantifies the duration of the time interval after completing the operation $D_{iwf\eta_3}^{(c,3)}$;

$\tilde{h}_{w'f'wf}^{(c,3)}$ is a given constant that quantifies the transition time of SC element B_i from the current state $S_{iw'f'}$ into the desired state S_{iwf};

$u_{iwf\eta_3}^{(c,3)}(t)$ is a binary control variable that equals 1 if the operation $D_{iwf\eta_3}^{(c,3)}$ needs to be executed, and equals 0 otherwise;

$\tilde{\tilde{u}}_{iwf\eta_3}^{(c,3)}(t)$ is an auxiliary control variable that equals 1 at the moment of operation $D_{iwf\eta_3}^{(c,3)}$ completion, and 0 otherwise;

$\tilde{u}^{(c,3)}_{iwf}(t)$ is a binary control variable that equals 1 if the transition of SC element B_i from current state $S_{iw'f}$ to the required state S_{iwf} needs to be executed, and equals 0 otherwise;

$a^{(c,3)}_{iwf}$ is a given duration for SC element B_i being in the functional state S_{iwf}.

Functional state control model at SC elements

$$\dot{x}^{(c,3)}_{iwf\eta_3} = u^{(c,3)}_{iwf\eta_3};\ \ \dot{\tilde{x}}^{(c,3)}_{iwf} = \sum_{w'=1}^{K_W}\sum_{f'=1}^{K_F}\frac{\tilde{h}^{(c,3)}_{w'f'wf} - \tilde{x}^{(c,3)}_{iwf}}{\tilde{x}^{(c,3)}_{iw'f'}}\tilde{u}^{(c,3)}_{iw'f'}; \tag{27}$$

$$\dot{\tilde{\tilde{x}}}^{(c,3)}_{iwf\eta_3} = \tilde{\tilde{u}}^{(c,3)}_{iwf\eta_3};\quad i = 1,\ldots, w = 1,\ldots,K_W; f = 1,\ldots,K_F; \eta_3 = 1,\ldots,Œ_3. \tag{28}$$

Constraints

$$\sum_{w=1}^{K_W}\sum_{f=1}^{K_F}\left(u^{(c,3)}_{iwf\eta_3}(t) + \tilde{u}^{(c,3)}_{iwf}\right) \le 1,\quad \forall i;\ \forall \eta_3; \tag{29}$$

$$\sum_{i=1}^{m}\sum_{w=1}^{K_W} u^{(c,3)}_{iwf\eta_3}(t) \le 1,\quad \forall f;\ \forall \eta_3; \tag{30}$$

$$u^{(c,3)}_{iwf\eta_3}(t) \in \{0,1\};\ \ \tilde{u}^{(c,3)}_{iwf}(t), \tilde{\tilde{u}}^{(c,3)}_{iwf\eta_3}(t) \in \{0,1\}; \tag{31}$$

$$\sum_{\eta_3=1}^{Œ_3} u^{(c,3)}_{iwf\eta_3}\cdot \tilde{x}^{(c,3)}_{iwf\eta_3} = 0,\quad u^{(c,3)}_{iwf\eta_3}\left(a^{(c,3)}_{iwf(\eta_3-1)} - x^{(c,3)}_{iwf(\eta_3-1)}\right) = 0; \tag{32}$$

$$\tilde{u}^{(c,3)}_{iwf}\left[\sum_{\alpha'\in\Gamma^{(4)}_{iwf1}}\left(a^{(o,2)}_{i\alpha'} - \tilde{x}^{(o,2)}_{i\alpha'}(t)\right) + \prod_{\beta'\in\Gamma^{(4)}_{iwf2}}\left(a^{(o,2)}_{i\beta'} - \tilde{x}^{(o,2)}_{i\beta'}(t)\right)\right] = 0; \tag{33}$$

$$\tilde{\tilde{u}}^{(c,3)}_{iwf\eta_3}\left(\tilde{\tilde{a}}^{(c,3)}_{iwf(\eta_3-1)} - \tilde{\tilde{x}}^{(c,3)}_{iwf(\eta_3-1)}\right) = 0. \tag{34}$$

Boundary conditions

$$t = T_0:\ x^{(c,3)}_{iwf\eta_3}(T_0) = \tilde{\tilde{x}}^{(c,3)}_{iwf\eta_3}(T_0) = 0;\ \ \tilde{x}^{(c,3)}_{iwf}(T_0) \in \mathrm{R}^1; \tag{35}$$

$$t = T_f:\ x^{(c,3)}_{iwf\eta_3}(T_f) \in \mathrm{R}^1;\ \ \tilde{x}^{(c,3)}_{iwf}(T_f) \in \mathrm{R}^1;\ \ \tilde{\tilde{x}}^{(c,3)}_{iwf\eta_3}(T_f) \in \mathrm{R}^1. \tag{36}$$

Functionals

$$J^{(c,3)}_{1wf\eta_3} = \sum_{i=1}^{m}\tilde{\tilde{u}}^{(c,3)}_{iwf\eta_3}(T_f); \tag{37}$$

$$J^{(c,3)}_{2i} = \int_{T_0}^{T_f}\sum_{w=1}^{K_W}\sum_{f=1}^{K_F}\tilde{u}^{(c,3)}_{ifw}(\tau)d\tau; \tag{38}$$

$$J^{(c,3)}_{3iwf} = \sum_{\eta_3=1}^{Œ_3} x^{(c,3)}_{iwf\eta_3}(T_f); \tag{39}$$

$$J^{(c,3)}_{4iwf} = \sum_{\eta_3=1}^{K_3}\left(a^{(c,3)}_{iwf} - x^{(c,3)}_{iwf}(T_f)\right)^2; \tag{40}$$

$$J^{(c,3)}_{5i\eta_3(\eta_3+1)} = \left[\tilde{\tilde{x}}^{(c,3)}_{iwf\eta_3} - \left(\tilde{\tilde{a}}^{(c,3)}_{iwf} + \tilde{\tilde{x}}^{(c,3)}_{iwf(\eta_3+1)}\right)\right]\Big|_{t=T_f}. \tag{41}$$

Constraints (29)–(34) determine the sequence of the control inputs. In Eq. (33), $\Gamma^{(4)}_{iwf1}$, $\Gamma^{(4)}_{iwf2}$ are the sets of running numbers of the operations (e.g., production, sourcing, logistics) at SC element B_i that are connected by the logical operators "and" or "or", respectively. This equation connects the functional state control model (model $M_c^{(3)}$) and operational control model (model $M_c^{(4)}$) which is out of the scope of this paper (see Ivanov et al. 2016a, b, c, d). The boundary conditions (10)–(11), (20)–(21) and (35)–(36) are solved with the procedure based on the principles of optimal control problems as described in Pontryagin et al. (1964), Lee and Markus (1967), Boltyanskiy (1973), Moiseev (1974) and Chernousko and Lyubushin (1982). In particular, as shown in Ivanov et al. (2016b), the problem formulated can be reduced to a two-point boundary problem with the help of the local cut method (Boltyanskiy 1973). After transforming into a boundary problem, a relaxed problem can be solved to receive optimal program control, for the computation of which the main and conjunctive systems are integrated subject to extremization of the control functionals. The basic peculiarity of the boundary problem considered is that the initial conditions for the conjunctive variables are not given in (10), (20), and (35). At the same time, optimal control should be calculated subject to the end conditions (11), (21) and (36). To obtain the conjunctive system vector, we use the Krylov–Chernousko method of successive approximations for optimal program control problem with a free right end which is based on the joint use of a modified successive approximation method (Krylov and Chernousko 1972).

Functional (37) allows the counting of the number of SC elements B_i which are in the state S_{iwf} at η_3 control cycle. Functional (38) allows the estimation of the total time during which SC element B_i was in transition between the functional states. Equation (39) allows the estimation of the total duration of SC element B_i in the structural state S_{iwf}. With the help of Eq. (40), i.e., Mayers's functional, total losses from violating the given duration of the state S_{iwf} for B_i can be assessed. Equation (41) allows assessment of the time interval in which SC element B_i transited to the state S_{iwf} at control cycles η_3 and $(\eta_3 + 1)$.

5 Computational algorithm

As is well-known, analytical methods for optimal control have been proven for small-dimension systems. Numerical methods which utilize the maximum principle have been applied in control engineering practice. A methodical challenge in applying the maximum principle is to find the coefficients of the conjunctive system which change in dynamics. Another methodical challenge of boundary problems is that the initial conditions for the conjunctive variables $\psi(t_0)$ are not given. At the same time, optimal program control should be calculated subject to the end conditions.

Figure 2 exemplifies the scenarios under which our modelling methodology would be deployed, as frequent communication and updated information request control of SC structural and operational states in different time points.

The upper part of Fig. 2 shows the SC structural dynamics control for performance degradation and recovery analysis. Four SC structural states have been considered that correspond to different disruption and performance levels. The dynamics depicted start with the degradation (state S_2) that lasts for 2 time units and continues with disrupted performance lasting one time unit (state S_1). The recovery can be observed lasting two time units, followed by operation normalization in the state (state S_3) lasting two time units. At time unit 7, a new disruption causes degradation to the state S_2 in which the SC stabilizes. Two other parts of

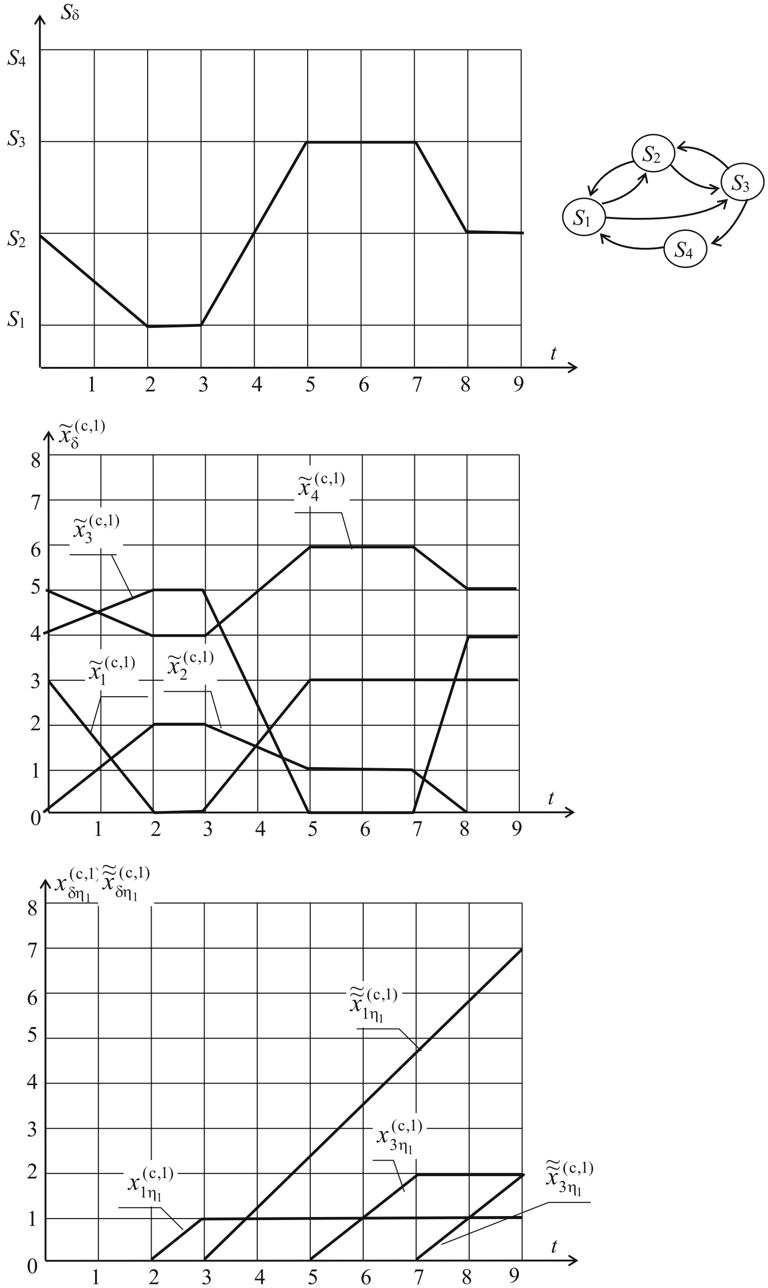

Fig. 2 Structural dynamics control modeling results

Fig. 2 depict the state variable dynamics following the structural changes. Similar patterns have been observed in the models $M_c^{(2)}$ and $M_c^{(3)}$ with regards to the changes in state variables.

The basic *computational idea* of the computational approach developed for the modeling complex described in Sect. 4 is the fact that structural dynamics control is dynamically distributed in time over the planning horizon. As such, not all operations need to be considered at the same time, unlike in combinatorial optimization. Therefore, the algorithmic solution to SC structural dynamics control models is based on partial solutions at each time point for small dimension problems and their further integration using the maximum principle. The multidimensionality and the combinatorial explosion of the problem is faced with decreasing connectivity under the network diagram of operations. This becomes possible using the model formulation in Sect. 4 via a dynamic interpretation of SC execution processes. After transforming into a boundary problem, a relaxed problem can be solved to receive an optimal program control; the main and conjunctive systems are integrated, i.e., the optimal program control vector and the state trajectory are obtained, for this computation. The optimal program control vector at time $t = t_0$ and for the given value of $\boldsymbol{\psi}(t)$ return the maximum to Hamiltonian.

Step 1 An initial solution $\bar{\mathbf{u}}(t),\ t \in (t_0,\ t_f]$ (a feasible control, in other words, a feasible schedule) is selected and $r = 0$.

Step 2 As a result of the dynamic model run, $\mathbf{x}^{(r)}(t)$ is received. In addition, if $t = t_f$ then the record value $J_G = J_G^{(r)}$ can be calculated. Then, the transversality conditions are evaluated.

Step 3 The conjugate system is integrated subject to $\mathbf{u}(t) = \bar{\mathbf{u}}(t)$ and over the interval from $t = t_f$ to $t = t_0$. For the time $t = t_0$, the first approximation $\boldsymbol{\psi}_i^{(r)}(t_0)$ is obtained as a result. Here, the iteration number $r = 0$ is completed.

Step 4 From the time point $t = t_0$ onwards, the control $\mathbf{u}^{(r+1)}(t)$ is determined ($r = 0,\ 1,\ 2, \ldots$ denotes the number of the iteration). In parallel with the maximization of the Hamiltonian, the main system of equations and the conjugate one are integrated. The maximization involves the solution of several mathematical programming problems at each time point.

We note that the use of state control variables in our model allows for status updates on SC degradation and recovery that in turn, feeds automated information feedbacks and control of execution and disruption detection. The latter launches the recovery procedure, comprehensively combining planning and adaptation decision within unified methodological framework of dynamic control theory. Such an integration allows for utilizing the advances in data analytics to enhance the SC resilience as pointed out by Ivanov et al. (2019) and Dubey et al. (2019). The cases in Fig. 2 exemplify the scenarios under which our modelling methodology would be deployed, as frequent communication and updated information request re-optimization in different time points.

6 Conclusions

SC resilience control aims to maintain the ability to sustain or restore functionality and performance following disruptions. In control terms, SC resilience can be modeled as a trajectory that is comprised of several degradation and recovery states. The transition between these states is accompanied by changes in SC structures. While the degradation process follows the disruption and is widely out of control, the recovery process control is of vital importance.

Recovery control is comprised of both structural and operational dynamics. Therefore, a problem of simultaneous structural–operational synthesis of SC recovery policies arises. This study developed an optimal control model and computational algorithm for simultaneous structural–operational design of SC structural dynamics and recovery policy control that integrates both structural recovery control in the SC as a whole and the corresponding functional recovery control at individual firms in the SC.

The purpose of developing an integrated structural–operational control model for SC resilience is to contribute to existing works by arguing that the consideration of structural dynamics and functional dynamics can be done within an integrated framework to enable proactive SC resilience control. The contribution of this study is therefore to integrate previously isolated decisions of structural reconfiguration and recovery policy optimization in a unified framework. The necessity for this integration is that it is commonly known that system recovery control in SCs, being socio-organizational, differs from technical systems where the feedback can be implemented almost immediately (Ivanov and Sokolov 2013). In SCs, the feedback information about disruptions first needs to be evaluated by managers and the adjustment recovery decisions need to be cross-organizational and coordinated among different departments in the firm.

As such, the differences in the structural states can be observed between the system state at the moment when adjustment recovery decisions are starting to be prepared on the basis of the feedback information and the system state at the moment of decision implementation. In other words, delayed feedbacks occur due to system inertia. The recovery decisions are then implemented in the SC which is structurally and functionally different from the SC that has been observed after the disruption and considered for reconfiguration decision planning. Therefore, the need for proactive control models arises for SC reconfiguration. Simultaneous control of both structural transformations and the related recovery policies seeks to bring the discussion forward by providing some ideas and rigorous technical elaboration on how to think and act in relation to these challenges.

The proposed approach can help explain and improve the firms' operations in multiple ways. First, the combination of structural and functional dynamics can help revealing the latent supply–demand allocations which would be disrupted in case of particular changes in the SC design. On the other hand, our model can be used to re-allocate supply and demand using functional flexibility in case of some structural changes due to disruptions. Finally, the developed model can be used to perform the dynamic analysis of SC disruption and recovery and to explain the reasons of SC performance degradation and restoration. In particular, the dependencies between the durations of different SC states and the performance dynamics can be uncovered. This analysis can be further used to improve SC risk mitigation policies and recovery plans.

The limitations exists, as with any study. First of all, the comprehensive integrated control framework would need to present all four control levels, including the operational control model. We described the reasons why we restricted ourselves to three models presented. Second, detailed numerical experiments in a particular SC design setting would enrich this study. However, the description of the case-study and detailed computational procedures would go beyond the scale and scope of a journal paper. We refer the latter point as a future research opportunity, along with further detailing of the control models themselves. In particular, the developed control model can be further extended by adding the parametric level in addition to the structural and functional levels according to recently introduced low-certainty-need (LCN) SC resilience framework by Ivanov and Dolgui (2019). This parametric level would include the control policies of inventory, production and shipment and therefore extend the presented model at a more detailed level of operations execution. In addition, the complexity of the model and algorithm need to be analysed in detail when the number of functional and structural states increases for large and complex SCs.

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