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Article

IMPROVING THE RESILIENCE AND PERFORMANCE OF ORGANIZATIONS USING MULTI-AGENT MODELLING OF A COMPLEX PRODUCTION–DISTRIBUTION SYSTEMS

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Abstract

Complexity is often viewed as principally concerning qualitative, evolutionary change over time. While this is true we look here at how multi-agent modelling, which is part of complexity science, can be used to explore the performance under fluctuating conditions of a given, structurally stable system composed of interacting agents. In a real organization of production and distribution, where different agents must decide how and when to act, it is usually almost impossible for them to learn in any systematic way how to “improve” the resilience and real performance of the organization as a whole because agents’ decisions interact and responses occur with delays. Clearly, when some shock occurs that takes the system out of its usual domain of functioning, then there is no way of knowing what will happen, and participants will have to improvise as best they can. Traditional mathematical modelling approaches are ineffective in dealing with such dynamic complex supply chains. Here, we propose the development of multi-agent models that are first calibrated on the observed production-distribution behaviour, creating a set of rules concerning the timing and nature of responses that actually mimics what has evolved heuristically in the system. Then, this model



is used and different perfectly possible agent behavioural rules are tried out in multiple experiments, so that resilience, real performance and the survival under shocks can be explored and tested, which would be impossible with the real system. This paper presents an agent-based computational framework for studying a multi-product complex multi-country supply chain subject to demand variability, production and distribution capacity constraints with the aim of improving operational resilience in terms of several supply chain performance measures. This demonstrates the use of complexity science not only for strategic exploration of structural change and major innovations, but also for improving the operational resilience of real systems.

Keywords

simulation; supply chains; production planning; multi-agent models; complex systems

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Introduction

Supply chains and organizations are the result of an evolutionary process of trial and error exploration, with emergent patterns of differential success and failure. Within each of these, there are multiple agents who have developed their knowledge over time, finding out by experience a set of responses that work well enough for the organization to have survived so far. However, this is a typical “satisficing” situation (Simon, 1957), that arises for real markets and business sectors, where there is no guarantee that the combined behaviours within an organization work really well, or deal well with any disturbance or shock. We only know that they work sufficiently well to be there, but do not know how well they could work, nor how they may respond to a shock that has not occurred before. Because of the interacting behaviours of its multiple agents, a supply chain network is highly non-linear and shows complex multi-scale behaviour through a complex interplay of its structure, environment and function. This complication and lack of predictability makes it difficult to manage and control them. Effective supply chain management in a dynamic environment is therefore a very common, but challenging task and calls for building resilience in supply chains, not just for recovery from the mishaps, but as a proactive, structured and integrated exploration of capabilities within the supply chain to resist and prevail against unforeseen events. The research described here attempts to address the question of improving operational resilience in a multi-product, multi-site, complex supply chain network.

Complex systems modelling

Complexity Science is the science of evolution, of changing organizational forms and structures, and of emergent capabilities and features. However, complexity science views such organizational evolution as resulting from the interaction of individuals. This is not simply a reductionist view because the individuals are changed internally by their interactions, and therefore give rise to genuine emergent, collective effects. It is also a view in contrast to that in which organizations are viewed as functional from a top-down perspective. It cannot be assumed that the interaction of the individuals will necessarily lead to the successful functioning of the organization, or that there is any scientific principle that ensures the functioning will be optimal, or indeed even maintained. Instead, complexity science sees an organization that is operating as being the result of a historical pathway of local experimentation that has led to a system that works well enough to have survived until now. Its operation affords no simple guarantee about future survival.

Complexity science is cognizant of the whole system in qualitative, holistic ways (McKelvey, 1999), recognizing that interactions in real systems exhibit non-linearity, and that this is the mechanism by which small causes and fluctuations at a lower level can generate disproportionate, structural evolution at a higher level above. It is sometimes called the butterfly effect (Lorenz, 1963), wherein a tiny effect of a butterfly flapping its wings could potentially change the emergent pattern of the large-scale atmospheric dynamics. However, in this example the variables and phenomena qualitatively are not changed qualitatively, while in general, complexity recognizes that structural evolution, emergent properties and capabilities are driven by the dialogue between the microscopic and the macroscopic levels of description of a system. In this way, Complexity Science also recognizes that history – luck, contingency, particular circumstances – really matters, since this evolutionary dialogue is path-dependent and is not reversible. The co-evolution of the agents within complex systems means that together their learning and adaptation trace a particular pathway into the future rather than a convergent one to some generic equilibrium structure. The system is sensitive to initial conditions as well as to events and circumstances along the way with an irreversibility expressing the ‘arrow of time’. These characteristics of organizations, as complex systems, need to be recognized in order for managers to recognize the constraints and opportunities to influence the evolution of their organizations.

A complex system does not exist in isolation. It both competes and collaborates with other organizations for resources and customers, at many layers within the organization, for example individuals, teams, departments. Co-evolution occurs when the direct or indirect interaction of two or more evolving units produces an evolutionary response in each other (Van Valen, 1973). An organization for example may co-evolve with one of its suppliers in the

development of a particular technology. The relevance of co-evolution is that regardless of the dimensions that each agent perceives at a given time, these dimensions will change over (CO) time, sometimes incrementally and sometimes suddenly as the consequence of a phase transition. Because of this, the variables, parameters and factors that we perceive in reality (ontology) CO time, and force some evolutionary change in our understanding and knowledge (epistemology), as well as the aims and goals (axiology) we have with respect to this domain.

Deconstructing complexity

In a series of papers (Allen, 1976, 1994; Allen and McGlade, 1987), the essential driving force of evolution and of complex systems was shown to be the micro-diversity (heterogeneous and idiosyncratic individuals) that exists below any chosen level of description of real systems. It was shown that micro-diversity provides an internal pool of adaptive and creative behaviours that drives the evolution of the system as a whole, through successive structures and organizations, changing both the macro-structure and also the internal beliefs, criteria and aims that underlie individual behavioural responses. In this way, the internal beliefs and views held by agents of a given kind are shaped by their experiences that in turn result from the organization and structures that they inhabit. These are, in their turn, also formed by the behaviour and interactions of the individual agents. This is a circular system that either is self-reinforcing, marking a period of stability, or is not, marking the occurrence of an instability. The complex system that represents organizational evolution is therefore about periods of structural stability, when rational analysis and knowledge can exist, separated by instabilities, when new variables and aspects invade the system, and rational decision making is impossible.

This can be understood by studying the assumptions and approximations made in arriving at a mechanical description or model of any evolved, and hence complex, part of reality. There are five assumptions:

1. That there is a system boundary, with the environment outside and the “system” inside.
2. That we can define and classify the content of the system – the variables, mechanisms, processes, elements and their interactions – and we see that over time these have changed qualitatively.
3. That we can describe the system in terms of average types.
4. That we need consider only most probable (average) micro-events.
5. That the system has run to an equilibrium.

This is illustrated in Figure 1 in which we see the different types of model and epistemology that arise as successively more constraining, simplifying assumptions are made.

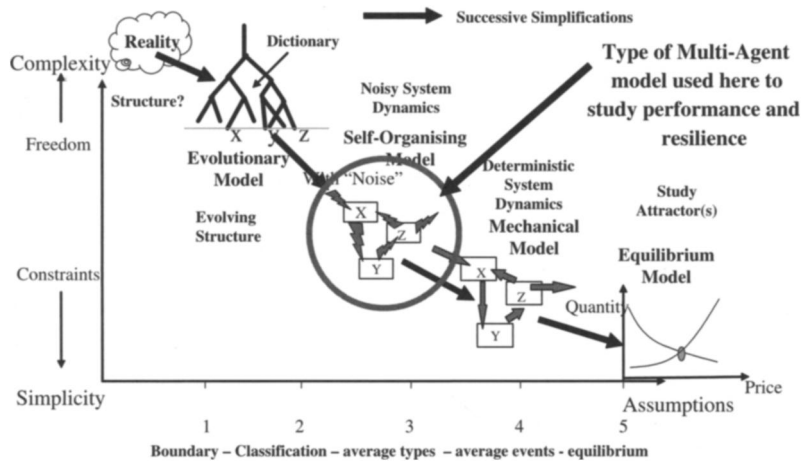


Figure 1 Successive assumptions are used to reduce reality to a simple, causal mechanical description, with models that can “run” but not evolve.

- With no assumptions, reality is simply subjective experience, and survival would rely on intuitive, spontaneous responses.
- With the definition of a boundary, and with the ability to classify the elements and content of a situation, we would arrive at an evolutionary view, because over time almost all situations of interest are characterized by a qualitatively changing structure, with new entities and dimensions emerging and earlier ones disappearing. Evolutionary models can be developed for example of evolving markets, organizations or ecosystems.
- Considering the present however, the classification of the entities present, together with the probability of interactions between them yields a description in terms of a probabilistic differential or difference equations, expressing the coupled behaviour of the system. Because of the usual presence of feedbacks and non-linearities such systems would normally possess multiple possible dynamic attractors, and the probabilistic interactions would allow the system to move between different possible attractor basins under the effects of noise and fluctuations. For this reason, they are referred to as “self-organizing” since the system could spontaneously jump from one configuration (attractor basin) to another. This kind of model could be used to test the spread of outcomes possible under various “what if” scenarios. They constitute the basis for contingency planning, risk analysis and for testing the resilience of an organization and this is the type of multi-agent model of a supply chain that we shall develop in this paper. However, this assumes that the organization and its environment does not evolve qualitatively, rendering the model incorrect.
- Making a further assumption that only the most probable events actually occur, we arrive at a system dynamical description of the system. This

corresponds to an apparently “causal” description of the behaviour of the system, one that supports rational decision-making, and with which participants feel comfortable. The behaviour of the system is apparently predictable, and can be used for “what if” scenario testing – and an exogenous “sensitivity analysis” can replace partially the effects of fluctuations and noise that the “self-organizing” model would treat more correctly.

- One further assumption that is often made is that of equilibrium. In particular, such methods as cost/benefit analysis of a possible decision rely on comparing the initial (equilibrium) situation with the final one. This is appealingly simple, but does ignore the probable fact that the system and its environment are never at equilibrium, and hence the calculation is false.

This cascade of assumptions concerns the degree of understanding that we have of a situation. As we make successive simplifications, we are increasingly clear in our description of the situation, despite the fact that our assumptions may be false. We can only claim to really understand something if we can state exactly what it is made of, and how the different parts interact. But, in complex systems, and in organizations, “what agents are” may be changing as they learn new things and formulate new preferences, and the way that the different agents interact may also be changing if new connections are formed, or if communication produces new knowledge, or beliefs. In short, the right-hand side of Figure 1 is where we feel we understand what is going on and how the system works, while reality remains firmly on the left, and forces us to re-form our thinking when the dissonance between left and right become too great.

Our understanding of reality is in terms of a set of interacting components that cannot evolve of themselves and the changes and innovations that occur in reality are merely taken account of by making a new, revised model of that reality. The mechanical, system dynamic, view of the “functioning” of the system at a given time is necessarily incomplete in that it does not include the micro-diversity within the agents that leads to new ideas and to learning, will in fact change and modify things. Figure 1 tells us therefore that the key assumption (3) in which we assume a description of the current situation in terms of the average types, or homogeneous elements, currently present, is the critical one in which the “evolutionary potential” is lost. In the real, complex system there is internal heterogeneity, multiple different perspectives and constructs, and differing aims and goals, and it is the interaction of these things over time that will lead to evolutionary, structural qualitative change. As we shall discuss later, if the system under discussion is an organization of people, then the information technology may only allow flows permitting (even optimizing) the functioning at this particular moment, according to its current functional structure. But in reality, this may be entirely inadequate to allow the agents within the organization to evolve and change enough for the organization to survive in its environment.

Many papers have been published (Allen, 1994, 2001a–c, 2004; Baldwin *et al*, 2003; Allen and Strathern, 2004; Allen *et al*, 2006) concerning the mathematical modelling of structural, strategic evolution as being the most important aspect of complexity thinking. However, in this contribution we want to demonstrate the importance of the stochastic non-linear systems models that correspond to making assumptions (1), (2) and (3). In this situation, we shall assume that the “structure” of the system is known and is not going to change, so that the agents and their role in the organization is already defined and will not change. However, what we shall explore is the different possible values of the parameters used by agents and the informational linkages between them, and the multiple possible performance of the organization in dealing with its environment, and the unpredictable variations that occur there.

Obtaining a balance between various dimensions of performance and the resilience of a supply chain becomes intractable for most conventional mathematical modelling approaches as supply chains grow both in levels and linkages. There exists a large body of literature on models dealing with uncertainty. While the solutions are elegant in their simplicity, they fail to address the key features of realistic supply chain problems, namely, multiple products sharing the same production and distribution facility, with capacity constraints and demands originating from multiple customers, which vary widely from forecasts.

Here, we shall develop a multi-agent computational framework in order to design and manage the performance and the resilience of a multi-product complex supply chains subject to demand variability, production and distribution capacity constraints.

Supply chain resilience

According to extant literature, resilience, in supply chain terms, has two aspects. The first is about the maintenance of the production system of a given product in the face of disruptions of various kinds. The second is about the agility of the process to respond to changes in customer needs and requirements. The first aspect has been studied by several authors in the form of management of uncertainty, risk management, reduction of vulnerability in supply chains (Christopher and Lee, 2001; Lee, 2002; Haywood and Peck 2003). The second aspect of resilience is stressed upon by many prominent authors. In supply chains, Christopher (2004, p 18) stated, “One of the most powerful ways of achieving resilience ... is to create networks, which are capable of more rapid response to changed conditions. This is the idea of agility.” Rice and Caniato (2003, p 25, 26) suggested a hybrid flexibility and redundancy approach for increasing supply chain resilience. A right mix of both factors is needed to improve resilience.

This paper presents operational resilience of the supply network as the ability of the production-distribution system to meet each customer demand for each product on time and to quantity. The ability to produce the correct material at the correct time and delivering it to the right market at the correct time holds the key to improving operational resilience in a complex supply network. The paper provides measures of operational resilience for complex supply chains and attempts at improvement by developing an agent-based computational framework.

Very few tools are currently available to model and suggest methods of improving the operational resilience of an integrated production/distribution system subject to multiple product demand uncertainty (Davidsson and Wernstedt, 2002; Blackhurst *et al*, 2005). Combining the activities of material management and physical distribution in a multi-product, multi-period model for improving operational resilience represents not only a linear chain of one-on-one business relationships but a web of multiple relationships. A key realization to tackle this problem is that supply chain networks should be treated as '*complex systems*' (which 'are any system that have within itself a capacity to respond to its environment in more than one way, and which selects among these in some way' (Allen, 2001a–c)). Choi *et al* (2001) emphasized a similar viewpoint and aimed to demonstrate how supply networks should be managed if they are to be recognized as complex adaptive systems. Agent-based simulation (ABS) modelling is regarded as one of the best candidates for addressing the research question identified above. Agent-based modelling provides a method of integrating the entire supply chain as a network system of independent echelons; different entities employ different decision-making procedure in most cases (Gjerdrum *et al*, 2001). Parunak and Vanderbok (1998) offer a general recommendation: ABS is appropriate for domains characterized by discrete decisions and composed of a high number of distributed local decision makers. Such situations occur increasingly more frequently in integrated production–distribution systems, where distributed decision making has been labelled as a fundamental building block enabling resilience (Christopher and Towill, 2000). In this paper, we propose an agent-based model to represent each entity in a complex supply chain, to capture non-linear decision making and allow implementation of realistic operational and strategic policies.

Description of the agents

Each member of the chain is modelled as an independent agent with autonomous decision-making ability based on the available information on resources and demand. The agent architecture is defined below. In order to make the agents true representation of real business units, the agent structure is divided into two stages: the functional and the decision-making stage.

The functioning stage of the factory agent, in conjunction with the decision making stage must implement the major functions of production and maintenance planning,

- Production, planning and control of one product at a time, while others wait in a queue. This is a continuous activity and occurs at fixed production rate.
- The decision-making stage selects the product to be produced based on a priority list, which changes whenever situation changes in the entire supply chain. Once a product is chosen for production, the factory agent continues the production until the stop condition is imposed. So this function is mainly concerned with the start and stop of production of a particular product.
- Naturally, the production function also includes a CO phase. This is the idle stage when no production is made and the machine is set up for the next product at the top of the waiting queue decided by the decision-making stage of the agent.
- Another function integrated in the production function is the preventive maintenance. No production occurs at this stage. This is also planned at this stage.

The functioning stage of the distribution centre agent must implement three major functions:

- Receipt of orders from customers and the aggregation of these orders. Comparing them with forecast demand. Storing the pattern of each product's demand variation in the form of statistical data in memory for using at decision-making level.
- Delivery of goods to customers, with determination of priority when insufficient finished goods are available to meet all current orders.
- Review of inventory position at regular intervals, receipt of materials from suppliers and generate an order to its preceding stock point to raise the inventory position to its order upto level.

The decision-making stage makes crucial decision on how much to order from the upstream stock point in order to avoid any stock-outs but at the same time keeping a low inventory to reduce holding and handing costs. So each stock holding location depicted by the distribution centre agent's decision-making stage has to decide a safety stock amount, target inventory level and the re-order levels.

Case study

The dynamics of the European supply chain of a multinational paper tissue manufacturing company are studied here. Thirteen final products are produced

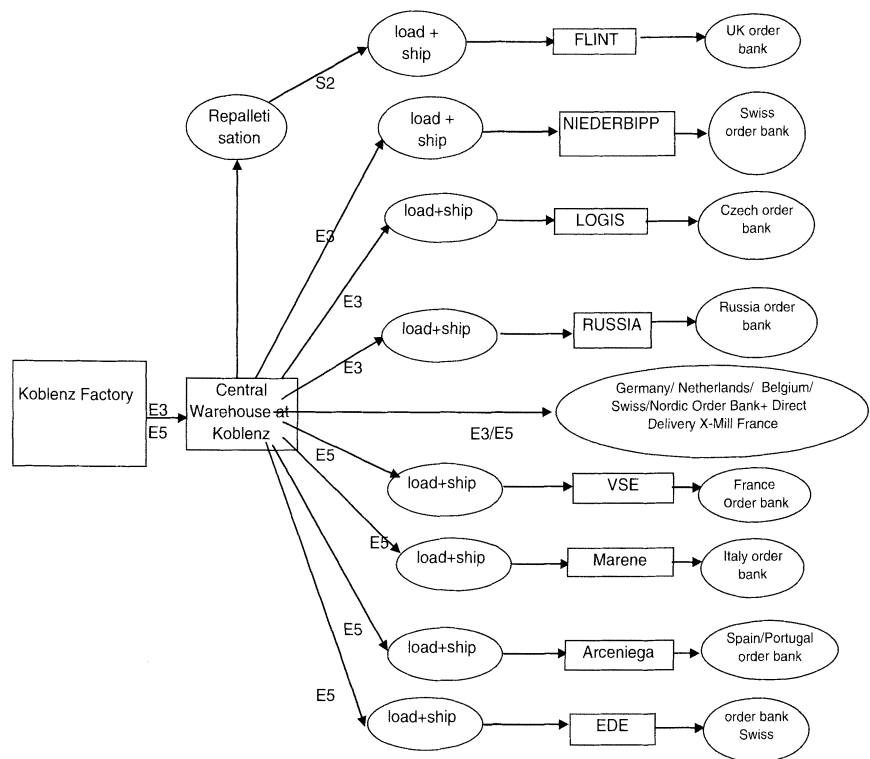


Figure 2 Supply network structure.

in a single location, Koblenz, in a single converting machine and sold in different countries from the country regional distribution centres (RDCs). The production facility is assumed to have infinite supply of raw materials. The existing supply chain of the company is shown in Figure 2. The factory is simulated by the factory agent described in previous section and the different country RDCs and the central warehouse re-represented by the distribution centre agents, dealing in variable product demand patterns, product types, lead times for delivery. All products are stored in different pallet sizes at the central warehouse (E5, E3 and S2). If the requested pallet type is E3 for a particular product and not enough stock is available in E3 pallet type, then repalletization from E5 to E3 pallets is made depending on E5 stock availability. The products are repalletized into S2 pallets manually after receiving orders from UK RDC. It is assumed that all inter-company orders are raised and delivered in multiples of pallet sizes. The backorders at the stock points will be fulfilled first before new demand or orders are given any priority. The 13 product codes are put into four categories for production at the factory, based on their quality. According to the categories, the CO times between the product codes also



Table 1 Actual and modelled stock and customer service levels

	<i>Actual Stock</i>	<i>Actual CSL (%)</i>	<i>Model Stock</i>	<i>Model CSL (%)</i>
(a)				
<i>Product code X2</i>				
Germany	5,176	100	6,612	100
France	311	100	328	100
NAVI	5,487		6,940	
<i>Product code X3</i>				
Niederbippf:	810	100	1,113	100
Germany	1,583		75	
NAVI	2,393		1,188	
<i>Product code X4</i>				
Niederbipp	151	100	840	100
Germany	719		17	
NAVI	870		863	
<i>Product code X5</i>				
Italy	3,321	100.0	1,108	100
France	656	99.8	775	100
Britain	825	100.0	429	100
Germany	15,315	100.0	17,551	100
Niederbipp	249	100.0	285	100
NAVI	20,166		20,148	
<i>Product code X6</i>				
Britain	625	100.0	417	100
Arceniega	269	95.8	275	100
France	215	100.0	89	90
Germany	8,753	100.0	10,567	100
NAVI	9,362		11,348	
<i>Product code X7</i>				
Britain	3,369	98.3	1,077	98.3
France	1,379	99.0	1,058	99.8
Germany	30,103	100.0	23,474	100.0
Italy	3,717	100.0	795	09.7
Niederbipp	299	100.0	248	100.0
Arceniega	221	94.3	265	100.0
NAVI	39,588		20,917	
(b)				
<i>Product code X8</i>				
Ede	2,061	100.0	2,153	1000
Koblentz	727		92	
NAVI	2,788		2,245	
<i>Product code X9</i>				
Ede	1,327	96.6	1,455	100.0
Koblentz	1,030		564	
NAVI	2,357		2,019	

Table 1 Continued

	<i>Actual Stock</i>	<i>Actual CSL (%)</i>	<i>Model Stock</i>	<i>Model CSL (%)</i>
<i>Product code X10</i>				
Germany	13,841	100.0	14,242	100
Britain	621	100.0	329	100
France	953	99.5	564	100
Italy	6,802	100.0	1,565	100
Niederbipp	547	97.6	363	100
Arceniega	199	84.0	567	100
NAVI	22,963		17,630	
<i>Product code X11</i>				
Germany	12,034	98.9	14,662	100
Britain	5,921	100.0	811	99.9
France	493	99.7	345	98.7
NBP	72	100.0	85	100
Arceniega	119	71.0	257	100
NAVI	18,639		16,160	
<i>Product code X12</i>				
Germany	4,662	95.7	11,082	1000
France	100	98.9	133	99.4
Britain	440	92.2	531	98.7
NBP	55	100.0	97	100.0
Arceniega	235	88.8	383	100.0
NAVI	5,492		12,226	

vary. The production capacity per hour per product for the machine is fixed. The maximum CO time between products is 18 days per year. Two products are introduced in most markets at the middle of the year.

The entire system cannot see the real end demand. Half of the company's customers are distributors and not real customers. So the company has to depend on history-based forecasts. This results in obvious sales-forecast mismatch. Consequently, the network is plagued with huge stocks in locations where it might not be required or less stock where there might be a surge in demand. This is specially aggravated by the long transactional/processing lead times for each step in the process. The long time in inter-country movement of materials results in back orders when there is surprise demand in a particular country and there is insufficient stock in the RDC and no stock in transit. The situation is far more worsened by the inability to cross-transfer materials between different country RDCs. The only source of finished goods is the Koblenz factory. So the factory production and distribution needs to be resilient to any changes in each country demand to minimize stock-outs and maximize customer service levels (CSLs) with least network inventory.

The factory planning is guided solely by forecasts. Thus, whenever there is an actual rise or fall of demand the factory reacts only after the event, when it

affects the total stock level. So this reactive production planning procedure reduced the ability to sense and respond to any changes. Application of the agent-based computational framework is done to improve the operational resilience in terms of the performance measures identified below.

Performance measures

The operational resilience of the supply chain will be judged in terms of the following performance measures for each product in each distribution centre and the factory.

- CSL is taken to be the total quantity sold to the end customer over the total quantity ordered, for that product market for the entire time horizon of the simulation. When the stock level is lower than the order quantity, only the stock available is sold and remaining is backlogged.
- Production CO time and number of COs.
- The average inventory (AVI) is the on-hand stock level of the products at each distribution centre averaged over the time horizon of each simulation run.
- The total average network inventory (NAVI) is the total on-hand stock level in the whole network across all distribution centres averaged over the time horizon of each simulation run.

Results and discussion

The improvement obtained with respect to the performance measures in each of the RDCs for each code is shown in Table 1a and b. It can be seen that, in all the products, the agent-based computational framework has been able to improve upon the actual performance with reduced average network inventory level and CSLs. Most importantly, for the single-market products X3, X4, X8, X9, the model has pushed the materials fully to the country RDCs rather than keeping them in Koblenz, where there are no demands. This has not only improved CSL but also reduced overall average network inventory level for these products. As can be seen for products X3 and X4, central warehouse actual average stock level is higher than the RDC stock level. This is particularly prone to disruption if there are sudden spikes in demand in the country markets. So in the model, to improve operational resilience, materials not directly sold from the central warehouse are pushed to the markets as soon as they are produced. This would not only make the system more resilient to uncertain demand but also would reduce the number of times these materials are produced because in this configuration, the factory will consider the entire network inventory position rather than just the central warehouse stock position for making decision to produce. Thus, it will enable the production facility to produce highly demanded materials for longer time and reduce the number of

costly machine set ups (from 130 to 80). The total CO time is found to be 8.7 days, which is much less than the actual 11.3 days. The decision rules used by the agents definitely provide improved operational resilience in terms of the network-wide performance measures.

Conclusion

It can be argued that when unpredictability is given, in the form of mismatch between actual demand and forecast, the only strategy that makes sense is a strategy to become adaptive – to sense early and respond quickly to abrupt changes in individual customer needs. As a result, a firm's operations must be driven by current customer requests – implicit as well as articulated – rather than by plans to make and sell what customers are forecast to want in the future. This research provides a novel methodology to understand the key issues essential for improving operational resilience in a complex production distribution system facing uncertain demand. Each member of the supply network needs to have a certain inherent ability to deal with the uncertainties, which is described by the functional stage of the agents. In order to improve the operational resilience, they need to have an adaptive ability to change their decisions with respect to changes in environment.

Several managerial insights for building an operationally resilient supply network can be extracted from the above agent-based computational framework. They can be summarized as:

- (1) knowing earlier (sensing and interpreting – this involved incorporating true sensors at different parts of the supply chain and monitoring them regularly, for example, forward cover at central location and throughout the network, cumulative sales over AVI ratio for each product aggregated over the network)
- (2) managing-by-wire (informed coordinated decision making that constitutes institutional memory and intelligence, for example, evident in the assembly of the model where each element has the full visibility of the entire network)
- (3) designing a supply network as a complex system (*integrate* all elements and their functions – in order to create an optimized, efficient and well-coordinated system)
- (4) production and dispatching capabilities from the customer request back (assemblage of modular, functional capabilities and roles, which are dispatched and coordinated in response to current customer requests, for example, evident in designing the production schedules based on real time customer requests, especially for single country products).

The main contribution of this research is to provide a generic agent-based computational framework for effective management of complex production

distribution systems. The case study depicted is used as an illustration of application of this framework. However, this framework can be applied to any complex production distribution system with any number of products with any demand profile, any forecast bias and errors and any number of distribution centres. This research finds the solution to a very generic supply chain management problem, which to our knowledge has not been attempted so far in contemporary research literature.

In general, we may say that almost all organizations function according to heuristically defined routines and rules, and learning by different agents within the organization is extremely difficult because of the feedbacks, time delays and multiple causations that are involved, and which confuse attempts at “sense making” following some action. Because of this, we may speculate that most organizations are good enough to exist and survive in the current “normal” range of disturbances, but nobody knows how much better they could perform, or how some abnormal disturbance might affect them. By building multi-agent models of the type described here, we can explore the outcomes of the system under an enormous range of possible agent behavioural rules, and environmental events, and so find improved levels of functioning and of resilience. The model could also be developed to explore the possible results of changing the structure of the organization, and in this way offer strategic as well as operational advice. Clearly, some structural choices may prove more resilient than others, and so this too can be studied. In summary then, we would suggest that this is an important practical way in which the performance and resilience of organizations can be improved.

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