Conceptual Modelling in Operational Simulation of Logistics

Subjects: Engineering, Industrial | Computer Science, Theory & Methods

Contributor: Zichong Lyu , Dirk Pons , Yilei Zhang , Zuzhen Ji

Logistics problems involve a large number of complexities, which makes the development of models challenging. While computer simulation models are developed for addressing complexities, it is essential to ensure that the necessary operational behaviours are captured, and that the architecture of the model is suitable to represent them. The early stage of simulation modelling, known as conceptual modelling (CM), is thus dependent on successfully extracting tacit operational knowledge and avoiding misunderstanding between the client (customer of the model) and simulation analyst.

simulation conceptual modelling discrete-event simulation agile method freight logistics

1. Introduction

Logistics problems involve a large number of complexities. These are introduced by the variety in vehicle fleet composition [1], vehicle allocation and routing [2], shipment consolidation and dispatching [3], diverse types of infrastructure, network design [4], day-to-day variability of customer consignments, difficulty of obtaining accurate parameter data [5], and complex operational systems [6]. Computer simulation methods including agent-based simulation (ABS), system dynamics (SD) and discrete-event simulation (DES) have been used to deal with randomness. They can represent the behaviour of logistics transportation systems with randomness: the process workflow; logical structure and decision modules; parameters of different types; stochastic uncertainty; interactions between agents; availability of resources; long-haul and short-haul and so on. Long-haul refers to intercity transport between depots/warehouses, and short-haul is pickup and delivery between customer locations and the depot/warehouse. However, a model must be created before it can be interrogated for results, and the complexity of logistics problems makes this a difficult undertaking.

Conceptual modelling (CM) is the most crucial and challenging part of simulation modelling because it determines the structure and accuracy of the future model [7][8]. It provides the initial layout of the model, and increases the validity of the final model [9][10]. There are three main issues in the early modelling stage or the conceptual modelling stage. The first is to design the architecture of the model [11], include the necessary factors, solicit the tacit knowledge, and ensure the model is extendable and refinable. The second is to obtain data on the various parameters and apply them to the simulation. The last is to validate the model, especially from the operational perspective [12]. Inadequacies in any of these stages may lead to technical debt in the future phases.

The data approach involves the industry client providing the simulation analyst with the data. Disadvantages of the conventional approach are the sometimes-unreasonable information burden placed on the client and the introduction of errors into the model due to undetected deficiencies in problem definition and data. Consequently, there is a risk of technical debt occurring, whereby the deficiencies are structurally incorporated into the architecture of the model, which then may have to be substantially reworked at a future time. Structural changes to models are effortful to change later because the validation partly depends on the structure of the model. This is because any validation process involves an element of tuning of parameters, and those parameters are determined by the structure of the model. Hence, reformulating the model at a future date involves changes to the tuneable parameters, and therefore a need for revalidation. Communication and collaboration with the client are necessary for model definition and validation. Client participation and facilitation improve the quality of the model, but can lead to other issues such as problems in gathering sufficient data [13], paradigm incommensurability, and cognitive difficulty [14].

Current methods for conceptual modelling have several weaknesses. First, there is a scarcity of simulation models with a systematic and explicit method for involving communication and collaboration with the client. Previous models including participative modelling and facilitated modelling have been proposed to alleviate these issues [13][15]. These methods mainly focus on client involvement rather than the model itself. Second, issues such as knowledge boundaries and tacit knowledge elicitation are seldom explicitly included, at least not in the simulation one. Third, client engagement is complex in terms of model definition, data acquisition, and data validation. There is a need for better methods to solve multiple information issues. Fourth, the process for transforming the conceptual model into a detailed model is not always clear.

2. Methods for Solving Logistics Problems

Logistics transportation problems can be categorised into long-haul (intercity transport between depots/warehouses) and short-haul (pickup and delivery between client location and depot/warehouse). Typical problems, which apply to both long- and short-haul differently, include vehicle allocation problems, vehicle routing problems, shipment consolidation and dispatching problems, and network design problems [3].

2.1. Analytical Methods

Operations problems of simple to medium complexity may be solved by analytical methods such as linear programming and regression analysis. Mixed-integer linear programming is a prevalent mathematical optimisation method that includes objective functions and constraints. This method is frequently applied to transportation problems; e.g., in multimodal transport [16][17], scheduling [18][19], rail transport systems [20], and transport energy analysis [21]. Although analytical models can be quickly developed, there are several limitations of these models. One limitation is the difficulty in describing dynamic and transient effects. Additionally, analytical models are limited to simulating randomness of the system due to the complexity of the calculations [6], so these models normally simplify real problems. For example, for routing models, analytical techniques lack considerations of path constraints and practical scheduling of vehicles [22]. Moreover, clients may struggle to interact with these models due to the mathematical formulations.

2.2. Computer Simulation Methods

Typical simulation approaches here include ABS, SD, and DES. ABS focuses on individual entities who make their own decisions; whereas DES concentrates on system analysis, and the process relies on model architecture. Therefore, from the perspective of consultation and collaboration between simulation analysts and industrial clients, DES is more straightforward, and has been widely implemented [23]. **Table 1** summarises recent applications of simulations in logistics.

Typical DES software includes Arena, SIEMENS Plant Simulation, and SIMUL8. These use program diagrams with logic to mimic real operational procedures [24]. Compared with traditional mathematical models, simulation models are able to analyse stochastic events by including logic functions (decision modules) and probability distributions (using Monte Carlo methods), so uncertainties such as delay time, arrival time, and arrival rate can be reflected in the system. Once the model is validated, simulations can quickly analyse different scenarios.

Table 1. Applications of ABS and DES on logistics.

Logistics Areas	Problems	Methods
Truck platoon planning	Investigate truck platoon possibilities and evaluate waiting times [1]	ABS
Freight operations	Evaluate freight-unloading operations [25] Freight pickup and delivery [26]	DES DES
Multimodal and intermodal transport	Analyse multimodal freight-routing system [27]	DES
Railway network design	Avoid collisions [28]	ABS
	Analyse queuing systems of rail network [4]	DES
Rail yard design	Design rail transhipment yard [29]	ABS
	Evaluate processing capabilities of rail yard [30]	DES
	Integrate high-speed rail lines with conventional railways [31]	DES
Port operations	Simulate container logistics [32]	DES
Supply chain management	Estimate last-mile distance [33]	DES
	Conduct inventory analysis [34]	DES

References

3. Conceptual Modelling Approaches

Simulations are used to solve real-world operations problems, and this requires collaboration between the industry client and the analyst. Figure 1 shows the conventional simulation modelling process based on Robinson [6]. The most critical steps of simulation modelling are conceptual modelling, detailed model creation, and experiment conduction [35]. The simulation modelling process is generally undertaken by the analyst with partial industry client participation.

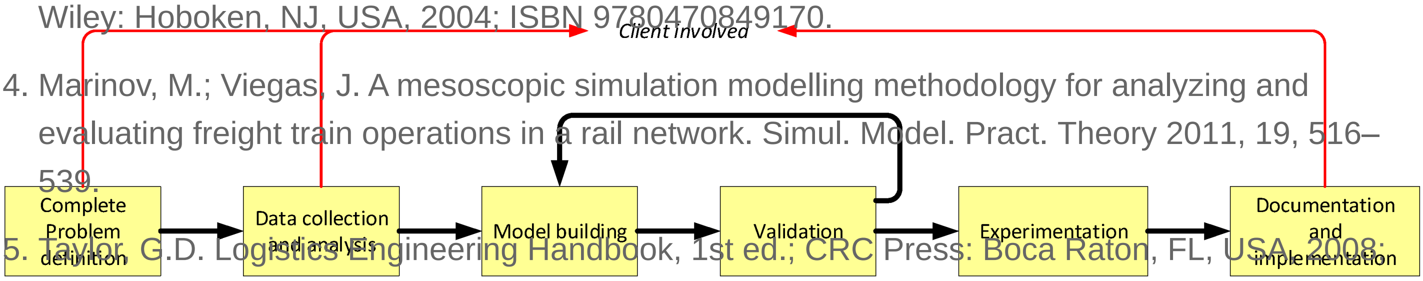

Figure 1. Conventional simulation modelling process, redrawn from Robinson [6].

Specifically, simulation model development at the early stage is important to a project. Scope and model definition, data collection, and collaboration with industry are the main challenges [11]. Proposed modelling methods include parallel and iterative methodology [36], applications of discrete-event simulation [37][38], and methods to support project objective definition [39]. CM has been widely used to create abstractive simulation models at the early modelling stage [9]. Knowledge elicitation and abstraction, validity, credibility, utility, and feasibility of CM are key aspects [40][41]. CM delivers crucial information to the future models [7]. The process may help identify relevant information [6][42] and increase the validity of the model [10].

The conventional CM approach tends to adopt a linear method of problem solving, and this is seen most strongly in the project management, waterfall, and stage-gate methods, which require each phase to be reviewed before approval is given to proceed to the next [43]. These methods all require complete scope definition at the outset, or sequential decisions against predetermined objectives [44]. In well-defined projects where the tasks are familiar to participants, these methods may work well. However, when complexity is high, e.g., for unfamiliar work streams and uncertain requirements, these methods struggle. The issues have been identified as ‘paradigm incommensurability’ and ‘cognitive difficulty of switching paradigms for stakeholders’ [14].

4. Client Participation and Stakeholder-Facilitated Modelling

Conventional CM lacks stakeholder engagement. Involving stakeholders in simulation modelling can improve the credibility of the model. Stakeholder engagement is emphasised in methods such as hybrid modelling [15] and facilitated/participative modelling [13][40][45].

Hybrid modelling introduces a second loop to involve stakeholders [15]. It illuminates that visualisation of simulation models supports analysts to clarify modelling ideas. Stakeholders were involved through the iterative development

1. Elbert, R.; Knigge, J.-K.; Friedrich, A. Analysis of decentral platoon planning possibilities in road freight transport using an agent-based simulation model. J. Simul. 2019, 14, 64–75.
2. Silva, B.C.; Fernandes, I.F.d.C.; Goldbarg, M.C.; Goldbarg, E.F.G. Quota travelling salesman problem with passengers, incomplete ride and collection time optimization by ant-based algorithms. Comput. Oper. Res. 2020, 120, 104950.
3. Ghiani, G.; Laporte, G.; Musmanno, R. Introduction to Logistics Systems Planning and Control; J. Wiley: Hoboken, NJ, USA, 2004; ISBN 9780470849170.
4. Marinov, M.; Viegas, J. A mesoscopic simulation modelling methodology for analyzing and evaluating freight train operations in a rail network. Simul. Model. Pract. Theory 2011, 19, 516–539.
5. Taylor, G.D. Logistics Engineering Handbook, 1st ed.; CRC Press: Boca Raton, FL, USA, 2008; ISBN 978-0-8493-3053-7.
6. Robinson, S. Successful Simulation: A Practical Approach to Simulation Projects; McGraw-Hill: London, UK; New York, NY, USA, 1994; ISBN 9780077076221. 0077076222.
7. Robinson, S. Conceptual modeling for simulation. In Proceedings of the 2013 Winter Simulations Conference (WSC), Washington, DC, USA, 8–11 December 2013.
8. Gabriel, G.T.; Campos, A.T.; Leal, F.; Montevechi, J.A.B. Good practices and deficiencies in conceptual modelling: A systematic literature review. J. Simul. 2020, 16, 84–100.
9. Robinson, S. Conceptual modelling for simulation Part I: Definition and requirements. J. Oper. Res. Soc. 2008, 59, 278–290.
10. Francisco, R.P.; Campos, D.P.; Frazzon, E.M.; Machado, R.L. On the application of modelling and simulation to compare human- and automation-based order-picking systems. IFAC-PapersOnLine 2016, 49, 1062–1067.
11. Robinson, S. Conceptual modelling for simulation: Progress and grand challenges. J. Simul. 2019, 14, 1–20.
12. Balci, O. Validation, verification, and testing techniques throughout the life cycle of a simulation study. In Proceedings of the 1994 Winter Simulation Conference, Buena Vista, FL, USA, 11–14 December 1994; IEEE: Buena Vista, FL, USA, 1994.
13. Franco, L.A.; Montibeller, G. Facilitated modelling in operational research. Eur. J. Oper. Res. 2010, 205, 489–500.
14. Kotiadis, K.; Mingers, J. Combining PSMs with hard OR methods: The philosophical and practical challenges. J. Oper. Res. Soc. 2006, 57, 856–867.

process. The validation conducted by this method was face validation. Participative modelling was applied to create a simulation conceptual model. As the system was created by DES through participative and facilitative conceptual modelling [40]. The model was evaluated using knowledge elicitation and abstraction, validity, credibility, utility, and feasibility.

Facilitated modelling was proposed to engage the client through interventions [13]. In this mode, the simulation analyst is also a facilitator to build relationships with the client. Compared with the conventional expert mode, the facilitated mode relies on the analyst's interventions with the client. This means the analyst needs facilitation skills including 'active listening', 'chart-writing', 'managing group dynamics and power shifts', and 'reaching closure'. A DES model for a hospital was developed, and a facilitated mode was included. The discussion with stakeholders included model understanding, face validation, problem scoping, and improvement. The client involvement was evaluated at each modelling phrase. The invention was achieved in this research, but the full facilitated mode was still challenging [45].

In the above, these stakeholder engagement modes increased stakeholder involvement during the initial modelling stage. Simplified models were developed in order to reduce the time. However, the detailed complexity of the DES model was difficult to obtain [45]. Boundary-spanning activities were presentations and group discussions. The validation of the facilitated model was mainly the face validation. The facilitator/analyst did not conduct enough operational observations to elicit tacit knowledge, which could not be noticed by stakeholders. Moreover, the communication hierarchy was unclear.

5. Agile Method

The agile method originated in software development. Agile is primarily directed at maximising collaboration between project stakeholders and directing work effort towards progressive development of the product [46][47]. Agile development typically uses a minimum viable product (MVP) approach. This refers to a product that embodies the primary functionalities with the least detail. The MVP perspective is complementary to the scrum process, which is a method for managing agile team interactions towards MVP outcomes [48][49]. The method puts a strong emphasis on getting the architecture of the system correct at the early stages, which it does via a structured communication process. Hence, a degree of validation of the model occurs much earlier in the process than in conventional simulation processes.

Some recent examples of the MVP software process are a hospital management system to improve communications [50], e-commerce systems [51], the Internet of Things [52] and enterprise management [53]. The method has been adapted to other disciplines such as project management and development [46][54] and entrepreneurship (business start-ups) [55][56]. The key advantages of MVP are the improvement in communication within the development team and with the client. MVP has the potential to reduce the *technical deficit* (or debt) [57][58]. This is the future cost of reworking the solution due to defects in the architecture of the initial solution. Offsetting that advantage is the disadvantage that the product might never move beyond the minimal state. However, MVP also requires resources, as recognised in the specific case of software start-up businesses [59].

15. Jones, W.; Kotiadis, K.; O'Hanley, J. Engaging Stakeholders to Extend the Lifecycle of Hybrid Simulation Models. In Proceedings of the 2019 Winter Simulation Conference (WSC), National Harbor, MD, USA, 8–11 December 2019.
16. Sun, Y.; Hrušovský, M.; Zhang, C.; Lang, M. A Time-Dependent Fuzzy Programming Approach for the Green Multimodal Routing Problem with Rail Service Capacity Uncertainty and Road Traffic Congestion. Complexity 2018, 2018, 8645793.
17. Zehendner, E.; Rodriguez-Verjan, G.; Absi, N.; Dauzère-Pérès, S.; Feillet, D. Optimized allocation of straddle carriers to reduce overall delays at multimodal container terminals. Flex. Serv. Manuf. J. 2015, 27, 300–330.
18. Zhang, M.; Wang, Y.; Su, S.; Tang, T.; Ning, B. A Short Turning Strategy for Train Scheduling Optimization in an Urban Rail Transit Line: The Case of Beijing Subway Line 4. J. Adv. Transp. 2018, 2018, 5367295.
19. Zikopoulos, C. Determination of freight rates under stochastic demand and freight consolidation savings. Int. J. Prod. Res. 2019, 57, 5556–5573.
20. Masoud, M.; Kozan, E.; Kent, G. Hybrid metaheuristic techniques for optimising sugarcane rail operations. Int. J. Prod. Res. 2018, 53, 2569–2589.
21. Mu, S.; Zhong, Z.; Ni, M. Multi-Destination Computation Offloading in Vehicular Networks. In Proceedings of the 14th International Wireless Communications and Mobile Computing Conference, IWCMC 2018, Limassol, Cyprus, 25–29 June 2018; Institute of Electrical and Electronics Engineers Inc.: Limassol, Cyprus, 2018.
22. Keenan, P. Modelling vehicle routing in GIS. Oper. Res. 2008, 8, 201–218.
23. Kogler, C.; Rauch, P. Discrete event simulation of multimodal and unimodal transportation in the wood supply chain: A literature review. Silva Fenn. 2018, 52, 9984.
24. Ji, Z.; Pons, D.J.; Pearce, J. Plant system simulation for engineering training workshops. Comput. Appl. Eng. Educ. 2019, 28, 17–30.
25. Voegl, J.; Fikar, C.; Hirsch, P.; Gronalt, M. A simulation study to evaluate economic and environmental effects of different unloading infrastructure in an urban retail street. Comput. Ind. Eng. 2019, 137, 106032.
26. Lyu, Z.; Pons, D.; Zhang, Y.; Ji, Z. Freight Operations Modelling for Urban Delivery and Pickup with Flexible Routing: Cluster Transport Modelling Incorporating Discrete-Event Simulation and GIS. Infrastructures 2021, 6, 180.
27. Zhao, Y.; Ioannou, P.A.; Dessouky, M.M. Dynamic Multimodal Freight Routing Using a Co-Simulation Optimization Approach. IEEE Trans. Intell. Transp. Syst. 2018, 20, 2657–2667.

28. Dalapati, P.; Padhy, A.; Mishra, B.; Dutta, A.; Bhattacharya, S. Real-time collision handling in railway transport network: An agent-based modeling and simulation approach. Transp. Lett. 2017, 11, 458–468.
29. Abourraja, M.N.; Oudani, M.; Samiri, M.Y.; Boudebous, D.; El Fazziki, A.; Najib, M.; Bouain, A.; Rouky, N. A Multi-Agent Based Simulation Model for Rail–Rail Transshipment: An Engineering Approach for Gantry Crane Scheduling. IEEE Access 2017, 5, 13142–13156.
30. Marinov, M.; Viegas, J. A simulation modelling methodology for evaluating flat-shunted yard operations. Simul. Model. Pract. Theory 2009, 17, 1106–1129.
31. Abbott, D.; Marinov, M.V. An event based simulation model to evaluate the design of a rail interchange yard, which provides service to high speed and conventional railways. Simul. Model. Pract. Theory 2015, 52, 15–39.
32. Li, L.; Qiu, M.; Wu, B.; Wang, X. Simulation Research on Road Transport in Container Port Based on Arena. In Proceedings of the 2010 International Conference of Logistics Engineering and Management, ICLEM 2010, Chengdu, China, 8–10 October 2010; pp. 1880–1888.
33. Rabe, M.; Klueter, A.; Raps, J. Evaluating different distance metrics for calculating distances of last mile deliveries in urban areas for integration into supply chain simulation. J. Simul. 2019, 14, 41–52.
34. Cigolini, R.; Pero, M.; Rossi, T.; Sianesi, A. Linking supply chain configuration to supply chain perfrmance: A discrete event simulation model. Simul. Model. Pract. Theory 2014, 40, 1–11.
35. Montevechi, J.A.B.; Pereira, T.F.; Silva, C.E.S.d.; Miranda, R.D.C.; Scheidegger, A.P.G. Identification of the main methods used in simulation projects. In Proceedings of the 2015 Winter Simulation Conference (WSC), Huntington Beach, CA, USA, 6–9 December 2015.
36. Andreasson, H.; Weman, J.; Nåfors, D.; Berglund, J.; Johansson, B.; Lihnell, K.; Lydhig, T. Utilizing Discrete Event Simulation to Support Conceptual Development of Production Systems. In Proceedings of the 2019 Winter Simulation Conference (WSC), National Harbor, MD, USA, 8–11 December 2019.
37. Chwif, L.; Banks, J.; Filho, J.P.D.M.; Santini, B. A framework for specifying a discrete-event simulation conceptual model. J. Simul. 2013, 7, 50–60.
38. Penn, M.; Monks, T.; Kazmierska, A.; Alkoheji, M. Towards generic modelling of hospital wards: Reuse and redevelopment of simple models. J. Simul. 2019, 14, 107–118.
39. Pereira, T.F.; Montevechi, J.A.B.; Miranda, R.D.C.; Friend, J.D. Integrating soft systems methodology to aid simulation conceptual modeling. Int. Trans. Oper. Res. 2014, 22, 265–285.
40. Kotiadis, K.; Tako, A.A.; Vasilakis, C. A participative and facilitative conceptual modelling framework for discrete event simulation studies in healthcare. J. Oper. Res. Soc. 2014, 65, 197–

213.

41. Robinson, S. Conceptual modelling for simulation Part II: A framework for conceptual modelling. J. Oper. Res. Soc. 2008, 59, 291–304.
42. Salt, J. The seven habits of highly defective simulation projects. J. Simul. 2008, 2, 155–161.
43. Roberts, S.; Wang, L.; Klein, R.; Ness, R.; Dittus, R. Development of a simulation model of colorectal cancer. ACM Trans. Model. Comput. Simul. 2007, 18, 1–30.
44. Furian, N.; O'Sullivan, M.; Walker, C.; Vössner, S.; Neubacher, D. A conceptual modeling framework for discrete event simulation using hierarchical control structures. Simul. Model. Pract. Theory 2015, 56, 82–96.
45. Robinson, S.; Worthington, C.; Burgess, N.; Radnor, Z.J. Facilitated modelling with discrete-event simulation: Reality or myth? Eur. J. Oper. Res. 2014, 234, 231–240.
46. Damodharan, S.; Muralidharan, V.; Muralidharan, V. Feature Driven Agile Product Innovation Management Framework. In Proceedings of the 2020 IEEE Technology and Engineering Management Conference, TEMSCON 2020, Detroit, MI, USA, 3–6 June 2020; Institute of Electrical and Electronics Engineers Inc.: Detroit, MI, USA, 2010.
47. Dennehy, D.; Kasraian, L.; O'Raghallaigh, P.; Conboy, K.; Sammon, D.; Lynch, P. A Lean Start-up approach for developing minimum viable products in an established company. J. Decis. Syst. 2019, 28, 224–232.
48. Bica, D.A.B.; da Silva, C.A.G. Learning Process of Agile Scrum Methodology with Lego Blocks in Interactive Academic Games: Viewpoint of Students. IEEE Rev. Iberoam. Tecnol. Aprendiz. 2020, 15, 95–104.
49. Tona, C.; Juárez-Ramírez, R.; Jiménez, S.; Durán, M.; Guerra-García, C. Towards a Set of Factors to Identify the Success in Scrum Project Delivery: A Systematic Literature Review. In Proceedings of the 2019 7th International Conference in Software Engineering Research and Innovation (CONISOFT), Mexico City, Mexico, 23–25 October 2019.
50. Younas, M.; Jawawi, D.N.A.; Mahmood, A.K.; Ahmad, M.N.; Sarwar, M.U.; Idris, M.Y. Agile Software Development Using Cloud Computing: A Case Study. IEEE Access 2020, 8, 4475–4484.
51. Conoscenti, M.; Besner, V.; Vetrò, A.; Fernández, D.M. Combining data analytics and developers feedback for identifying reasons of inaccurate estimations in agile software development. J. Syst. Softw. 2019, 156, 126–135.
52. Nguyen-Duc, A.; Khalid, K.; Bajwa, S.S.; Lønnestad, T. Minimum Viable Products for Internet of Things Applications: Common Pitfalls and Practices. Futur. Internet 2019, 11, 50.
53. Grangel, R.; Campos, C. Agile Model-Driven Methodology to Implement Corporate Social Responsibility. Comput. Ind. Eng. 2019, 127, 116–128.

54. Cheng, L.C. The mobile app usability inspection (MAUi) framework as a guide for minimal viable product (MVP) testing in lean development cycle. In Proceedings of the 2nd International Human Computer Interaction and User Experience Conference in Indonesia, CHIuXiD 2016, Jakarta, India, 13–15 April 2016; Association for Computing Machinery, Inc.: Jakarta, India, 2016.

55. Xu, Y.; Koivumäki, T. Digital business model effectuation: An agile approach. Comput. Hum. Behav. 2018, 95, 307–314.

56. Ghezzi, A. Digital startups and the adoption and implementation of Lean Startup Approaches: Effectuation, Bricolage and Opportunity Creation in practice. Technol. Forecast. Soc. Chang. 2019, 146, 945–960.

57. Holvitie, J.; Licorish, S.A.; Spínola, R.O.; Hyrynsalmi, S.; MacDonell, S.G.; Mendes, T.S.; Buchan, J.; Leppänen, V. Technical debt and agile software development practices and processes: An industry practitioner survey. Inf. Softw. Technol. 2018, 96, 141–160.

58. Li, Z.; Liang, P.; Avgeriou, P. Chapter 9—Architectural Debt Management in Value-Oriented Architecting. In Economics-Driven Software Architecture; Mistrik, I., Bahsoon, R., Kazman, R., Zhang, Y., Eds.; Morgan Kaufmann: Boston, MA, USA, 2014; pp. 183–204. ISBN 978-0-12-410464-8.

59. Tripathi, N.; Oivo, M.; Liukkunen, K.; Markkula, J. Startup ecosystem effect on minimum viable product development in software startups. Inf. Softw. Technol. 2019, 114, 77–91.