Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 52-13 (2019) 355–360

Intellectualization of control: cyber-physical supply chain risk analytics

Dmitry Ivanov[1], Alexandre Dolgui[2], Boris Sokolov[3], Marina Ivanova[1]

[1]Berlin School of Economics and Law, Department of Business Administration
Chair of International Supply Chain Management, 10825 Berlin, Germany
Phone: +49 3085789155; E-Mail: divanov@hwr-berlin.de
[2]IMT Atlantique, LS2N, CNRS
La Chantrerie, 4, rue Alfred Kastler, 44300 Nantes, France
email: alexandre.dolgui@imt-atlantique.fr
[3]St. Petersburg Institute for Informatics and Automation of the RAS (SPIIRAS)
V.O. 14 line, 39 199178 St. Petersburg, Russia; E-Mail: sokol@iias.spb.su

Abstract: In the frameworks of supply chain risk management, dynamics, and resilience, control theoretic approaches can be considered as useful tools to tackle the issues of performance achievement under operational and disruption risks. New analytics technologies in the framework of Industry 4.0, big data analytics and artificial intelligence resulted in the creation of new domains, i.e., cyber physical supply chains and supply chain risk analytics. As such two trends can be observed, i.e., integration of analytics into control theory (so called intellectualization of control) and integration of analytics into supply chain risk management (so called cyber-physical supply chains and risk analytics). This study brings the discussion forward by integrating these two perspectives. It analyses how control theory can enhance the risk analytics in the cyber-physical supply chain. Based on literature and case-study analysis, the frameworks of cyber physical supply chain and risk analytics control are derived. In this setting, further development of interdisciplinary approaches to supply chain optimization and simulation with disruption risk considerations on the basis of control analytics is argued.

Keywords: supply chain, control, cyber-physical, Industry 4.0, resilience, disruption, recovery, analytics

1. INTRODUCTION

In the frameworks of risk management in the supply chain (SC), dynamics, and resilience, control theoretic approaches can be considered as useful tools to tackle the issues of performance achievement under uncertainty in regard to bullwhip and ripple effects (Disney and Towill 2002, 2005, Dejonckheere et al. 2004, Disney et al. 2006, Lalwani et al. 2006, Ivanov and Sokolov 2010, Spiegler et al. 2012, Ivanov et al. 2012, Ivanov and Sokolov 2012a, 2013, Ivanov et al. 2014a,b,c, 2015, 2016a, 2018, Fu et al. 2015, Spiegler et al. 2016, Ivanov 2018, Dolgui et al. 2018). Control theory has been widely used for studying multi-stage, multi-period dynamic production, logistics, and SC systems. A broad range of control theory applications can be explained by a rigor quantitative basis for feedback-based and optimal control policies including differential games and stochastic systems, stability of controlled processes and non-linear systems, controllability and observability, and adaptation (Sethi 1978, Perea et al., 2000; Sethi and Thompson, 2000, Sethi et al. 2002, Ortega and Li 2004, Sarimveis et al. 2008, He et al. 2009, Ivanov et al. 2010, Khmelnitsky et al. 2011, Scholz-Reiter et al. 2011, Ivanov and Sokolov 2012, Ivanov et al. 2014a,b,c, 2016a,b,c, Spiegler et al. 2016, Dolgui et al. 2018). These tools can be applied for a wide range of discrete linear and stochastic non-linear systems with both stable and dynamically changing structures. New digital technologies Industry 4.0 provide multiple directions for future development of control approaches to the SC domain. One of these direction is SC risk analytics that refers to usage of emerging analytics techniques to analyzing, monitoring, mitigation, identification, predicting, control, assessment, simulation and the disruption risks in the SC and to the recovery in the case of disruptions (Heckmann 2016, Dolgui et al. 2019, Dubey et al. 2019, Panetto et al. 2019, Hosseini et al. 2019).

Industry 4.0 SCs evolve through adaptation and reconfiguration of their structures. Therefore, structural dynamics control needs to be developed further (Ivanov et al. 2010, Ivanov 2018). With the help of smart sensors and plug-and-produce cyber-physical systems, the stations in the assembly system are capable of changing the operation processing and setup sequences according to actual order incoming flows and capacity utilization. Levalle and Nof (2016) develop a link to resilient enterprise and provide evidence of how collaborative control can be used in supply chain resilience analysis. In the front opening unified pods technology in semiconductor industry, robots are used in real-time operation sequencing. Collaborative robots read the information about the products from sensors and tags and decide flexibly where to forward a wafer batch next (Mönch et al. 2012).

Short-term SC scheduling in smart factories Industry 4.0 is challenged by temporal machine structures, different processing speeds at parallel machines and dynamic job arrivals. Indus-try 4.0 technology is based on the concepts of flexibility and dynamic assembly system design. This enables new production strategies and creates new challenges for job shop scheduling. In particular, manufacturing processes for differ-

2405-8963 © 2019, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2019.11.146

ent customer orders may have individual machine structures, whereas the flexible stations are able to execute different functions subject to individual sets of operations within the jobs. Control approaches can be applied to job shop scheduling in a customized manufacturing process and job sequencing of operations within the jobs in order to support flexible, distributed scheduling in the emerging field of Industry 4.0-based innovative production systems (Ivanov et al. 2016b, 2017).

Feedback control principles, including new developments such as Active Disturbance Rejection Control (ADRC) are of vital importance in real-time manufacturing, inventory and shipment tracking & tracing control in combination with RFID, sensor, and blockchain transaction data. Other applications of real-time control are seen in the SC resilience area as well as production-inventory control algorithm advancements.

2. CONCEPT OF CYBER-PHYSICAL SUPPLY CHAIN

According to Zhuge (2011), the evolution from the cyberspace and systems to the cyber-physical-social space and systems can be described by three extensions. It distinguishes two types of cyber spaces: the first one allows users to read the information in the cyber space like the Web, and the other one allows users to read and write information in the cyber space. Both rely on humans to add information to the cyber space in order to share it with others.

The first extension to this basic concept depicts the extension of the cyber space to the physical space through various sensors. Any significant information in the physical space can be automatically sensed, stored and transmitted through the cyber space. Internet of Things can be considered as a kind of cyber-physical space.

The second extension is that user behaviors can be sensed and feedback to the cyber space for analyzing the patterns of behaviors, and humans can remotely control the actuators to behave in the physical space through the cyber space. This enables the cyber space to adapt his services according to the feedback since behavior change may indicate some psychological change.

In the third extension, i.e., the cyber-physical system, not only individual's behaviors, but also social interactions can be feedback into the cyberspace for further processing. Users are considered with their social characteristics and relations rather than as isolated individuals. Sensors are limited in their ability to collect all information in the physical space, so users still need to directly collect the significant information in the physical space and then put them into the cyberspace after analysis (including experiment). Users can also manipulate physical objects in the physical space, which can also be feedback into the cyber space to reflect the real-time situation]. Users' status, interests and knowledge evolve with social interaction and operations in the cyber space.

The afore-mentioned analysis can be presented as digital cyber-physical SC framework (Fig. 1).

Analysis of digital SC framework allows formulating two important insights.

2.1. From competition between the SCs to competition between the information services and analytics algorithms

At the times of SCM introduction into the management practices, it was popular to say that the company is as good as the SC behind it. Christopher (2005) formulated the proposition that the competition is not between the firms but rather between the SCs. Today and looking at near future, the specialists say that the SC is as good as the digital technology behind it. Consider two example to support this proposition.

The first one is the logistics service provider UPS. Development of additive manufacturing leads to the possibility to produce the modules, components and even end products at one place, and actually at any place in the SC (Khajavi et al. 2014, Li et al. 2017). This implies SC design changes, a lower number of supplier layers and suppliers as such, and the reduced need in transportation which is a threat for logistics companies. UPS and SAP developed a joint technology which allows UPS to manufacture the items using 3D printing directly at the distribution centers. This contributes to a faster and more efficient SC.

Such an integration of production, sourcing and distribution is also positive for reactions to possible disruptions in the SC. The second example is blockchain technology. Contracts in SCs often involve multi-party agreements, with regulatory and logistic constraints. Further complexities may arise from operations in different jurisdictions, as well as dynamic features embedded in the contracts. The flow of information in a SC plays a critical role in the efficiency of the operations. Regulatory processes (e.g. customs) can be expedited by improving confidence in documentations. This, in turn, will reduce wastage, risk and insurance premiums.

IBM and Maersk are collaborating to create trust and transparency in global SCs. They develop a distributed contract collaboration platform using Blockchain technology. Maersk estimates that shipping a single container of flower from Kenya to Rotterdam needs nearly 200 communications. How to improve the efficiency of the global SC? In their approach, each distinct entity involves in the transaction are allowed to access this system. Shipping from the port of Mombasa requires signatures from three different agencies and six documents, the smart contract will automatically generate after the system receive the signatures. Simultaneously, when the documents about inspection, sealing of refrigerator, pick up by the trucker and approval from customs communicated to port of Mombasa are uploaded, all the participants can see the data in the meantime, allowing the related entity to prepare for the container.

These and further recent examples of digital technology applications to SCs (Ivanov et al. 2018b, Yang et al. 2017, Cavalcantea et al. 2019) allow for the new proposition that the competition is not between the SCs but rather between the SC services and analytics algorithms behind the SCs. The services may be ordered in packages or as individual modules. The success in the SC service competition will be highly dependent on the analytics algorithms in combination with optimization and simulation modelling. Initially intended for process automation, digital technologies now disrupt markets and business models and significantly impact the SC management and engineering

As such, new disruptive SC business models will arise where SCs will not more be understood as a rigid physical system with a fixed and static allocation of some processes to some firms. Instead, different physical firms will offer services of supply, manufacturing, logistics, and sales which will result in dynamic allocation of processes and dynamic SC structures. Indeed, this ideas is not really new. We can recall the virtual enterprises concept developed about 15-20 years ago (Camarinha-Matos and Macedo 2010).

The SCs in virtual enterprises were expected to be formed dynamically thru so-called competence cell or agents networking (Ivanov et al. 2004, Teich and Ivanov 2012, Ivanov and Sokolov 2012b,c). In essence, the suppliers were integrated in a tool that contained their technological processes and the related operational parameters (e.g., costs and lead-times). A customer was able to place an order specification, and an automatic algorithm was able to find the suppliers needed to be networked to fulfil this customer order. So while the individual contributors (e.g., robots, sensors, RFID – radio frequency identification, agents, modular factories, etc.) are not really new, they are becoming more practical and companies more receptive to using them to stay competitive.

In addition, an attempt to interconnect these local solutions using the progress in data processing technologies can be observed in practice. For example, with the help of smart sensors and plug-and-produce cyber-physical systems, the stations in the assembly system are capable of changing the operation processing and setup sequences according to actual order incoming flows and capacity utilization. As such, this trend calls for new principles and models to support SCM of such future factories.

2.2. From decision support systems (DSS) to decision analysis, modelling, control and learning systems (DAMCLS)

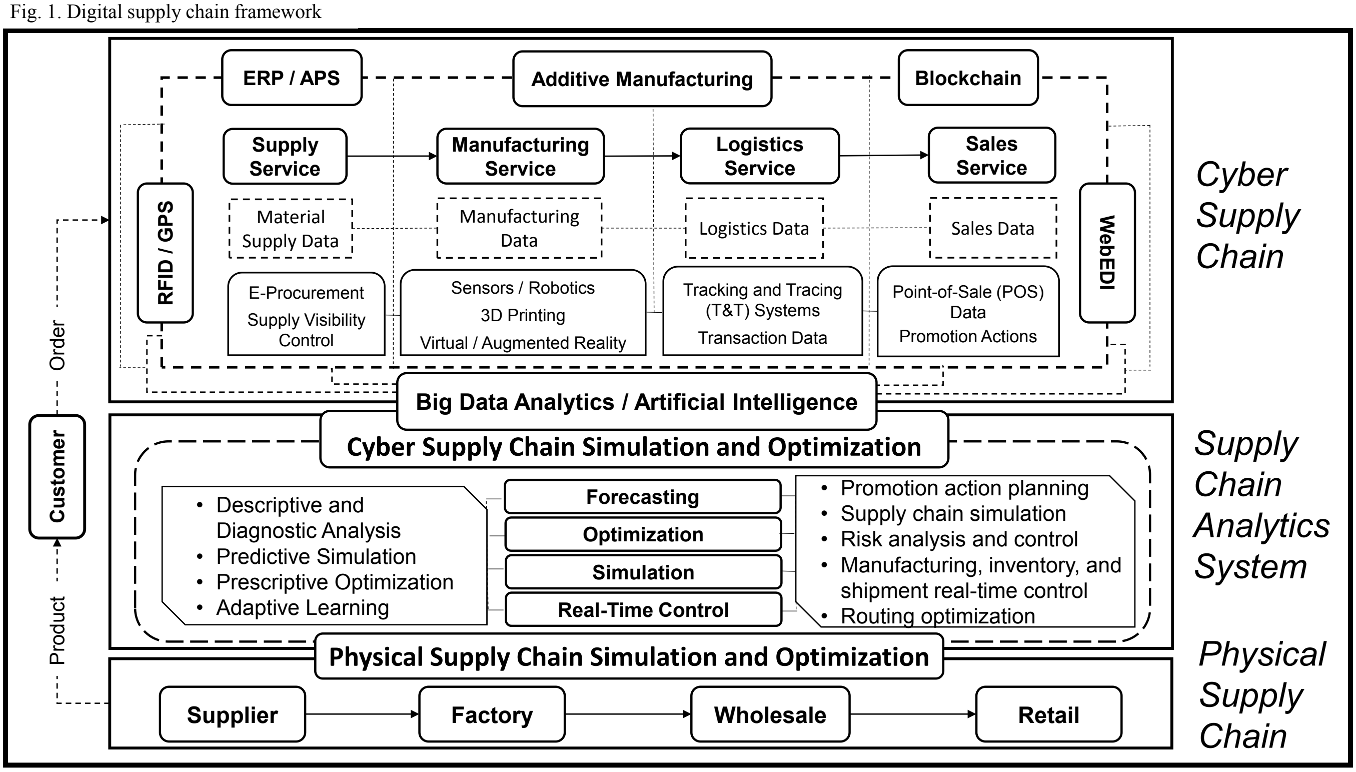
The second observation concerns the quantitative analysis methods in SCM. In the past decades, simulation and optimization have played significant roles in solving complex problems in SCM. Successful examples include production planning and scheduling, SC design, and routing optimization, just to name a few. However, many problems remain challenging because of their complexity and large scales, and/or uncertainty and stochastic nature. In addition, the major application of the optimization and simulation methods in the last decades was seen in the decision support, meaning that decision-makers were to manually provide the model input and interpret the model output. On the other hand, the rapid rise of business analytics provides exciting opportunities for the Operations Research and to re-examine these hard optimization problems, as well as newly emerging problems in SC management.

Examples of SC and operations analytics applications include logistics and SC control with real-time data, inventory control and management using sensing data, dynamic resource allocation in Industry 4.0 customized assembly systems, improving forecasting models using Big Data, machine learning techniques for process control, SC visibility and risk control, optimizing systems based on predictive information (e.g., predictive maintenance), combining optimization and machine learning algorithms, and simulation-based modeling and optimization for stochastic systems.

The application areas of SC Analytics can be classified in four areas, i.e.:

- Descriptive and diagnostic analysis
- Predictive simulation and prescriptive optimization

Fig. 1. Digital supply chain framework



- Real time control, and
- Adaptive learning

Sourcing, manufacturing, logistics and sales data are distributed among very different systems such as ERP, RFID, sensors, and blockchain. Big Data Analytics integrates this data to information used by artificial intelligence algorithms in the cyber SC and managers in the physical SC. For example, electronic retailers are using their extensive transactional and behavioral data of their customers to offer them new ways of trying, experiencing and purchasing their products.

PwC is working with a large car company looking to introduce autonomous vehicles for the public. Part of this work employs deep reinforcement learning to develop rules. Together with simulation, deep reinforcement learning is used to determine 'optimal' decision rules that allow the vehicles to maximize efficiency while also satisfying customer trip demand. The software environment for the project uses the extensible and practical environment of AnyLogic multi-method simulation software to lever the capabilities of DL4J for the deep learning environment. Autonomous cars are becoming more common and the features are already in many consumer cars. These examples show that artificial intelligence becomes more pervasive in the real world with every project, and necessarily it must be part of simulation.

With regards to SC risks, Resilience360 at DHL allows comprehensive disruption risk management by mapping end-to-end SC, building risk profiles and identifying critical hotspots in order to initiate mitigation activities and alert in near-real time mode on incidents that could disrupt the SC (DHL 2018).

Finally, collaborative control theory is considered as one of the milestones in development of decentralized control systems (Nof 2007). The major idea of collaborative control is to com-bine decentralized agent-oriented control in the framework of bio-inspired coordination and control, adaptation and learning. Nayak et al. (2016) extend the collaborative control concept in direction of decentralized resource sharing in the CPS setting. Moghaddam and Nof (2017) formulated the principles of collaborative factory of future through the collaborative control theory operators in order to address the challenges of scalability, resilience and sustainability.

3. DIRECTIONS AND EXAMPLES OF CONTROL AND ANALYTICS COMBINATIONS

Digital technology in the Industry 4.0 framework provides constructive basis to implement CT models and algorithms. CT is favorable in the cases of many dynamically changing control parameters, obtaining analytical solutions or properties, and in investigating different mutual impacts of SC planning and control parameters (e.g., demands, resource and channel capacities, lead-time, lot-sizes, and inventories) on the SC tactical and operative performance (i.e., service level and costs). In some cases (e.g., if many changes, many stages, and many periods), it is convenient to transit from a discrete problem statement to continuous solution procedure, and then represent the result again in discrete terms due to particular accuracy of continuous time models.

The system control has two impacts upon the system. First, this is the tuning – the changing of uncertain coefficients in the structure of the differential equations of the system, taking account that the greater number of these coefficients implies a more accurate system response to a changing environment. Second, this is the learning – the imposing new restrictions on the system behavior. The number of arbitrary coefficients, in the structure of equivalent equations, changes in the process of learning, of consecutive imposing new and new restrictions on the system behavior. In the systems with more than six variables the number of arbitrary coefficients increases first, and then, passing through the maximum begins to decrease.

This phenomenon makes it possible to explain the processes of system growth, complication and death. The existence of maximum adaptability phenomenon is observed in numerous biological, economical and physical-engineering systems. It is important that we describe a system with a full sum of combinations and have all the variants of decisions. The lingual-combinatorial simulation is a useful heuristic approach for investigation of complex, poorly formalized systems.

For technical formalization of the risk analytics in service-oriented cyber-physical SCs (cf. Fig. 1), a complex of control theoretical models is currently under development that includes an optimal control model of dynamics service coordination based on the approach developed in (Ivanov et al. 2012b, 2014b).

4. DIRECTIONS OF SUPPLY CHAIN RISK ANALYTICS BY CONTROL

Fig. 2 presents a framework that summarizes contributions of control analytics to SC risk management in a cyber-physical SC. At the risk analysis stage, descriptive and diagnostic analysis with regards to disruption impact analysis in the past, performance analysis, resilience analysis, and recovery analysis is performed. Control theoretic attainable sets can be used at this level (Ivanov et al. 2016a,b, Ivanov et al. 2018)

The modelling stage is devoted to predictive simulation and prescriptive optimization. Structural dynamics control approach in combination with mathematical optimization can be used (Ivanov et al. 2013, 2014b, 2016). Real-time control area contains supply flow real-time control, disruption identification, and real-time performance and recovery control.

It is commonly known that feedback control in socio-organizational differs from technical systems where the feedback can be implemented almost immediately. In socio-organizational systems, the feedback information first needs to be evaluated by managers and the adjustment decisions need to be coordinated among different department in the firms or even cross-organisational.

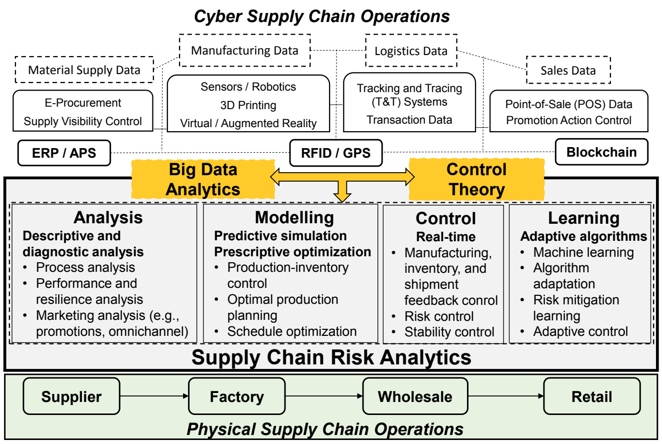


Fig. 2. Supply chain risk and control analytics

As such, the differences in the system states can be observed between the system state at the moment of starting to prepare the adjustment decisions 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 correction (adaptation) decisions need to be implemented at the object or system which is different from the object or system that has been considered for the reconfiguration decision planning.

Finally, learning stage is comprised of risk mitigation learning, disruption recovery learning, and disruption pattern recognition. A combination of control algorithms and artificial intelligence can provide a number of new insights in the given area.

5. CONCLUSIONS

In the frameworks of SC risk management, dynamics, and resilience, control theoretic approaches can be considered as useful tools to tackle the issues of performance achievement under operational and disruption risks. New analytics technologies in the framework of Industry 4.0, big data analytics and artificial intelligence resulted in the creation of new domains, i.e., cyber physical supply chains and supply chain risk analytics.

As such two trends can be observed as follows:

- integration of analytics into control theory (so called intellectualization of control) and
- integration of analytics into supply chain risk management (so called cyber-physical SC and risk analytics).

Control theory provides a variety of methods and tools for SC management and takes into account dynamics, real dimensions, non-linearity and non-stationary of SC processes. In addition, with the help of control theory, non-stationary performance indicators such as robustness and stability can be investigated in their fullness and consistency with operations planning and execution control with-in a conceptually and mathematically integrated framework.

This study brings the discussion forward by integrating these two perspectives. It analyses how control theory can enhance the risk analytics in the cyber-physical SC. Based on literature and case-study analysis, the frameworks of cyber physical supply chain and risk analytics control have been derived.

The derived frameworks show that the incorporation of intelligent IT into CT, also known as intellectualization of control in the framework of digital SC and operations management control in Industry 4.0, can provide a variety of methods and tools for dynamics in the SC domain. This can become the area where the knowledge of SC and operations managers and control specialists can be effectively integrated taking advantages of modern IT, e.g., for investigating SC dynamics or applying RFID to SC monitoring and adaptation.

Finally, a combination of control and analytics methods may have a potential to create pioneering solutions to SC and operations reconfiguration based on the feedbacks. It is commonly known that feedback control in socio-organizational differs from technical systems where the feedback can be implemented almost immediately. In socio-organizational systems, the feedback information first needs to be evaluated by managers and the adjustment decisions need to be coordinated among different department in the firms or even cross-organisational.

As such, the differences in the system states can be observed between the system state at the moment of starting to prepare the adjustment decisions 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 correction (adaptation) decisions are implemented at the object or system which is different from the object or sys-tem that has been considered for the reconfiguration decision planning. Therefore, the need for proactive control models arises. There are a number of possible combinations of control and analytic methods in this direction, e.g., attainable set and predictive analytics combination.

References

Camarinha-Matos, L.M., Macedo, P. (2010), 'A conceptual model of value systems in collaborative networks', Journal of Intelligent Manufacturing, 21 (3), 287-299.

Cavalcantea, I.M., Frazzon E.M., Forcellinia, F.A., Ivanov, D. (2019). A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. International Journal of Information Management, https://doi.org/10.1016/j.ijinfomgt.2019.03.004

Christopher M (2005) Logistics and Supply Chain Management: Creating Value-Adding Networks. Financial Times Prentice Hall, Dorchester

Dejonckheere, J., Disney, S.M., Lambrecht, M.R., Towill, D.R., (2004). The impact of information enrichment on the bullwhip effect in supply chains: A control engineering perspective. European Journal of Operational Research, 153(3), 727–750.

DHL (2018). https://resilience360.com/ (accessed on February 4, 2018)

Disney, S.M., & Towill, D.R., (2002). A discrete linear control theory model to determine the dynamic stability of vendor managed inventory supply chains. International Journal of Production Research, 40(1), 179–204.

Disney, S.M., Towill, D.R., & Warburton, R.D.H. (2006). On the equivalence of control theoretic, differential, and difference equation approaches to modeling supply chains. International Journal of Production Economics, 101, 194–208.

Disney, S.M., Towill, D.R., 2005. Eliminating inventory drift in supply chains. International Journal of Production Economics 93–94, 331–344.

Dolgui, A., Ivanov, D., Sethi S.P., Sokolov, B. (2019a). Scheduling in production, supply chain and Industry 4.0 systems by optimal control. International Journal of Production Research, 57(2), 411-432

Dolgui A., Ivanov D., Potryasaev S., Sokolov B., Ivanova M., Werner F. (2019b). Blockchain-oriented dynamic modelling of smart contract design and execution control in the supply chain. International Journal of Production Research, in press.

Dolgui, A., Ivanov, D., Sethi S.P., Sokolov, B. (2018). Control theory applications to operations systems, supply chain management and Industry 4.0 networks. IFAC-PaperOnLine, Proceedings of IFAC INCOM 2018 Symposium.

Dubey R., Gunasekaran A., Childe, S. J. Wamba S.F., Roubaud D., Foropon C. (2019). Empirical Investigation of Data Analytics Capability and Organizational Flexibility as Complements to Supply Chain Resilience. International Journal of Production Research, DOI: 10.1080/00207543.2019.1582820

Fu D., Ionescu CM, Aghezzaf EH (2015) Quantifying and mitigating the bullwhip effect in a benchmark supply chain system by an extended prediction self-adaptive control ordering policy. Computers and Industrial Engineering 81, 46-57.

He, X., Prasad, A., & Sethi, S.P. (2009). Cooperative Advertising and Pricing in a Stochastic Supply Chain: Feedback Stackelberg Strategies. Production and Operations Management, 18 (1), 78–94.

Heckmann I. (2016). Towards Supply Chain Risk Analytics: Fundamentals, Simulation, Optimization. Springer-Gabler.

Hosseini S., Ivanov D., Dolgui A. (2019). Review of quantitative methods for supply chain resilience analysis. Transportation Research: Part E, 125, 285-307.

Ivanov D., & Sokolov B. (2013a). Control and system-theoretic identification of the supply chain dynamics domain for planning, analysis, and adaptation of performance under uncertainty. European Journal of Operational Research, 224(2), 313–323.

Ivanov D., Sokolov B. (2012b), 'Structure dynamics control-based service scheduling in collaborative cyber-physical supply networks, in Camarinha-Matos, L., Xu, L., Afsarmanesh, H. (Eds.) Proceedings of the IFIP Conference on Virtual Enterprises PRO-VE 2012 IFIP AICT 380, pp.280-288.

Ivanov D., Sokolov B., Dilou Raguinia, E.A. (2014b) Integrated dynamic scheduling of material flows and distributed information services in collaborative cyber-physical supply networks, International Journal of Systems Science: Operations & Logistics, 1(1), 18-26.

Ivanov D., Sokolov B., Dolgui, A. (2014a) Multi-stage supply chain scheduling in petrochemistry with non-preemptive operations and execution control, International Journal of Production Research, 52(13), 4059-4077.

Ivanov, D. (2018). Structural Dynamics and Resilience in Supply Chain Risk Management. Springer, New York.

Ivanov, D., Dolgui, A., Sokolov, B. (2019b). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. International Journal of Production Research, 57(3), 829-846.

Ivanov, D., Sethi S., Dolgui A., Sokolov, B. (2018a). A survey on the control theory applications to operational systems, supply chain management and Industry 4.0. Annual Reviews in Control, 46, 134-147.

Ivanov, D., Arkhipov, A., Sokolov, B. (2004): Intelligent Supply Chain Planning in Virtual Enterprises. In: Virtual Enterprises and Collaborative Networks, Proceedings of the IFIP Conference on virtual enterprises PRO-VE 2004, edited by L. Camarihna-Matos, Kluwer Academic Publishers, 2004, pp. 215-223.

Ivanov, D., Dolgui, A., Sokolov, B. (2017). A dynamic approach to multi-stage job shop scheduling in an Industry 4.0-based flexible assembly system. In: Lödding, H., Riedel, R., Thoben, K.-D., Kiritsis, D., von Cieminski, G. (Eds.) Advances in Production Management Systems. The Path to Intelligent, Collaborative and Sustainable Manufacturing. IFIP WG 5.7 International Conference, APMS 2017, Hamburg, Germany, September 3-7, 2017, Proceedings, Part I, pp. 475-482.

Ivanov, D., Dolgui, A., Sokolov, B. (2018a). Scheduling of recovery actions in the supply chain with resilience analysis considerations. International Journal of Production Research, 56(19), 6473-6490.

Ivanov, D., Sokolov B. (2012a) Dynamic supply chain scheduling, Journal of Scheduling, 15(2), 201-216.

Ivanov, D., Sokolov B. (2012c) The Inter-Disciplinary Modelling of Supply Chains in the Context of Collaborative Multi-Structural Cyber-Physical Networks, Journal of Manufacturing Technology Management, Vol. 23(8), 976-997.

Ivanov, D., Sokolov B., Dolgui, A. (2012) Applicability of optimal control theory to adaptive supply chain planning and scheduling, Annual Reviews in Control, 36, 73-84.

Ivanov, D., Sokolov, B. (2010), Adaptive Supply Chain Management, Springer, London et al.

Ivanov, D., Sokolov, B., & Kaeschel, J. (2010). A multi-structural framework for adaptive supply chain planning and operations with structure dynamics considerations. European Journal of Operational Research, 200(2), 409–420.

Ivanov, D., Sokolov, B., Dolgui, A. (2014c) The Ripple effect in supply chains: trade-off 'efficiency-flexibility-resilience' in disruption management, International Journal of Production Research, 52:7, 2154-2172.

Ivanov, D., Sokolov, B., Dolgui, A., Solovyeva,I., Jie, F. (2016a). Dynamic recovery policies for time-critical supply chains under conditions of ripple effect. International Journal of Production Research, 54(23), 7245-7258.

Ivanov, D., Sokolov, B., Dolgui, A., Werner, F., Ivanova, M. (2016b). A dynamic model and an algorithm for short-term supply chain scheduling in the smart factory Industry 4.0. International Journal of Production Research, 54(2), 386-402.

Ivanov, D., Sokolov, B., Hartl, R., Dolgui, A., Pavlov, A., Solovyeva, I. (2015). Integration of aggregate distribution and dynamic transportation planning in a supply chain with capacity disruptions and ripple effect considerations. International Journal of Production Research, 53(23), 6963-6979.

Khajavi SH, Partanen J., Holmström J. (2014) Additive manufacturing in the spare parts supply chain. Computers in Industry, 65(1), 50-63

Khmelnitsky E, Presman E., Sethi S.P. (2011) Optimal production control of a failure-prone machine. Ann Oper Res 182:67-86

Lalwani C, Disney SM, Towill DR (2006), Controllable, observable and stable state space representations of a generalized order-up-to policy. Int. J. Production Economics 101 (2006) 172–184

Levalle R R, Nof S Y (2017). Resilience in supply networks: Definition, dimensions, and levels. Annual Reviews in Control, 43(1), 224–236.

Li J., Jia G., Cheng Y., Hu Y. (2017). Additive manufacturing technology in spare parts supply chain: a comparative study. International Journal of Production Research, 55(5), 1498-1515

Moghaddam M., Nof S.Y., "The collaborative factory of the future," 2017, International Journal of Computer Integrated Manufacturing, 30 (1), pp. 23-43.

Mönch L., Fowler J.W., Mason S. (2012). Production Planning and Control for Semiconductor Wafer Fabrication Facilities: Modeling, Analysis, and Systems. Springer Science & Business Media.

Nayak A., Reyes Levalle R., Lee S., Nof S.Y., "Resource sharing in cyber-physical systems: model-ling framework and case studies," 2016, International Journal of Production Research, 54(23), 6969-83.

Nof, S.Y., "Collaborative control theory for e-work, e-production, and e-service, Annual Reviews in Control, 31(2), 2007, 281-92.

Ortega, M. and Lin, L. (2004). Control theory applications to the production-inventory problem: a review. International Journal of Production Research. 42, 2303–2322.

Panetto H., Iung B., Ivanov D., Weichhart G., Wang X. (2019). Challenges for the cyber-physical manufacturing enterprises of the future. Annual Reviews in Control, https://doi.org/10.1016/j.arcontrol.2019.02.002

Perea, E., Grossmann, I., Ydstie, E. and Tahmassebi, T. (2000) Dynamic modeling and classical control theory for supply chain management. Computers and Chemical Engineering, 24, 1143–1149.

Sarimveis, H., Patrinos, P., Tarantilis, C.D., and Kiranoudis CT. (2008). Dynamic modeling and control of supply chain systems: A review. Computers & Operations Research, 35, 3530–3561.

Scholz-Reiter, B., Dashkovskiy, S., Görges, M., and Naujok, L. (2011). Stability analysis of autonomously controlled production networks. International Journal of Production Research, 49(16), 4857-4877.

Sethi SP (1978) A Survey of Management Science Applications of the Deterministic Maximum Principle. TIMS Studies in the Management Science, 9:33-68.

Sethi SP, Yan H, Zhang H, Zhang Q. (2002) Optimal and Hierarchical Controls in Dynamic Stochastic Manufacturing Systems: A Survey. Manuf Serv Oper Mant, 4(2):133-170.

Sethi, S.P., Thompson, G.L. (2000). Optimal control theory: Applications to Management Science and Economics, second edition. Springer: Berlin.

Spiegler, V., Naim, M. and Wikner, J. (2012). A control engineering approach to the assessment of supply chain resilience. International Journal of Production Research 50:6162-6187.

Spiegler, VLM, Naim, M. M., Towill, D. R., Wikner, J. (2016). The value of nonlinear control theory in investigating the underlying dynamics and resilience of a grocery supply chain. International Journal of Production Research, 54(1):265-286

Teich, T., Ivanov, D. (2012) Integrated customer-oriented product design and process networking of supply chains in virtual environments, International Journal of Networking and Virtual Organizations, 11(1), 48-61.

Yang, Y., et al. (2017). "Mitigating supply chain disruptions through interconnected logistics services in the Physical Internet." International Journal of Production Research 55(14): 3970-3983.

Zhuge, H. (2011), 'Semantic linking through spaces for cyber-physical-socio intelligence: A methodology. Artificial Intelligence, 175 (5–6), 988–1019.