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Assessment the effect of rapid prototyping implementation on supply chain sustainability: a system dynamics approach

Nazanin Hosseini Arian[1] · Alireza Pooya[1] · Fariborz Rahimnia[1] · Ali Sibevei[2]

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Abstract
The present study aimed to assess the effect of implementing Rapid Prototyping (RP) in the product development phase on the sustainability of a conventional supply chain. The sustainability indicators of RP utilization were identified through a critical literature review and consulting two experienced RP practitioners to determine the key variables regarding the potential impact of RP on the supply chain components, with an emphasis on sustainability pillars. A generic system dynamics modeling was provided to simulate the RP-adapted supply chain and measure its sustainability performance. The simulation results indicated that RP utilization in the design phase could decrease the number of the assembly parts and material consumption in conventional manufacturing, while indirectly affecting the reduction of waste generation, logistics, CO2 emissions, processes, and the total costs which are related to environmental and economic aspects of the sustainable supply chain. Findings indicated that significant increase in operational skills and knowledge as the main indicators of the social dimension could remarkably reduce the failure rates and increase the quality of the products. This indicator plays a pivotal role in operational success and could be enhanced through training programs. Social sustainability indirectly affects environmental and economic sustainability. This was the first model-based research to examine the potential effects of RP on the sustainability of a conventional manufacturing. The proposed generic model encompassed the variables that could be applicable in every scenario to help decision-makers change values or add more variables within specific industry settings and choose the applicable ones, which in turn, accelerating the RP adoption in supply chains and providing insights for operational decisions regarding product design stage.

Keywords Rapid prototyping · Additive manufacturing · Supply chain · Sustainability · System dynamics

1 Introduction

Currently, competition is based on the application of sustainability-oriented innovations in supply chains, which has attracted the attention of management experts in the research area regarding the application of new technologies (Dubey et al. 2017; Son et al. 2021). Manufacturers have become more obliged to minimize production costs and the adverse environmental effects of their products such as wastes and pollution in the first stages of the design process. As a dynamic process, the design and prototyping stage have a considerable impact on enhancing the sustainability of a supply chain (Rocha et al. 2019). On average, 80% of the total production costs are determined by the product design since this stage largely influences the machinery, tools, material selection, and workforce required for the production process (Favi et al. 2016). Therefore, utilization of innovations and new technologies in design and prototyping stage can enhance the competitiveness of manufacturers and their sustainability performance (Oettmeier and Hofmann 2017; Yadav et al. 2020). Moreover, sustainability practices require proper management support and should be considered from the initial product design process (Khan and Yu 2020).

✉ Alireza Pooya
alirezapooya@um.ac.ir

Nazanin Hosseini Arian
nazanin.h.arian@alumni.um.ac.ir

Fariborz Rahimnia
r-nia@um.ac.ir

Ali Sibevei
alisibevei@modares.ac.ir

[1] Department of Management, Faculty of Economics and Administrative Sciences, Ferdowsi University of Mashhad, Mashhad, Islamic Republic of Iran

[2] Department of Management, Faculty of Economics and Management, Tarbiat Modares University, Tehran, Islamic Republic of Iran

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Additive manufacturing (AM) is widely recognized as the next industrial revolution (Berman 2012). It refers to the process of directly producing objects from digital design models by joining the materials layer-by-layer, which is opposed to subtractive manufacturing technologies (Weller et al. 2015). RP is considered to be the primary application of AM technology. RP allows the rapid iteration of the design and production of customized complex components by eliminating the limitations of conventional prototyping processes, thereby resulting in shorter product development process (Berman 2012; Attaran 2017). Considerable effort has been devoted to research regarding AM technologies (Lopez and Wright 2002; Berman 2012; Yılmaz 2020; Son et al. 2021) and several studies have qualitatively implied that AM implementation has potential effects on supply chain sustainability (Le Bourhis et al. 2013; Khajavi et al. 2014; Niaki and Nonino 2018; Yadav et al. 2020). The current literature on AM is mainly focused on the sustainability features of 3D printing machines (Niaki and Nonino 2017a, b; Sharma and Dixit 2019), their production costs and technical aspects (Piller et al. 2015; Yang and Li 2018). According to Ashour Pour et al. (2017) less than 10% of the AM literature has investigated the effects of AM on the supply chain costs and performance. Social sustainability aspect of AM has remained underdeveloped and limited knowledge regarding that has led to a considerable gap in literature (Matos et al. 2019; Matos and Jacinto 2019; Naghshineh et al. 2020) because it has complicated nature and is difficult to be quantified (Ma et al. 2018). However, some recent studies have introduced the variables associated with the social dimension of sustainability, which could be affected by the implementation of AM technologies (Pérez-Pérez et al. 2018; Naghshineh et al. 2020; Ribeiro et al. 2020).

Despite the popularity of RP, the diffusion and utilization of this technology have been slower than its evolution and adoption (Ashour Pour et al. 2017; Zheng et al. 2019; Tavassoli et al. 2020). Some studies have indicated the main barriers to AM adoption are the shortage of trained workforce to utilize RP and inadequate knowledge regarding the possible effects of AM systems on supply chains (Thomas-Seale et al. 2018; Ituarte et al. 2019; Alabi et al. 2019; Yang et al. 2020). It is also hard for managers to make decision about uncommon practices since risks and gains are difficult to assess, especially when little or no precedent exists. Applying new technologies in manufacturing systems involves complexity, multiple objectives, and dynamic interactions (Wu et al. 2010; Rodríguez and Aguirre 2013). Furthermore, the expected results may be delayed, and there are numerous uncertainties about the benefits, costs, and required changes that may increase the risks involved in the adoption and utilization of technological innovations.

As a complex structure, supply chain networks encompass a large number of key parameters with significant interrelationships. The analysis of the interactions between indicators of sustainability and supply chain parameters is the key step toward determining their performance optimization (Özbayrak et al. 2007). According to Fritz et al. (2017), the sustainability indicators of a supply chain should be examined within a specific period.

The present study aimed to quantitatively assess the key sustainability indicators and their behavior in a supply chain which implemented RP in the design phase of manufacturing. Our research addresses the following research questions (RQs):

- *RQ1: What are the key sustainability indicators in a supply chain that are affected by RP implementation?*
- *RQ2*: *How does RP implementation affect the sustainability of a supply chain?*

In their research regarding the gaps for further investigations on Sustainable Supply Chain Management (SSCM), Khan et al. (2020) have reported that only a few studies have investigated SSCM through simulation or mathematical formulations, providing opportunities to academic researchers to further examine the subject matter. Since the consequences of technological implementation represent a dynamic process (Hekkert et al. 2007), the current research addresses the mentioned RQs by providing a generic model using the System Dynamics approach (SD), which is a computer simulation modeling technique used to recognize the dynamic behavior of complex systems (Sterman 2000). Most analytical models only consider few variables. They overlook other important factors and their dynamic behavior in a period of time. The predictive capability of a model could be enhanced by adding more variables. However, this may increase the complexity of the model.

SD models are considered to be a reliable approach to overcoming these limitations in the case of multiple interconnected factors within a system. SD model encompasses multiple components, factors, operational processes, and their relationships, as well as the feedback links in a supply chain. In addition, it can evaluate the sustainability indicators affected by the implementation of RP through identification of structures and key interrelations which leads to changes. To the best of our knowledge and based on an extensive literature review, no SD modeling approaches are currently available for the sustainability assessment of RP implementation. Therefore, the current research contributes to the better recognition of the impact of RP on the sustainability of a conventional supply chain using a simulation model. The simulation results highlight the mechanisms which cause the behavior of a system and provide the required information to the managers who are skeptical about the implementation of rapid prototyping. The paper is structured as follows: Following the Introduction, we have presented the literature review and identified the sustainability indicators affected by RP utilization. Dynamic hypothesis, causal loop, stock and flow diagram, model validation, simulation, and the obtained results have also been presented. The article ends with discussion, conclusion, and practical implications for further research.

2 Background and literature review

This section provides research background and literature review regarding AM technology with an emphasis on its major application (i.e., Rapid Prototyping), sustainable supply chains, and the potential impact of RP on the sustainability of supply chains. Afterwards, we have discussed the identified gaps that motivated the current research.

2.1 Rapid prototyping

Additive manufacturing is considered to be a major development in the 4th industrial revolution and offers numerous production advantages (Ghadge et al. 2020). It refers to the layer-based manufacturing technique, which is the process of creating objects from the virtual Computer-Aided Design (CAD) data by joining the materials layer-by-layer (Weller et al. 2015). In conventional manufacturing, the tools or Control Numeric Computerized (CNC) machines remove pieces of materials from the solid pieces. The terms AM, 3D printing and RP are often used interchangeably. However, major application of this technology is RP, which rapidly generates the prototypes of a product or its components for further examination before mass production (Attaran 2017). With the advancement of RP materials, prototypes have attained similar features to final products, thereby validating physical product testing and minimizing the costs of design change in the future (Chung et al. 2020). Gibson et al. (2014) found that compared to conventional manufacturing technologies, RP has some significant benefits such as visualization, verification, iteration, optimization, and the functional testing of prototypes within a shorter time. For aircraft shape optimization, Chung et al. (2020) utilized the RP technology to produce wind tunnel models. They showed that RP can significantly reduce the time and costs of prototyping. Some of the studies have evaluated the benefits of rapid prototyping, such as increase in agility of manufacturing (Vinodh et al. 2009; Berg et al. 2020), higher quality and innovativeness of the products (Friesike et al. 2019), and business competitiveness (Niaki and Nonino 2017a, b). Arrighi and Mougenot (2019) also addressed the reduction of design constraints using a modular digital tool based on RP. According to the obtained results, RP facilitates optimization of products for better function and customization based on the customer's desire. RP enables designers to identify design flaws at the earlier stages of the product development process, which could improve the prototyping pace and decrease the time and costs of this stage (Jin et al. 2017).

On the other hand, some researchers found that RP has some limitations such as inadequate quality standards in producing parts (Weller et al. 2015; Li et al. 2020) and technical limitations of 3D printers (Berman 2012; Thomas-Seale et al. 2018). In this regard, Yılmaz (2020) developed an optimization model and concluded that the applied technology could complement the production processes that are currently implemented. In addition, early adoption of AM can enhance the competitiveness of manufacturers, which is mainly influenced by factors such as company size (Zheng et al. 2019), time, and aim of use (Niaki and Nonino 2017a, b). Based on the aforementioned studies, it could be inferred that this technology is currently inefficient and cannot fully compete with conventional manufacturing in mass production, while it could be used successfully in the design and development of new products.

2.2 RP and sustainable supply chain

Integrating the concept of sustainability with supply chain management has been of great interest in academic and practitioner fields and is becoming increasingly important in maintaining the competitiveness of manufacturers (Dubey et al. 2017). Furthermore, sustainability has become a principle not only in production processes, but also in initial design stages in order to maximize supply chain profitability and social well-being, while minimize adverse environmental effects (Diegel et al. 2010; Hassini et al. 2012). A more recent definition of sustainable supply chain management has been proposed by Ahi and Searcy (2013), emphasizing on the integration of environmental, economic, and social considerations through supply chains in order to efficiently manage the materials and information associated with production and distribution.

The economic dimension is a major driver of SSCM, which is traditionally assessed based on indicators such as flexibility, speed, total costs, and profit. Manufacturers could gain a competitive advantage by measuring these parameters over time (Fritz et al. 2017). Among these factors, cost minimization is a dominant indicator in the evaluation of economic dimension (Narimissa et al. 2020). The environmental dimension of SCM refers to the concepts that describe environmental performance, aiming to minimize resource usage, energy, and hazardous/toxic substances. The main indicators of this dimension include the reduction of resource usage, waste generation, and pollutant emissions (e.g., greenhouse gases), as well as the improvement of product quality and durability extension (Glavič and Lukman 2007; Tajbakhsh and Hassini 2015). The social dimension of sustainability refers to the wellbeing of individuals and communities (Choi and Ng 2011). The measurement of social sustainability is more difficult compared to other dimensions due to its subjectivity and intangible nature (Weller et al. 2015; Narimissa et al. 2020). The main indicators of social sustainability are work conditions, health, safety, employee empowerment, and staff training with the aim of improving their qualifications (Chen et al. 2015; Alabi et al. 2019).

RP is considered to be a sustainable and zero-waste manufacturing system owing to its capability to manufacture additively without the need for subtraction processes, which decreases the usage of materials and energy in prototype production (Le Bourhis et al. 2013; Peng et al. 2018). Moreover, RP has distinctive features that can contribute to sustainable growth; for instance, RP allows the direct production of any complex design from 3D CAD models (i.e., tool-less feature), thereby supporting the customization process without time and cost penalties (Kondoh et al. 2017).This could also promote creativity and increase functionality, which in turn leads to higher customer satisfaction (Arrighi and Mougenot 2019).

The reduction of assembly parts, also referred to as part consolidation, could potentially affect production costs, assembly operations, procurement, and supply chain components. (Greer et al. 2004; Jung et al. 2021). Realizing the opportunities provided by RP, Yang et al. (2015) proposed a part consolidation method to decrease parts of a triple clamp from 19 to 7 with a less weight by 20% and improve performance. Through Design for Manufacturing and Assembly (DFMA) and RP utilization, Prakash et al. (2014) redesigned a fluid control valve consisted of 18 components into eight parts with better function. Optimized design and customer satisfaction were also reported as the main outcomes. Nie et al. (2020) also presented an approach that resulted in a 25% reduction in the production time and a 20% reduction in production costs using metal additive manufacturing. Furthermore, they observed an important tradeoff between the number of the consolidated parts and the supporting structures, which could increase the production costs and time. Analyzing the total costs affected by consolidation through RP, Knofius et al. (2019) denoted that efforts to reduce assembly parts could decrease the costs of assembly, while exerting unexpected and indeterminate effects on the repair and service costs as RP often leads to higher total costs due to a loss of flexibility. Furthermore, some studies have utilized various techniques to model the costs of different processes of AM technologies and their application in different sectors and industries (Li et al. 2017; Yang and Li 2018; Sharma and Dixit 2019; Baumers et al. 2019). Through a classification review of the cost estimation models, Kadir et al. (2020) claimed that knowledge regarding AM cost models is still limited in several aspects. According to Some studies (Wright and Fulton 2005; Rinaldi et al. 2021), the main sources of greenhouse gas emissions are the energy consumption of machines in the production process and the transportations associated with the number of the suppliers providing raw materials and spare parts. Therefore, optimization of the mentioned variables will contribute to the economic and environmental sustainability of supply chains. In this regard, Peng et al. (2018) presented an overview of the sustainability of AM, focusing on energy and environmental impacts from a lifecycle perspective. The obtained results indicated that the eco-design feature enabled by AM has a great potential in reducing energy and materials. Son et al. (2021) utilized the genetic algorithm approach and showed that the AM hub and part consolidation model could effectively improve the sustainability of the entire lifecycle, concluding that the combination of AM and conventional manufacturing could respond to the demand for customized products and reduce the negative environmental impact by minimizing production wastes. Some researchers have also investigated and compared the energy consumption of various AM machines and their effects on environmental sustainability with other manufacturing techniques (Le Bourhis et al. 2013; Chen et al. 2015). The results of these studies are often inconclusive since the economic and environmental effects of AM are highly case-specific and depend on factors such as machine utilization, production volume, design optimization parameters, and supply chain configurations.

From a social perspective, some studies have predicted the potential social implications of AM (Jiang et al. 2017; Pérez-Pérez et al. 2018; Sharma et al. 2020). For instance, a critical literature review by Naghshineh et al. (2020) showed that the existing research on social domain and its indicators is quite fragmented. They provided a stakeholder-driven framework consisting of the indicators to measure some of the identified AM social impacts. In order to carry out a prospection of AM in terms of training and employment, Pérez-Pérez et al. (2018) used the Delphi method and found that recruiting technicians with specific qualifications and skills requires changes in the current training syllabus. Furthermore, Thomas-Seale et al. (2018) assessed the barriers to the adoption of AM technologies in UK industries, observing that the knowledge of engineers regarding AM was insufficient. In terms of work conditions and workers' health as major social indicators, Ford and Despeisse (2016) claimed that RP allows operators to avoid long-term exposure to potentially hazardous work environments. However, a systematic literature review conducted by Franco et al. (2020) showed no consensus regarding whether AM adoption exerts positive or negative impacts on health and safety conditions. Huang et al.

(2013) also reported that the health effects are essentially based on the type of the AM technology, handling, use, and disposal of the materials employed in various AM processes. Moreover, a clear design framework is lacking for the implementation of the design process using AM technologies (Mellor et al. 2014; Friesike et al. 2019), leading to trial-and-error in operating 3D printing machines and determining the optimal setting for various 3D models. The reviewed literature in the present study indicated that previous studies have been focused on the sustainability features of AM technologies without considering the sustainability of supply chains, which must be taken into account by manufacturers before technology adoption.

2.3 Gaps identified in the existing literature

Research regarding RP has been rapidly expanding and most of the studies have qualitatively implied the great potential of RP in affecting the sustainability of supply chains. To date, limited research has analyzed the degree to which these potential advantages may occur. Moreover, no findings have explained the effects of RP-enabled part consolidation, which is the most promising benefit at the early stages of design, on the sustainability indicators of supply chains. In this regard, Ribeiro et al. (2020) reviewed critically the literature on AM sustainability, observing the lack of research integrating the economic, environmental, and social dimensions so far. According to Narimissa et al. (2020) and Franco et al. (2020), systematic sustainable performance assessment is essential to the evaluation of various supply chain segments. However, they reported lack of data on the indicators affected by RP in the evaluation of social sustainability. Previous research in this regard provides no clear discussions on the social sustainability of RP due to its complicated nature and difficulty in quantification, while the potential variables and indicators that could measure the social impacts of RP have been partly recognized (Naghshineh et al. 2020). Occupational hazards, health risks, training, skills and knowledge of workforce were among the indicators that have attracted the attention of management scholars more than other indicators. The criteria for work conditions are rather difficult to be evaluated quantitatively. Thus, the novelty and main contribution of our research is shedding light on the training, skills, and knowledge of the workforce as the prominent factors being affected by RP adoption. Notably, these variables also play a key role in the successful implementation of RP. Furthermore, the current literature lacks consistency. A model-based research is absent on the explicit benefits of RP utilization in the sustainability of conventional supply chains. RP utilization can affect several constituents of the supply chain, necessitating a systematic view and quantitative approach to configure the affected segments.

SD is an appropriate simulation method for modelling the sustainability of a supply chain, which is a complex system characterized by the nonlinear interactions of multiple factors, causal loops, and information feedback. The current research contributes to the model-based research regarding SSCM by considering the changes that RP introduces into the supply chain domain based on the analysis of the key variables patterns of the dynamic complexity, and behavior of a system over time. As a result, we could determine the range of the changes that RP offers to improve the supply chain sustainability, which largely depend on tactical and operational decision-making regarding the product design stage.

3 Methodology and modeling

SD is a methodology that was originally developed by Professor Jay Forrester at the Massachusetts Institute of Technology in the 1950s, applying computer simulation to analyze the dynamic behavior of complex, nonlinear, and multi-loop feedback systems. Two common usage of SD modeling are exploring plausible futures and studying the implications of different policies. SD models are empirical and descriptive rather than normative. SD is a potent tool for focusing on feedback loops, accumulation processes, and delays (Größler et al. 2008). The associations between the components of a system define the "structure" of that system, thereby generating dynamic behavior patterns over time (Angerhofer and Angelides 2000). Thus, the model structure should provide a valid description of real processes (Sterman 2000). The main purpose of SD models is to dynamically describe, simulate, analyze complex issues and determine how and why the dynamic behaviors are generated so as to search for effective policies to improve the function of system. Moreover, SD measures the tendency of changes rather than the specific values of variables, thereby facilitating system analysis over time (Lee et al. 2012).

Making decision regarding the supply chain is sophisticated since it encompasses suppliers, the manufacturer, distribution, and logistics. Complicated interactivities between each segment can influence supply chain performance. As support tools, simulation models contribute to the process of manufacturing decision-making and enable the recognition of the long-term impact of policies and decisions on relevant domains such as sustainability of the supply chain. Lack of research regarding SD has provided the opportunity to develop system dynamics in SSCM applications (Fontes and

Freires 2018). SD is considered to be a practical approach to the modeling sustainability of a supply chain, which is a complex system. SD uses both quantitative and qualitative modeling methods (Zhang et al. 2013). Furthermore, it enables the modeling of multiple components, factors, and operational processes in a supply chain, and evaluates the sustainability indicators affected by the implementation of the new technology. As such, an analysis may vary in different supply chains. We have proposed a model as generic as possible to facilitate its implementation in a wide spectrum of real cases.

Generic structures are useful method in transferring knowledge, contributing to the literature by offering holistic view of the system (Lane and Smart 1996). This generic model provides a systematic basis to develop specific customized models for actual manufacturers, thereby evaluating their managerial policies through simulations. For this purpose, its parameters should be re-configured depending upon specific industrial settings (Bonev 2012). A simple numerical example illustrates the function of this model. In this paper, Vensim software (version 7.2) was applied for the system dynamics modeling and simulation.

3.1 System modeling

3.1.1 Indicators for the sustainability assessment

The SD model encompasses a large number of variables (factors) and their interactions (behaviors). The first step in the model development was the identification of factors and their interactions. In sustainability assessment, the indicators for each domain (economic, environmental and social) should be defined. To develop analytical models to assess sustainability, the selected indicators should meet the following criteria (Irfani et al. 2019; Sterman 2000):

1. The key indicators should be selected based on their significance and relevance to the scope of the research problem. Based on extensive literature review, the potential key sustainability indicators affected by RP utilization in the supply chain were progressively defined and presented in Table 1, which was used as a basis for the quantitative model. It was found that total production costs are a dominant indicator in the evaluation of the economic dimension. Material consumption, waste generation, CO2 emission and product quality are among the most significant indicators of the environmental dimension and are affected by RP implementation. Regarding social dimension, a commonly overlooked aspect in RP utilization in prototyping processes is failed prototypes, which are associated with the shortage of skills and need for more iterations, which increase the total costs (da Silva Barros 2017). Therefore, researchers have emphasized the effects of RP implementation on skills development and training requirements (Please refer to Table 1).
2. Empirical validation is necessary for indicators collected from the literature since they need to be

Table 1 Sustainability Indicators

Dimension	Indicators	Reference	Definition and scope
Economic	Total production costs	(Li et al. 2020) (Yang et al. 2020) (Yang and Zhao 2018)	The financial domain was quantified in terms of the monetary value and included all the functions related to the income and expenditure of a firm. This variable is the sum of total repair cost, tooling cost, material purchasing cost, inventory cost, training cost for operators using RP, transportation cost and carbon penalty cost, which are indirectly influenced in the conventional supply chain through RP utilization. This indicator is necessary to achieve competitive advantage. Several studies have noted costs as the most important indicator in assessment of economic sustainability
Environmental	Material consumption Waste generation CO2 emission Product quality	(Ford and Despeisse 2016) (Kellens et al. 2017) (Peng et al. 2018) (Dornfeld 2011)	Environmental domain of sustainability refers to the reduction of pollution and consumption of natural resources. The selected indicators in the present study were the variables most significantly influenced by RP implementation. In the current research, we primarily focused on "reduction" as a relative concept rather than an absolute quantity
Social	Workforce skill and knowledge	(Yang et al. 2020) (Alabi et al. 2019) (Carter and Rogers 2008) (Ribeiro et al. 2020) (Taddese et al. 2020) (Khalid and Peng 2021)	The social domain considers societal benefits and human safety. Knowledge is the ability of organizations to effectively learn and implement changes based on what they have learned. Knowledge consists of the training, experience, skill and insights of managers and workers in an organization

relevant to practice. In the present study, a list of potential key variables affected by RP implementation was prepared. Afterwards, interviews were conducted with two experienced practitioners (more than six years) who had worked as senior technical manager of supply chains and product design director of various manufacturers in additive manufacturing because interviewing as a means of using expert judgment is an effective strategy in finding the key indicators within a system (Diker et al. 2005). The experts selected indicators based on their relevance, significance and priority.

3. Based on interview with experts, the indicators were selected in such a way that it was possible to simulate them from the available data. For this purpose, selected indicators had the potential to be quantified. For example, assessing the social sustainability of RP implementation is inherently complicated. Although multiple indicators are associated with social dimension, it is difficult to quantify most of them (Mani et al. 2018). In the current research, the number of the iterations in the prototyping process and training duration (in weeks) were used to measure the knowledge and skills of the operators.
4. Literature review and experts interview revealed that there should be causality between the leading indicators since their interaction with other key variables of the system over time will lead to the modification of the overall behavior of the system, which is referred to as dynamic behavior. Moreover, the selected indicators in system dynamics approach should assess both short-term and long-term effects (Please refer to Figs. 1, 2, and 3 and their explanations).
5. General models in system dynamics approach are flexible. They should encompass the fundamental variables that could be applicable in every scenario to help practitioners start the process properly. Decision-makers may also change values or add more variables depending on the local conditions within an industrial setting and choose the applicable ones. Therefore, the practical and technical aspects of various indicators should be considered for improving the quality of the entire system. In the present study, part consolidation was considered as the main benefit of RP implementation, which could affect technical variables in the manufacturing systems. For instance, training duration in the social domain is assessed by the gap between the existing and required skill, which differs in various industries. Moreover, CO_2 emissions are measured based on the key influential factors that could be adjusted based on the performance of manufacturers. Total costs also are affected through many direct and indirect interrelationships among empirical variables.
6. In general models, selected variables and indicators should enable managers to recognize a broader prospective and allow decision-makers to focus on the processes that are most appealing or convenient. These indicators should also affect and optimize the model system-wide rather than locally since managers look forward to the requirements and long-term planning strategies that reduce the risks of new technology adoption. In the development of the proposed framework, we observed that RP implementation increases the demand for a qualified workforce. Furthermore, skills development is a social indicator that indirectly affects the sustainability of an entire supply chain in terms of cost reduction and waste generation (Corsini and Moultrie 2019). Furthermore, material consumption and total costs were considered as environmental and economic dimension, respectively which were affected significantly by RP adoption.

3.1.2 Dynamic hypothesis and causal loop diagram (CLD)

The core of SD approach is the feedback structure in the system, which is the aim of building CLD (Sterman 2000). CLD is the graphical visualization which represents different feedback processes and interactions among variables of the system and is useful for the conceptualization and depiction of its structure (Morecroft 1982). CLDs present information in visual context which is easy to understand. Based on the selected indicators, the causal relationships within each dimension were identified. The set of variables in CLD are linked together by arrows. The relationships are labeled as positive (+) or negative (−). The positive (+) sign implies that an increase in cause leads to an increase in effect above what it would have otherwise have been. Likewise, the negative (−) sign denotes the opposite (Sterman 2000). These mechanisms create either positive (reinforcing) or negative (balancing) feedback loops. The loops are represented in the figures by R and B, respectively. The interaction of both types of loops jointly determines the dynamics of the system. According to Sterman (2000) balancing and reinforcing feedback loops are the result of uncertainties in the innovation process that affect the whole structure of a system. Figures 1, 2, and 3 represent the CLDs of this research and the integrated CLD is provided in Appendix 1. The identified feedback loops in the CLDs can assess the impact of the RP utilization on the sustainability indicators. CLDs served as a frame to develop the stock and flow diagram, which is discussed in the following section.

Fig. 1 Manufacturing CLD

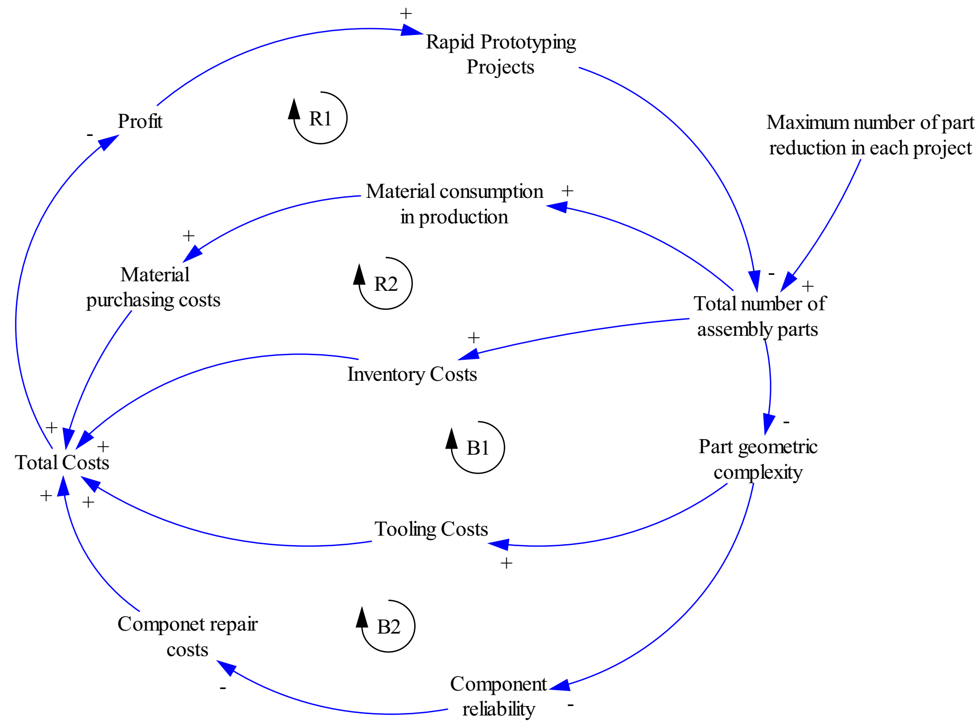


Figure 1 illustrates the effect of RP utilization on the product development phase in manufacturing processes. This CLD is built on the assumption that the main advantage of rapid prototyping is the consolidation of various parts and their integration into one component, which eventually leads to changes in different key variables of a manufacturing system. The interrelationships among the variables in feedback loops are discussed in detail in the following paragraphs:

R1: The implementation of RP projects with the aim of consolidation reduces the number of the assembly parts in manufacturing, thereby resulting in lower material consumption for the production of these parts in mass production and decreased material purchasing costs. As a result, the total costs would decrease, which in turn increases the profit and investment to run more prototyping projects.

R2: Reducing the number of assembly parts lowers inventory costs, thereby decreasing the total costs and reinforcing more RP projects to be implemented similar to the previous loop.

B1: Consolidation increases the geometric complexity of the parts and enhances the tooling and total costs. On the other hand, profit reduction will decrease the number of RP projects and hinder the associated benefits.

B2: Increasing the geometric complexity of assembly parts decreases the reliability of the components (Yang and Zhao 2018; Jung et al. 2021), which is considered to be a limiting factor in continuous part reduction and restricts RP projects. The reliability of a component refers to the likelihood that a component could function without failure, which is correlated with the geometric complexity of the parts (Fagade et al. 1998). According to Knofius et al. (2019), consolidation might increase repair costs since the replacement of sub-components becomes impossible, and the component should be replaced entirely; consequently, the total costs will increase.

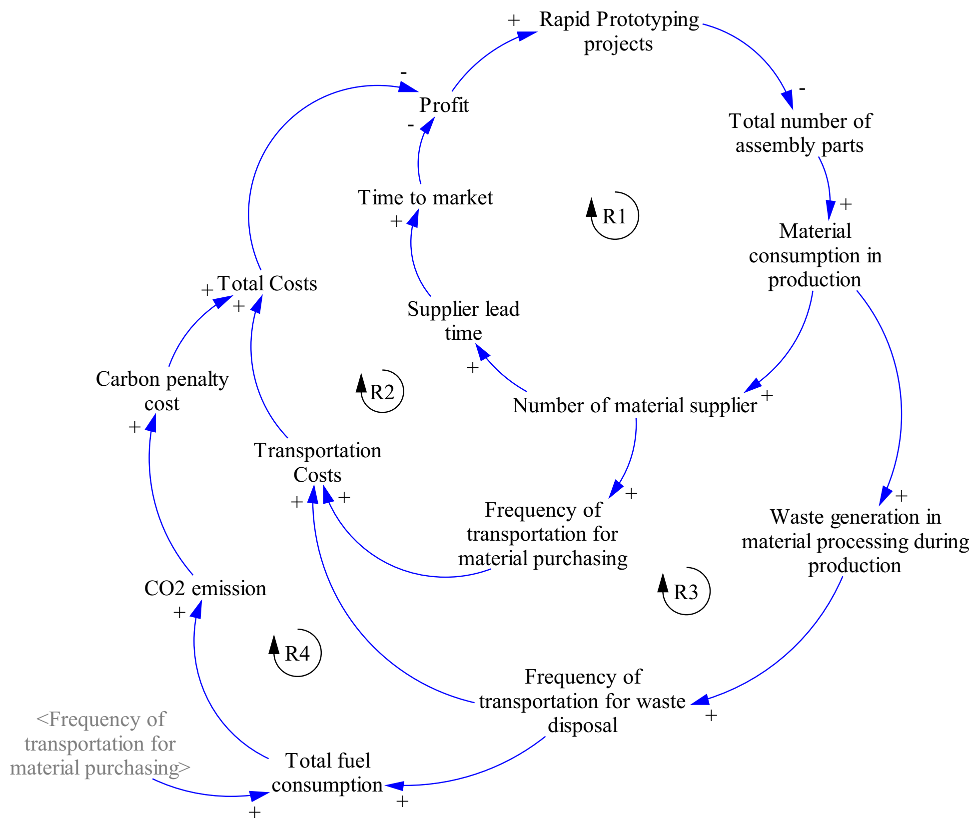


Fig. 2 Suppliers and Transportations CLD

Figure 2 shows the reinforcing loops consisting of the key variables associated with the suppliers and logistics of a supply chain, which are affected by RP utilization.

R1: Since various components of a product require different materials, extensive ordering from different suppliers is essential. Therefore, reducing material consumption through consolidation could decrease the supplier base for purchasing various materials, while also reducing the supplier lead time and time to market, thereby enhancing profits

R2: Consolidation through RP projects decreases material consumption and the number of the material suppliers. Therefore, the frequency of transportation for material purchasing and transportation costs will decrease, thereby reducing the total costs and increasing profit and RP projects.

R3: Minimizing waste production in material processing is another outcome of reducing material consumption. As a result, the number of long-distance disposal transportations, transportation costs, and total costs will decrease, thereby increasing the number of RP projects.

R4: With the decreased frequency of transportation for waste disposal and raw material, total fuel consumption will decrease as well. Consequently, CO_2 emission (Dornfeld 2011), carbon penalty costs, and total costs will also decrease.

Fig. 3 Workforce Skill CLD

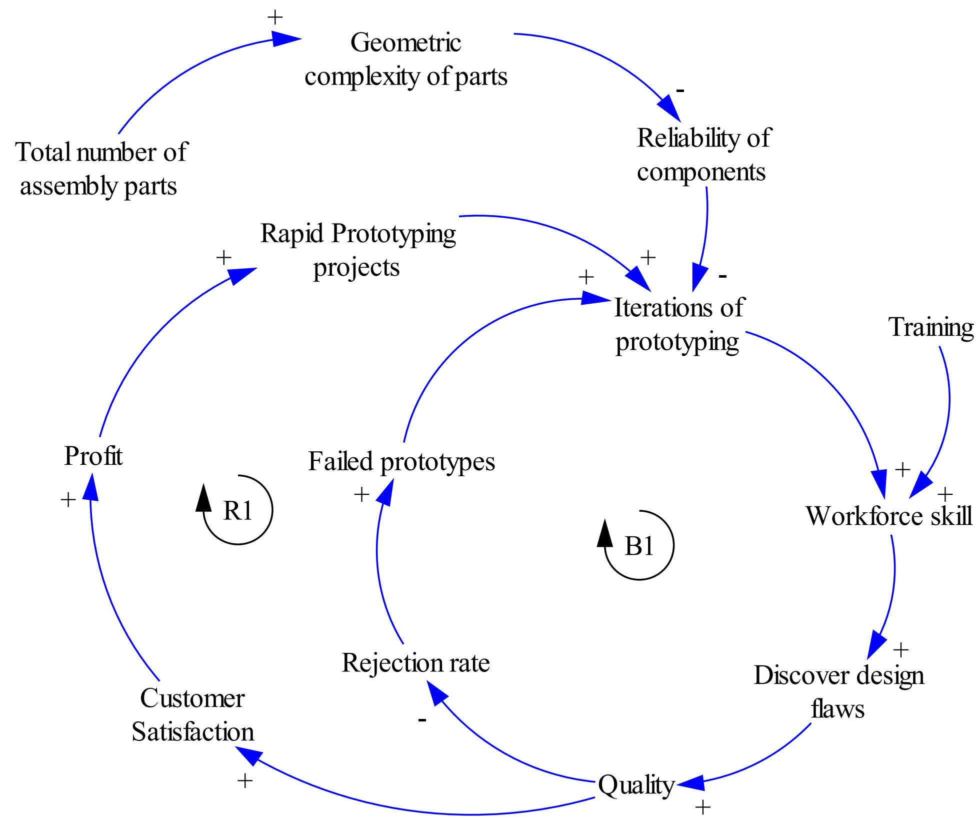


Figure 3 illustrates the effects of RP implementation on the social sustainability indicators. In prototyping processes, a commonly overlooked aspect is failed prototypes, which are associated with a lack of skilled operators and designers and lead to higher costs due to more iterations (da Silva Barros 2017). Feedback loops show the extent to which operators' skills and knowledge increase as a result of RP implementation. The proper application of the RP technology with the aim of reducing failed prototypes forces employees to be updated and develop new skills, and the skills of operators increase through trial-and-error and part-time training. In the current research, the feedback loops indicated that operators' skills not only were affected positively by RP implementation but also were enabler for successful RP implementation in sustainable supply chain. As a result, the proposed indicator is considered an essential strategy in the proposed model.

R1: This reinforcing loop shows the role of iterations for prototyping in workforce skills development. The skills of operators could be enhanced through trial-and-error in each iteration to result in the discovery of design flaws at the early stages of prototyping. Furthermore, this process improves the quality of the products and customer satisfaction, thereby increasing profit. These benefits encourage the implementation of more rapid prototyping projects.

B1: As mentioned earlier, consolidation may decrease the reliability of assembly parts, thereby necessitating more iterations in the prototyping phase. In the RP workflow, the assembly parts that are built through 3D printing should have acceptable quality in order to pass functional tests, which ensure their appropriateness for mass production. RP operators are responsible for assessing the quality of these parts. In case of rejection, the failed prototypes in prototyping phase will increase, and the components will have to be re-built. Part-time training is essential to the development of workforce skills since the lack of qualified experts is a crucial barrier to successful RP implementation (Colletti 2016; Ghadge et al. 2020; Li et al. 2020). Therefore, RP implementation prompts operators to participate in training and professional requalification to develop new skills (Naghshineh et al. 2020).

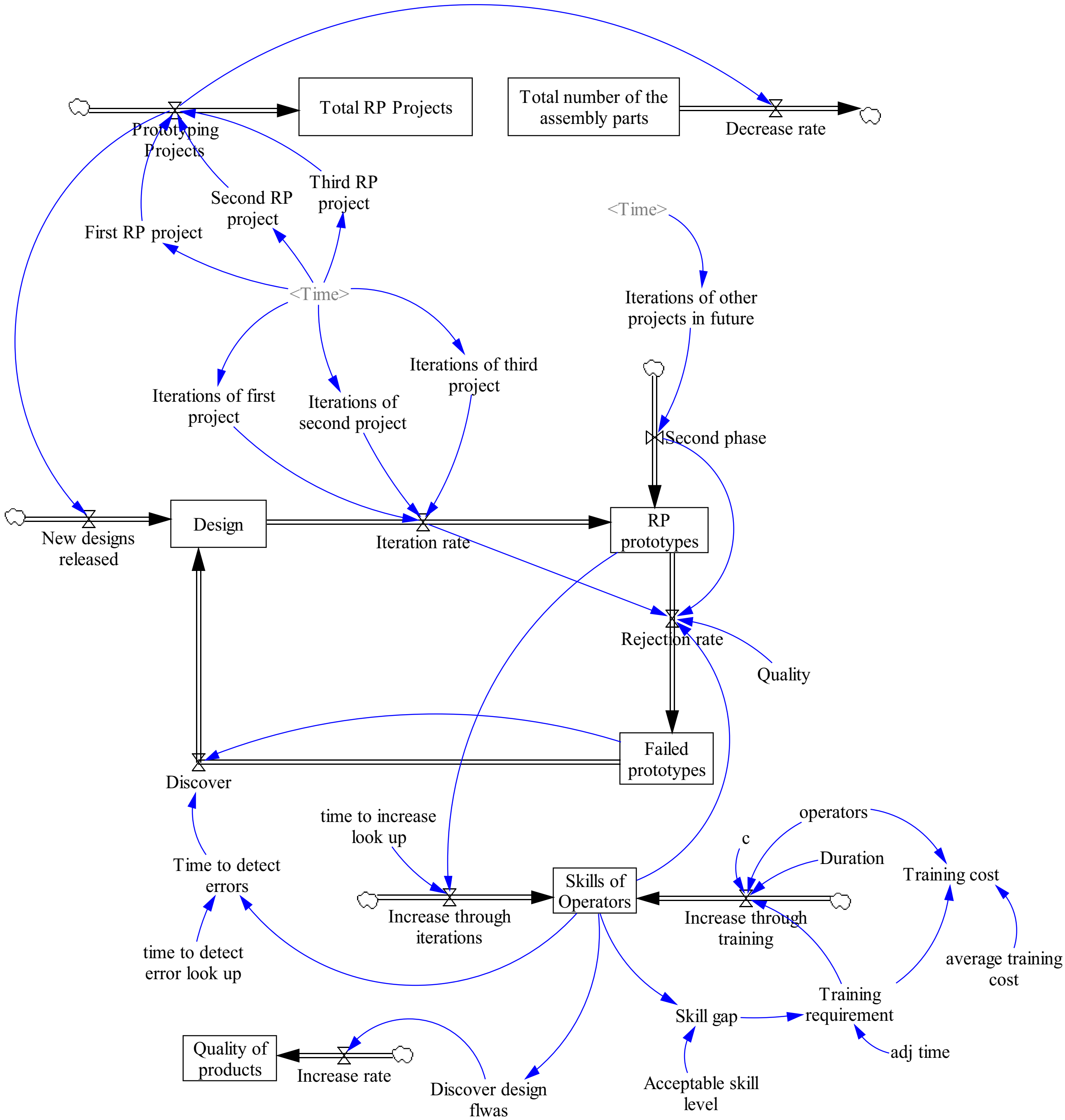


Fig. 4 SFD for Rapid Prototyping Process

3.1.3 Stock and flow diagram (SFD)

Stock and flow diagram is the quantitative form of CLD. SFD is used to establish the mathematical equations in order to run various simulations of the model, analyzing the dynamic behavior of the system. There are four types of variables in SFD: (1) flow, (2) stock, (3) converter (or auxiliary) and (4) connectors. Stock variables are the states of the system and refer to the accumulations in the system. Stock variables are accumulated or depleted depending by flows (change rates) across time. Flow variables represent the rates at which stock variables change. Converters are represented by general variables, acting as intermediate variables in calculations. Connectors are shown by simple arrows and represent the cause and effect directions. Stocks are usually quantities while flows must be measured in the same units per time period (Sterman 2000). Stock variables are generally represented as a box whereas the flow variables are represented as a valve on the pipe connected to the box. For example, in this model workforce skill is considered as a stock variable because it is accumulated through iterations and training over time. Therefore, two latter mentioned variables are flow variables. Due to the high number of variables and their complex interrelationships, SFD of this research is presented in 2 subsystems, namely rapid prototyping process and benefits of RP implementation (Figs. 4 and 5).

Subsystem A: rapid prototyping process Figure 4 illustrates the RP utilization in the design and product development phase. In the current research, the proposed model assumes that a manufacturer utilizes RP to redesign assembly parts with the aim of consolidation. Therefore, the total number of assembly parts will decrease if more RP projects are run in the design phase. Initially, designs are prepared, and prototypes are built by a 3D printing machine. It is assumed that the manufacturer will be capable of running three prototyping projects within one year, followed by other projects in the future. Therefore, the stock of the RP prototypes will increase through the iteration rate, which is the sum of the prototypes built during three projects and the second phase (iterations in future projects). RP prototypes may be rejected or accepted after functional tests through comparison with the desired quality. In case of rejection, the components have to be re-built. This process is repeated after discovering errors and design flaws. Simultaneously, the model shows the skill development of the operators who are involved in the projects. The skill of the operators could increase through training programs and self-learning (trial-and-error with numerous iterations). In addition, the need for training is determined by a skills gap, which is measured based on the comparison of the current status and the acceptable level of skills. Improving the skills of operators will decrease the time required to detect errors, thereby helping the operators to discover more design flaws and increase the quality of the products. The model also shows variables such as the number of the operators, training costs, and training duration in processes.

Subsystem B: benefits of RP implementation Figure 5 shows the long-term effects of RP implementation on the main segments of a conventional supply chain. The proposed model encompasses variables such as geometric complexity, tooling cost, repair cost, transportation cost, number of material supplier, amount of CO2 emission, frequency of transportations, and reliability of components, etc. Note that double lines across the arrows indicate delay flows. Logically, effects of the reduced number of assembly parts on the total material consumption in mass production, number of the suppliers, and total inventory costs often involve significant delays. The figure also demonstrates variables such as average distance to material suppliers, average distance to the waste disposal sites, and their effects on the total fuel consumption and transportation costs. The interaction between the variables has been discussed in detail in the previous section regarding CLDs. Some auxiliary variables have also been provided in the figure, which were required for the mathematical equations (please refer to Appendix 2).

Finally, we listed a number of assumptions throughout the analysis in order to simplify the system and facilitate the modeling process by focusing on the most important factors in this regard:

- Each assembly part is produced 5,000 times.
- Simulation period is 520 weeks (10 years).
- Post-processing related to prototyping is not considered.
- Part-time training is implemented for the technicians that are familiar with subtractive manufacturing processes in order to enhance their skills in the RP field. The key advantage of this policy is flexibility for the participants, briefer absences on the job, and lower costs of recruiting new professional staff.
- We only considered CO_2 emissions through the logistic operation, and the produced emissions in the manufacturing or 3D printing processes were disregarded.
- (1) Truck capacity for material purchasing is 22000 Kilograms (Kg), (2) truck capacity for waste disposal is 15000 kg, (3) number of material supplier is 1/5 of total assembly parts
- All the assembly parts are produced by one manufacturer. Therefore, consolidation will only decrease the material supplier base.

3.1.4 Mathematical formulation

In order to simulate the SFD model, it should be translated to different equations. Note that the exact values of the parameters were not as important as the recognition of the changes in the behavior of the system in various scenarios. Moreover, the generality of the model provides the opportunity for decision makers to change and customize values within different products and industries (Poles 2013) since numbers lack significance in the SD simulation, while the trend analysis is prioritized. However, numbers should be close to real situations (Boateng et al. 2017). In this generic SD model, assumptions, equations and constant parameters for exogenous variables were derived from extensive search in secondary data sources (e.g. scientific papers, academic articles, business reports and case studies). The most critical relations were assessed based on discussion with two

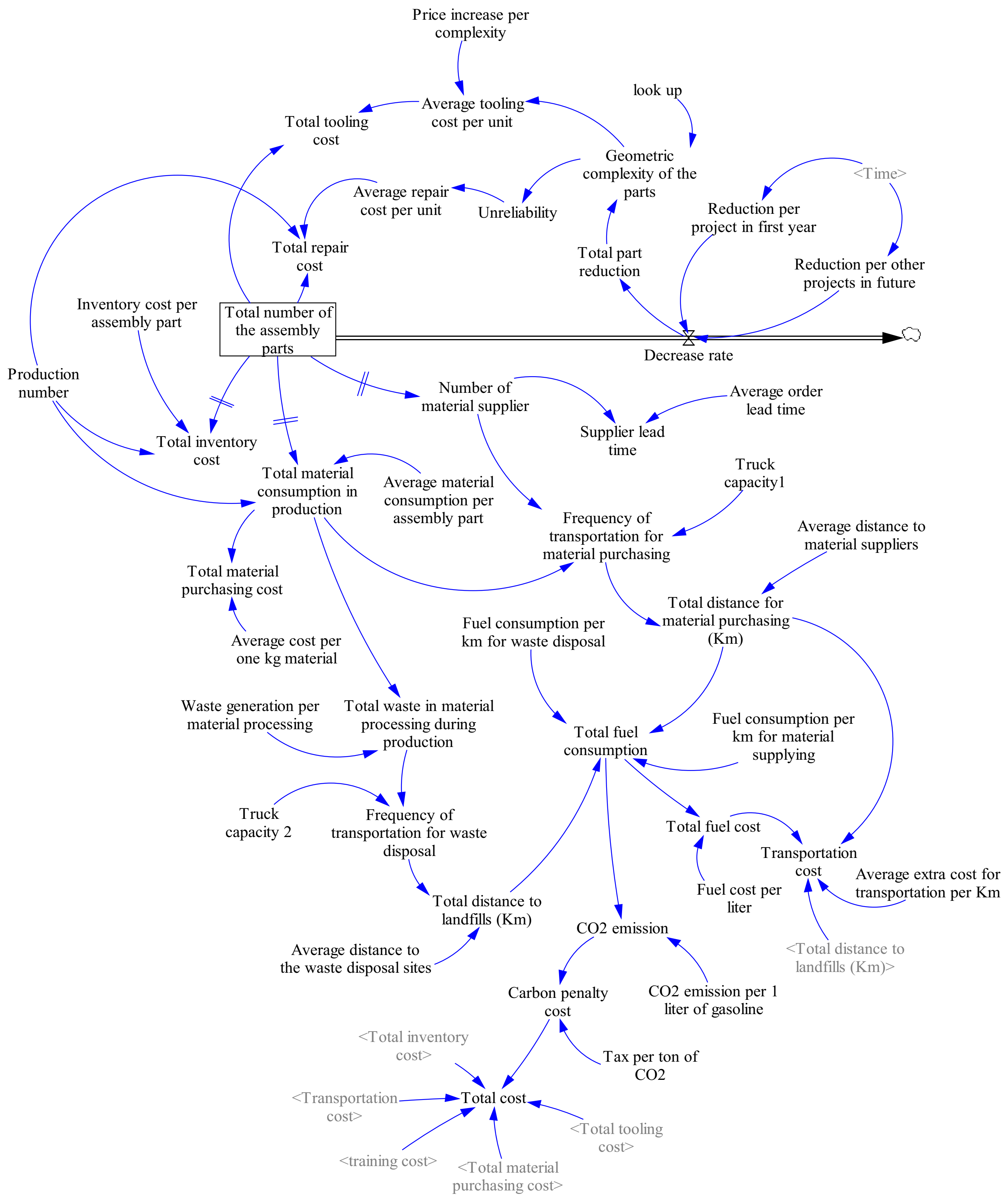


Fig. 5 SFD for Benefits of RP implementation

experienced practitioners and some equations were written by common logic. Some of the equations regarding the important variables were presented in Table 2 (Main equations are provided in Appendix 2).

Table 2 Main Equations

Variable	Description	Equation
Total material consumption in production	It was assumed that average material consumption per assembly part equals 300 Grams. Moreover, delay function is used to show the delay between design phase and manufacturing process	DELAY1 (total of assembly parts*production number*average material consumption per assembly part, 53)
Inventory cost	It was assumed that the average inventory cost per assembly part equals 0.4$. Moreover, delay function is used to show the delay involved between manufacturing and inventory process	DELAY1 (total of assembly parts*inventory cost per assembly part*production number, 54)
Waste generation in material processing during production	During manufacturing and material processing, some wastes will be generated. 200 kg per 1000 kg of steel will become unusable waste during manufacturing process (Chakravarty and Panigrahi 1996). Therefore, we assumed that waste generation per material processing equals 0.2	Total material consumption in production* waste generation per material processing
Total fuel consumption	This variable is sum of fuel consumption for material supplying (from the supplier to the manufacturer) and fuel consumption for waste disposal (from manufacturer to landfill)	(Fuel consumption per kilometers (km) for material supplying*total distance travelled for material purchasing) + (total distance travelled for waste disposal*fuel consumption per km for waste disposal)
Workforce skill	This stock variable is affected by two flow (rate) variables. Because labor skill increases through (1) self-learning (trial-and-error) and iterations during prototyping process and (2) part time-training. This was formulated based on the research by da Silva Barros (2017)	INTEG (increase through iteration + increase through training, 0.1)
Frequency of transportation for material purchasing	This variable indicates the required number of transfers from material suppliers to the manufacturer. Truck capacity is assumed 22,000 kg	Number of material supplier* (total material consumption in production/truck capacity)

3.2 Model validation

According to Barlas (1989) structural and behavioral validity tests are essential to the validation of system dynamic models. Structural validity evaluates the structure of a model to be representative of real structures. Behavioral validity assesses the capability of a model for the production of an acceptable output behavior. Structure validation is achieved by the comparison of model equations with the available theory and real system relationships. Behavior validation is achieved by determining whether the behavior patterns generated by the model are close to the major patterns exhibited by the real system, along with the examination of the model behavior under different circumstances. Due to the long-term orientation of the model in the behavior validity tests, emphasis should be placed on the pattern prediction rather than point prediction (Barlas 1989). Moreover, interviewing as a means of using expert judgment is regarded as an effective strategy in model validation (Diker et al. 2005). For this purpose, we reviewed the industrial case reports and relevant prior research in order to validate the model structure. In addition, interviews were conducted with two experienced practitioners who work for more than six years as senior technical manager for the supply chain and product design director of different manufacturers in additive manufacturing. We enquired these experts about their opinion regarding CLDs and SFD to ensure that the model met their assumptions and mental maps since each model element must have a counterpart in the real world, and the behavior of the model should reflect historical data (Sterman 2000). Afterwards, we discussed our findings with these experts, and they confirmed that RP utilization most significantly affects the proposed indicators that are feasible in any industrial contexts. They also confirmed that model structure could provide a valid description of the real processes, and model prediction was sufficiently similar to the actual behavior of system. Therefore, the model considered valid and accurate for forecasting purposes. Finally, the two most significant and practical indirect structural tests (extreme condition and behavior sensitivity analysis) were applied to ensure the validity of the model.

3.2.1 Extreme conditions test

Extreme conditions test is used to determine whether the model behaves appropriately when the inputs take on extreme values, such as zero or infinity (Sterman 2000). Through this test, extreme values were assigned to the selected parameters in order to compare the generated behavior with the predicted behavior of the real system under extreme conditions. Sensitivity testing is the process of changing assumptions about the value of the constants in a model and examining the resulting output. The sensitivity test was applied in order to search for errors in models, and recognize the relationships between the inputs and outputs (the link between structure and behavior), and examine the robustness of the outcomes for a base case scenario. It is often recommended to test the sensitivity of a model to small and even extremely large parameter changes. If the model could be run at the maximum values with no error, the robustness of structure would be confirmed (Pruyt 2013). Two extreme condition tests are presented in this section.

Extreme conditions test1: a sudden drop in the part reduction rate In the base run, the decreased rate of the total assembly parts was affected by both variables of reduction per first three projects (first year of the simulation) and reduction per other projects. Suppose that suddenly and unexpectedly, the reduction rate drops to zero after 1 year. What would happen to the behavior of the system?

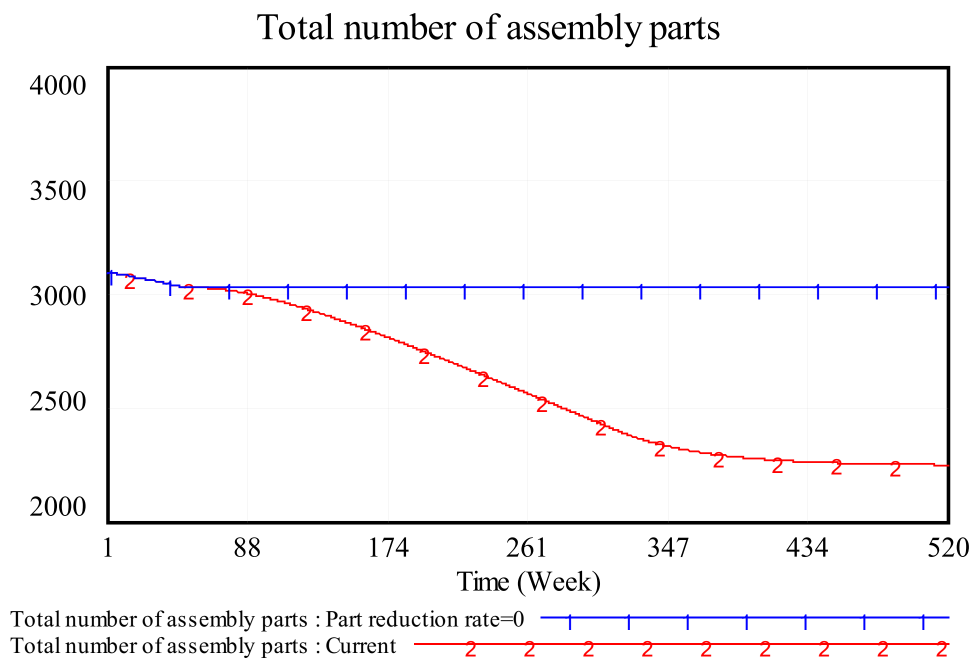
Apparently, if there is no reduction rate for other projects run, number of the assembly parts will remain constant. The behavior resulted from the model matched to our expectation (Fig. 6). So, the model passed the extreme condition test 1. This test confirmed that the model structure yielded meaningful behavior under extreme parameter values and this behavior was in line with the empirical and theoretical evidence.

Extreme conditions test2: eliminating distance in supply chain processes In this test, we assumed that the value of the distance parameter decreased to zero for both material purchasing and waste disposal. In this extreme scenario, no fuel consumption and carbon emissions are expected. The behavior resulted from the model successfully met our expectation under this extreme test and demonstrated the robustness of the structure. The result is shown in Fig. 7.

3.2.2 Sensitivity analysis

Sensitivity tests primarily indicate that without certainty regarding the exact values of the parameters, the conclusions drawn from the model could be supported. Through this test, the modeler's uncertainty about the behavior decreases because it shows that changes in the parameter value does not produce extreme reaction. Due to the large number of variables and their complex interrelationships, a comprehensive sensitivity analysis is not possible since it requires testing all combinations

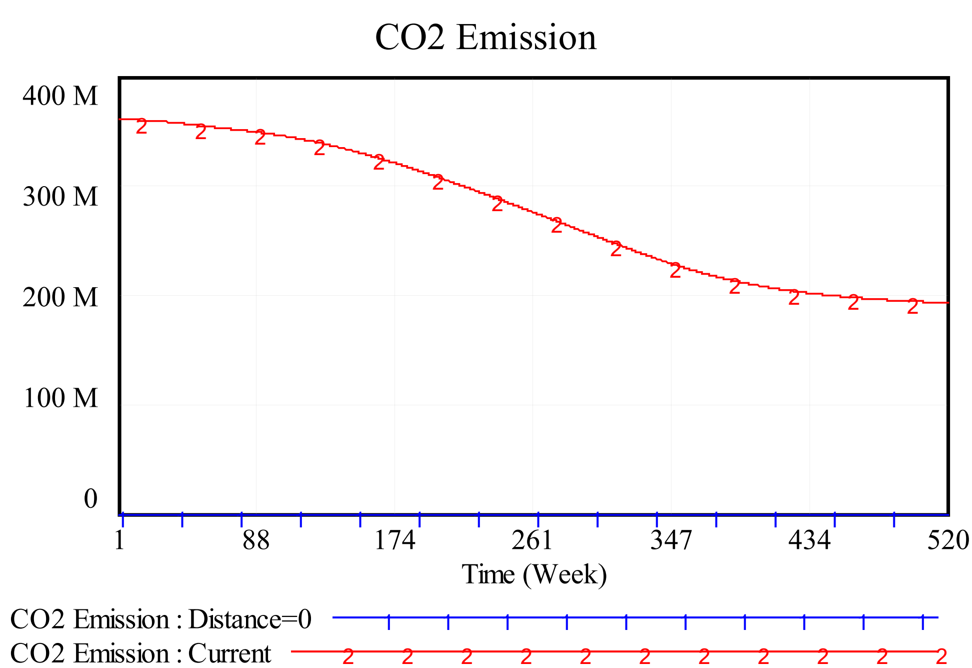
Fig. 6 The system behavior in extreme conditions test 1



of assumptions over their possible range of uncertainty. Two sensitivity analysis tests were executed as described below.

Sensitivity analysis test 1: value of distance to the disposal site In the base run test it was assumed that distance to the waste disposal sites equals 4000 Kilometers. As no data were available to estimate this parameter accurately, we ran the model with the value of 1,000 in sensitivity analysis test to determine possible changes in behavior. A set of behaviors with a similar pattern resulting from the two runs is illustrated in Fig. 8. This test indicated that some differences are obvious in the behavior of model due to changes in the value of parameters. However, the general behavior is relatively insensitive to changes in parameters. (Note that total distance travelled by vehicles for waste disposal = frequency of

Fig. 7 The system behavior in extreme conditions test 2



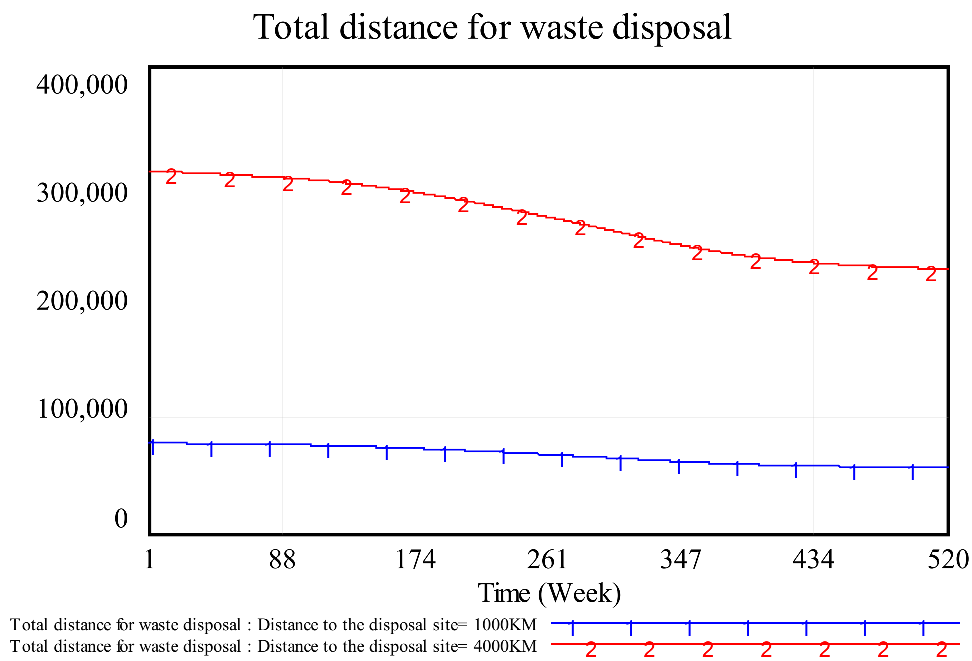


Fig. 8 The comparison of the model behavior in sensitivity analysis test 1

transportation for waste disposal * distance to the disposal site).

Sensitivity analysis test 2: Duration of training In simulation of base (current) model, we initially assumed the training duration of 15 weeks for each operator. Then we changed it to 30 weeks. As shown in Fig. 9, the behavior pattern of the skill in both runs did not change greatly. The only difference was that it took the system longer to reach an acceptable level of skills with a shorter training duration, which corresponded to real situations.

4 Simulation and results

In this section, model behavior is analyzed through a graphical presentation using Vensim. Time horizon for simulation was set at 520 weeks (10 years), assuming that during this specific timespan, a firm would be capable of running three prototyping projects within one year, followed by other projects in the coming years. The effects of RP utilization on the supply chain sustainability were simulated. Figure 10 illustrates the total number of the assembly parts after RP utilization in the design phase of the product development,

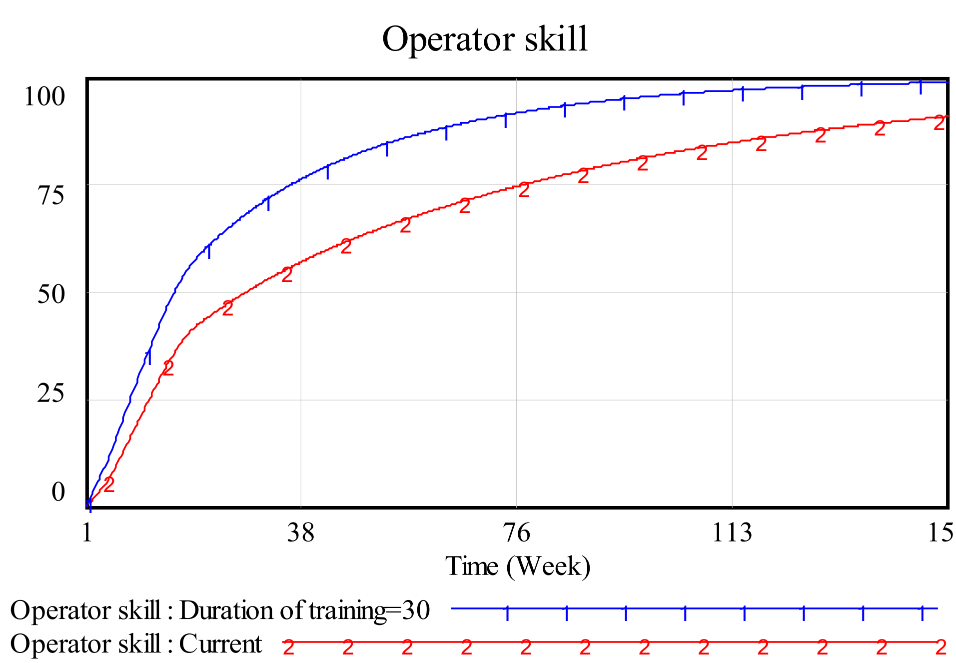
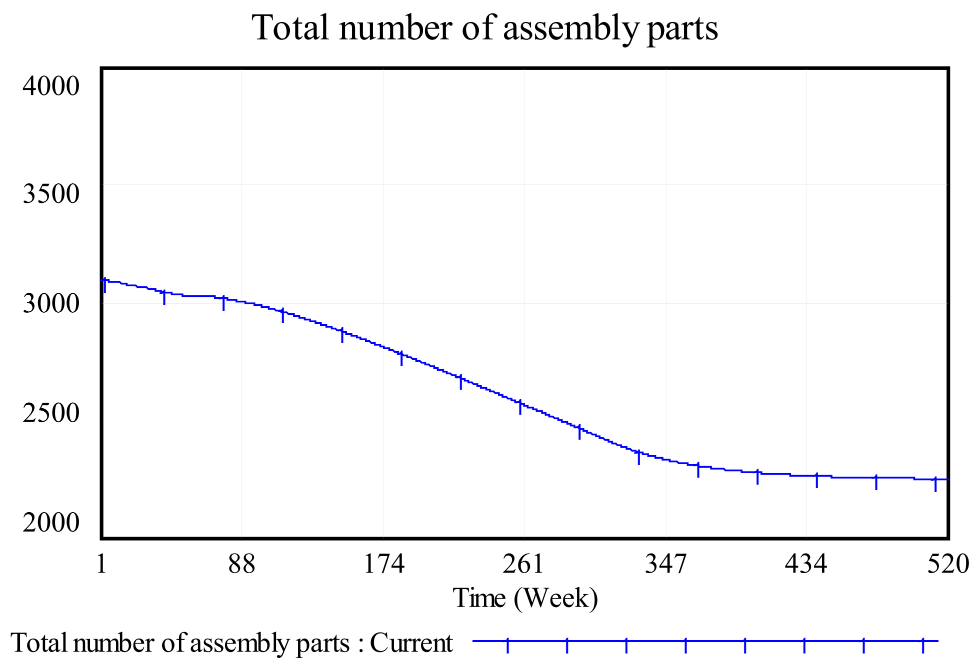


Fig. 9 The effect of change in the duration of training

Fig. 10 Simulated dynamic behavior of total number of assembly parts



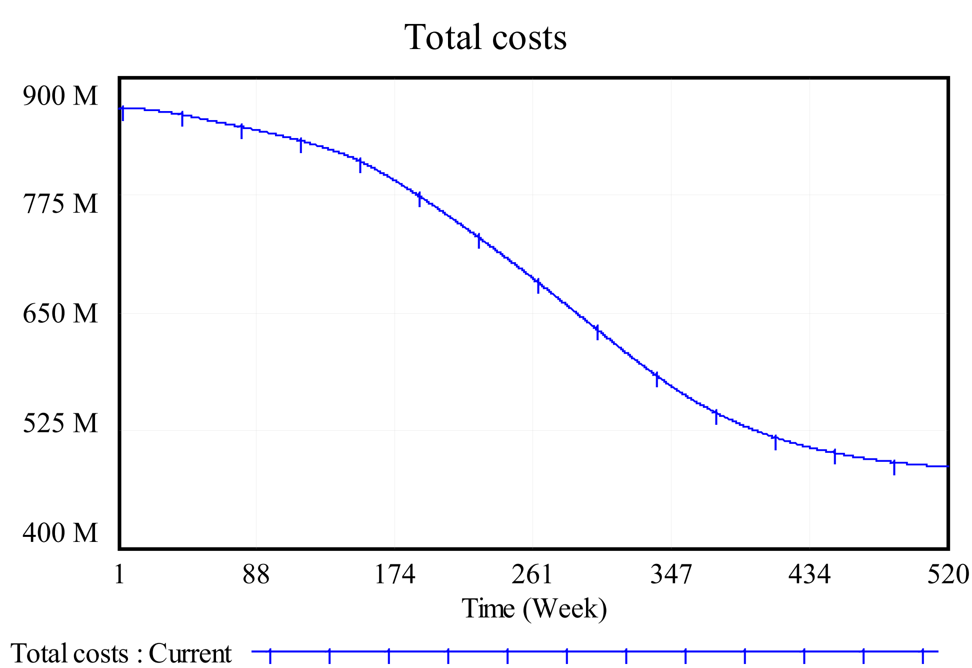
demonstrating descending goal-seeking behavior. Therefore, it is concluded that RP utilization could decrease the number of assembly parts. However, the balancing loops encompassing variables such as the tooling costs, and reliability of the components reduced the speed of the process over time. In other words, the geometric complexity of the parts as a limiting factor must be considered in the consolidation process because it plays a key role in the tooling costs and reliability of the parts.

4.1 Sustainability indicators

4.1.1 Economic dimension

Figure 11 shows the behavior of the total costs in simulation period. Notably, the average repair and tooling cost for each part increased due to the increased geometric complexity of the parts. However, total cost keeps on decreasing due to the reduction in number of assembly parts and other costs in the system.

Fig. 11 Simulated dynamic behavior of total cost



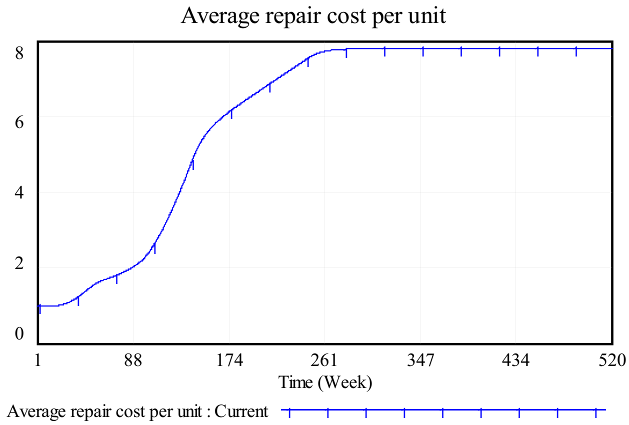


Fig. 12 Dynamic behavior of average repair cost per unit

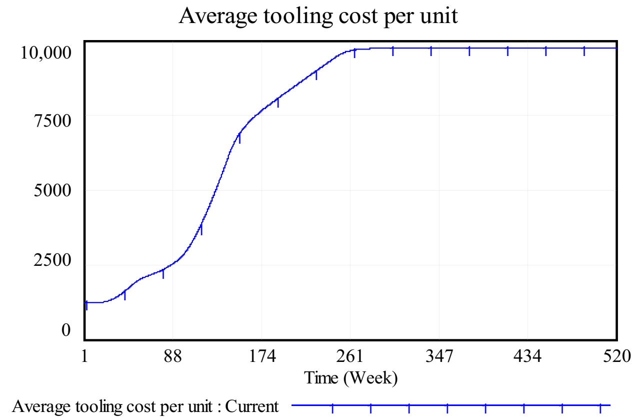


Fig. 14 Dynamic behavior of average tooling cost per unit

The S-shaped limited growth behavior of the average repair cost per assembly part could be attributed to the increase in complexity and unreliability of the components, which is in line with expert opinions and the literature in this regard. Initially, the growth behavior was exponential, then gradually plunged to reach the system equilibrium level; as a result, the outcome resembled an extended S. The total repair costs indicated S-shaped growth with an overshoot behavior and a slight reduction after the determined period, which was due to the fact that the total number of the assembly parts also decreased over the period. Similarly, such behavior is observed in the average tooling costs per part. According to expert opinions, tooling costs mainly depend on the geometric complexity of the parts. Although complexity enhancement could increase the total tooling costs, reduction in the number of assembly parts could limit its upward trend (see Figs. 12, 13, 14, and 15).

4.1.2 Environmental dimension

Quality of products Quality of products increased exponentially, which was affected significantly by skill of operators. As their skill increases through iterations and training, they can discover more design flaws, contributing to quality of products. Figure 16 indicates that quality of products has quadrupled through RP utilization.

Total material consumption and waste generation A substantial reduction was observed in the assembly parts, as well as the material consumption in the production process; this also reduced waste generation during material processing, as shown in Figs. 17 and 18.

CO2 emission According to the findings, the reduction in the number of parts leads to the reduction of the suppliers of raw materials and the frequency of transportation in the supply chain. As mentioned earlier, transportation is one of

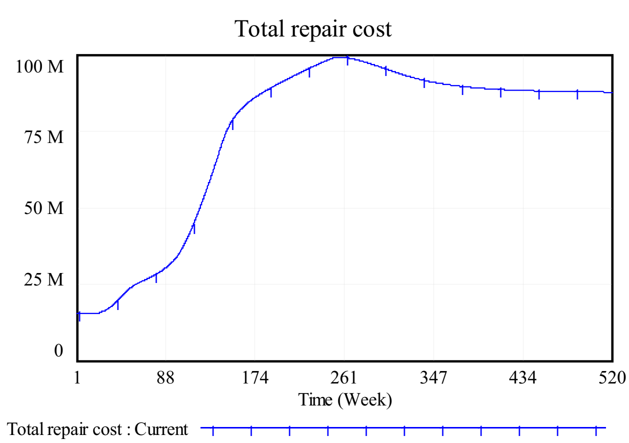


Fig. 13 Dynamic behavior of total repair cost

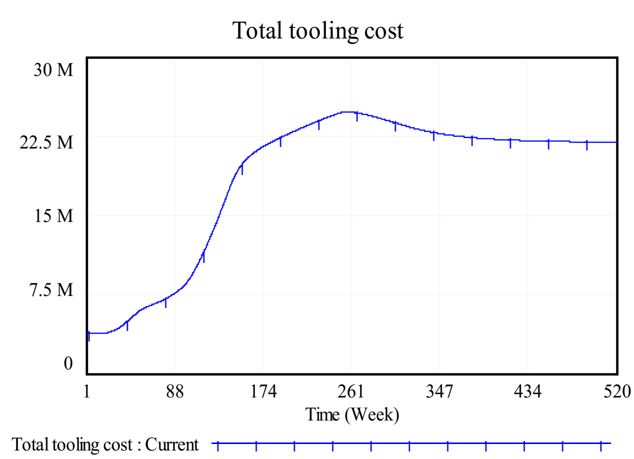


Fig. 15 Dynamic behavior of total tooling cost

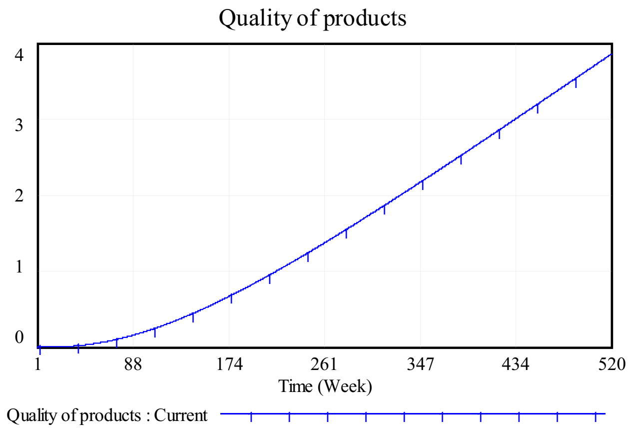


Fig. 16 Simulated dynamic behavior of Quality

the main sources of CO_2 emissions. The simulation results demonstrated at least 35% decrease in fuel consumption and $C0_2$ emissions. Figure 19 illustrates the descending behavior of mentioned variables.

4.1.3 Social dimension

Skill of operators As depicted in Fig. 20, several iterations to find an appropriate design lead to self-learning through trial-and-error. Moreover, training programs could improve the skills of the operators. Goal-seeking behavior regarding this variable is generated since the process of building prototypes continued until reaching the acceptable quality; in other words, the system achieved its goal and stabilized. Figure 21 illustrates the failed prototypes in the prototyping process, and the graph shows an oscillation behavior since the workforce with fewer skills failed in building the prototypes during the initial projects. Furthermore, an oscillation occurred in the process between the two stocks (i.e., operators' skills and failed prototypes), and the degree of oscillation was affected by a delay in the system. By increasing the operator's skill after one year, the rate of the failed

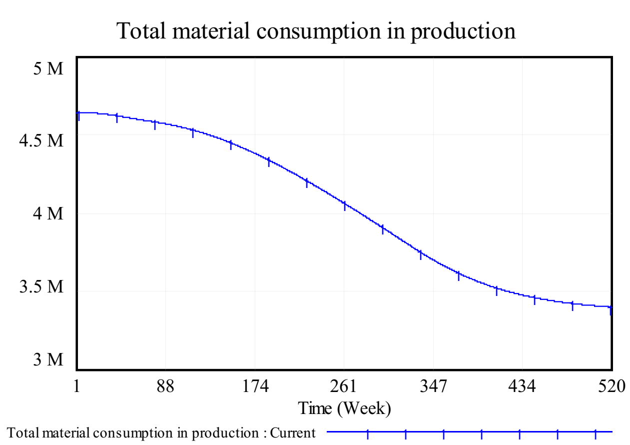


Fig. 17 Dynamic behavior of material consumption

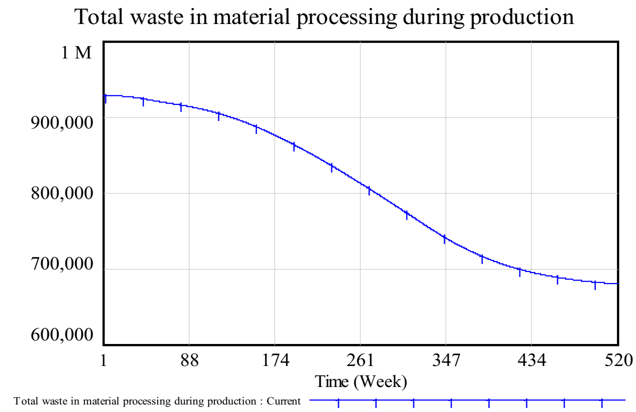


Fig. 18 Dynamic behavior of waste generation

prototypes decreased. Therefore, it could be concluded that the skills of the operators play a pivotal role in reducing failed part in the prototyping process.

5 Discussion

RP implementation in the design phase of products has potential effects on the sustainability pillars. The existing research qualitatively has implied the possible effect of RP on supply chains. SD moldels provide an appropriate framework to help decision makers in recognizing the behavior of a system within a specific period. Organizations can cope with the uncertainty of new technologies through learning and knowledge management (Sterman et al. 2015). The

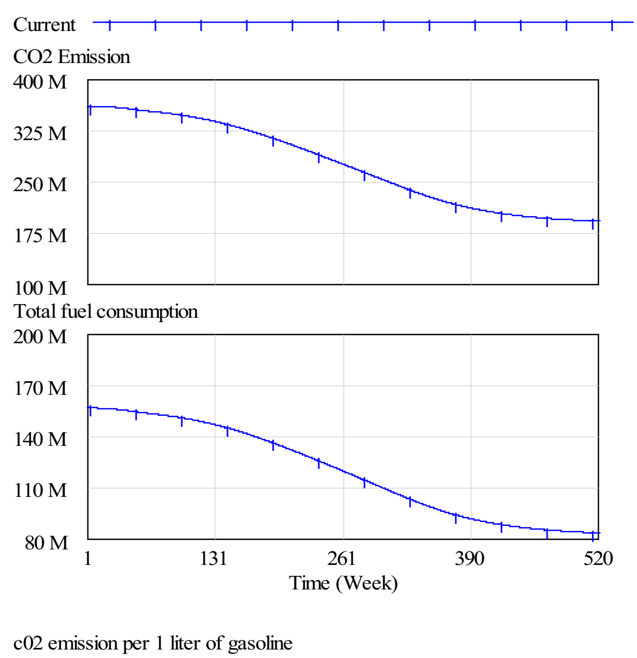


Fig. 19 Simulated dynamic behavior of fuel consumption and CO2 emission

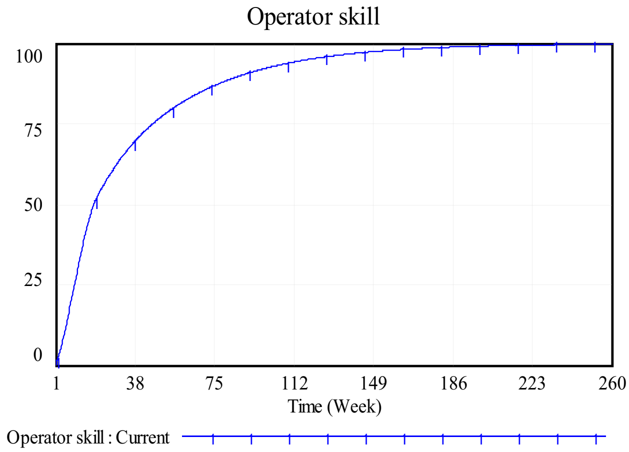


Fig. 20 Dynamic behavior of operator skill

present study aimed to bridge the gap in literature by providing a simulation model that could practically and quantitatively increase the knowledge of managers and asses the prospected benefits in different segments of a supply chain, thereby assisting the decision-making process regarding technology implementation. For this purpose, a generic model was developed with an emphasis on measuring the sustainability of the supply chain based on key indicators. Provided simulation model can practically and quantitatively increase knowledge of managers and asses the prospected benefits to different segments of a supply chain. The main factors considered in the simulation of the model were the total costs, material consumption and waste generation during production, quality of the products, CO_2 emissions through the transportations in the supply chain, and skills of the operators working with 3D printing machines.

According to the simulation results, part consolidation is the main benefit of RP implementation and has numerous effects on several constituents of the supply chain. In addition, design stage significantly influences costs as an economic domain of sustainability through multiple

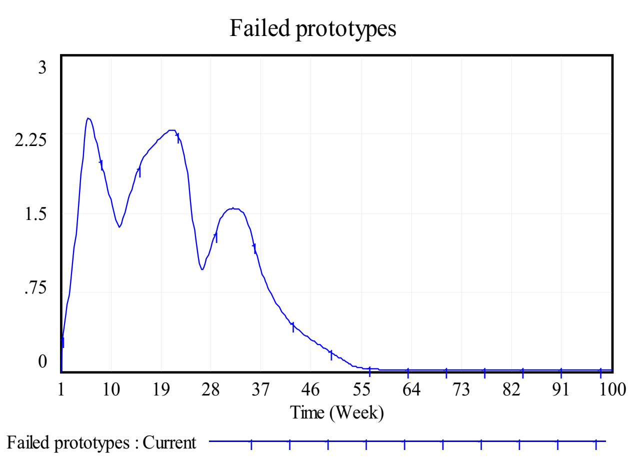


Fig. 21 Dynamic behavior of failed prototypes

segments of the supply chain. Total costs are affected by variables such as costs of material purchasing, inventory, tooling, component repair, transportation, and carbon penalty through several short-term and long-term feedback loops. By determining the effects of the total costs through RP adoption at various stages of SC, this research deepens our understanding of the complex nature of SC, thereby providing insight into having a systematic perspective. The total costs of a system will decrease if more RP projects are run in the design phase since no tooling will be required in RP, and the designers will be able to conduct various iterations without cost penalties (with the exception of the failed prototypes in the prototyping process). This finding is in line with literature regarding potential benefits of RP implementation reported previously (Li et al. 2017, 2020; Yang and Zhao 2018; Yang et al. 2020).

RP enables design optimization which minimizes waste generation and material consumption, thereby decreasing the number of the suppliers providing raw materials and spare parts, shortening the supply chain by eliminating unnecessary actors, and reducing the logistics and long-distance transportation. As a result, logistics and CO_2 emissions will decrease, contributing to economic and environmental sustainability. In other words, RP improves product development processes and decreases the number of stages in a conventional supply chain, which will in turn reduce supply chain complexity and costs. These findings are consistent with the contention of the previous studies in this regard (Niaki and Nonino 2017a, b; Yang and Zhao 2018; Rinaldi et al. 2021). Correspondingly, part consolidation increases the geometric complexity and tooling costs in mass production. The replacement of subcomponents is not possible due to consolidation, forcing the replacement of the entire defective part, which increases the repair costs. This finding complements pervious research carried out in this regard (Knofius et al. 2019).

One of the main barriers to RP implementation is a lack of professionals in design and 3D machine operating (Thomas-Seale et al. 2018; Seidel and Schätz 2019; Matos and Jacinto 2019). Implementing new technologies in an organization requires organizational learning and proper training programs. RP adoption changes the work structure and requirements for the development of new skills, which is a social sustainability indicator. Simulation results indicated that designers who are unfamiliar with RP processes may experience numerous failures, which will in turn increase the iteration rate in prototyping phase, waste production during the printing process and RP material consumption. Our findings shed light on the role of part-time training and iterations (learning by doing) in knowledge development, which significantly reduce the rate of failure, production stages, printing duration, and material waste by discovering design flaws at an earlier phase. Skill development also contributes to the quality of products. The present study complements previous research findings (Friesike et al.

2019; Ghadge et al. 2020). The findings of the current research are in line with the human capital theory, which refers to investment in human skills through on-the-job training and 'learning by doing' with aim of increasing labor productivity, which influences the overall sustainability of organizations (Šlaus and Jacobs 2011). The results also indicated that workforce skills development is both a goal in itself and a means to successful RP implementation in a sustainable supply chain. Hence, it could be inferred that the social domain also influences the manufacturing indirectly through the financial and environmental domains. Such measures could guarantee success in the short-term and long-term use of the technology (Colletti 2016; Thomas-Seale et al. 2018; da Silva Barros 2017).

6 Conclusion and direction for further research

An innovation process is highly complex and unpredictable depending on multiple variables and their interactions. Innovation and technology management are dynamic and complex phenomena that evolve over time. Decision regarding the adoption of new technologies is often made with uncertainty about cost and benefit. Khan and Yu (2020) reported that the successful implementation of innovations such as sustainable practices depends on the support and awareness of the senior managers. Sustainable technologies will affect not only a single firm, but also the entire supply chain, thereby necessitating each segment to manage the new changes and uncertainties (Jiang et al. 2017). Making decision in the uncertain world of business, managers must have adequate knowledge and a systems-oriented perspective about the interactions, nonlinearities, and feedbacks among supply chain entities, which often involve significant delays. SD models are recognized as learning models since they consider complex factors and time lags in decision-making processes (Rodríguez and Aguirre 2013). As a strategic management tool, SD models encompass the uncertainty, structure, and complex concepts that help decision-makers to increase their knowledge about RP adoption. In the current research, the key motivation to use an SD model for RP adoption was to allow managers to understand future changes, explore the effects of different decisions, and learn about factors that may influence outcomes. Our findings demonstrate the long-term impact of RP adoption by providing a holistic view of the system and the challenges that need to be overcome, developing the knowledge of manufacturers within the context of Industry 4.0. An important insight derived from the simulation was that RP adoption leads to organizational changes, shortens logistics chains, and decreases the number of suppliers, thereby reshaping the SC structure to be flattened, increasing the flexibility and resilience of the SC operations, and reducing the complexity of management.

RP adoption has several managerial implications such as configuration in design processes, suppliers, and logistic chains. The findings revealed that geometric complexity of the parts as a limiting factor plays a key role in tooling costs and the reliability of the parts and must be considered in the consolidation process. Therefore, designers should consider the trade-off between environmental and economic benefits. Another important contribution of our model is introducing the technical and operational variables that indicate the inconclusive effects of RP adoption. According to the simulation results, successful RP implementation is highly dependent on the operator's knowledge. A lack of design guidelines increases iterations, failed prototypes, and costs. Therefore, it is suggested that managers invest in technology-based training to increase operators' skills and maximize economic and environmental benefits by reducing the total costs and waste generation. According to Niaki and Nonino (2018), the technicians who are familiar with digital manufacturing systems (e.g., CNC machines) could be trained through specific educational courses as they are more likely able to learn the operating of AM technologies. Some AM-related skills include designing models for 3D printing, material selection, material specification/properties, material reuse, process selection, testing, measurement, and machine maintenance (Despeisse et al. 2017). Skill improvement is highly effective in operational success.

By using the proposed model in the current research, managers will be able to determine intended, unintended, short-term, and long-term consequences and identify the benefits of RP to decide whether switching from conventional methods to RP is worthwhile in the product development and design phases. The current research is among the first studies to provide a generic simulation model within a technology implementation context. The primary benefit of the proposed generic model is that it is potentially applicable to a wide range of industries. Furthermore, the flexibility of the model enables adjustments, expanding boundaries, and more sophistication, which improve its utility and help managers with long-term strategic planning, policy evaluation, and scenario analysis. Our general model could also be used as a reference to develop specific customized models for actual manufacturers to evaluate their managerial policies and conduct risk-free experiments through simulation. Notably, model validity tests confirmed the significant structural flexibility of the proposed model, and its parameters could be reconfigured in any case with an emphasis on the firm's costs and profits. In the present study, we used numerical examples to examine the potential applicability of our model. We believe that our findings lay the groundwork for industrial RP applications since recognizing the benefits of these technologies will largely influence the adoption process in the long run.

The proposed model did not encompass variables such as assembly time/costs, assembly complexity, and other factors associated with the manufacturing process in order to limit the scope of the study. Although these factors might significantly affect the supply chain performance, they largely depend on specific business cases and are not proper for generic models. Moreover, the unavailability of some reference values or empirical data were the main limitations of the current research, and further investigation is recommended to develop and expand the proposed model.

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Availability of data and materials All data and material is available upon request.

Code availability Software application is available upon request.

Declarations

Consent for publication The manuscript is not currently being considered for publication in another journal.

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Appendix 1 Integrated causal loop diagram

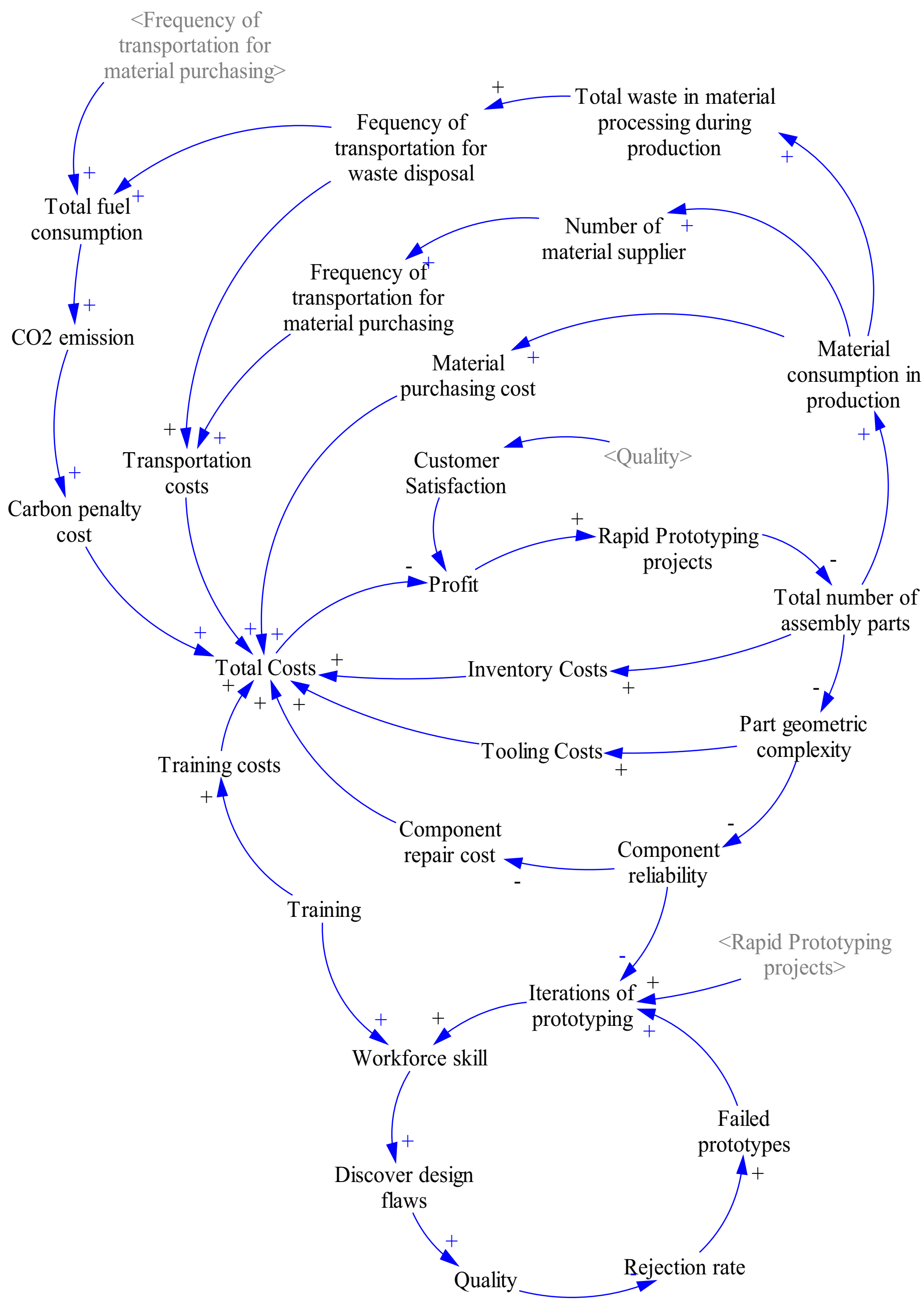

Fig. 22 Integrated causal loop diagram.

Appendix 2 Equations

Acceptable skill level = 100%

Average tooling cost = complexity* Price increase per complexity

(Based on the model purpose, it is assumed that increase in geometric complexity will increase tooling costs)

Average order lead time = 1 week

(It is assumed that average order supplier lead time is one week)

Total fuel consumption = (fuel consumption per km for material supplying*total km for material purchasing transportation) + (total km for waste disposal*fuel consumption per km for waste disposal)

Quality = INTEG (increase,0)

Increase through iterations = time to increase look up (RP prototypes)

time to increase look up([(0,0)-(120,10)],(0,0.1),(5,0.3),(8.80734,0.701755),(13.7615,1.35965),(19.3761,1.57895),(29,1.66667),(30,1.5),(35,1.4),(40,0.9),(45.107,0.745614),(48,0.5),(50,0.2),(120,0))

(Increase in skill of operators through iterations is based on the time and number of prototypes they make)

Discover = RP failed prototypes /time to detect

Increase through training = (training requirement*c)/personnel*duration

RP Prototypes = INTEG (iteration rate + second phase-rejection rate)

(This is the sock variable which is sum of the input rates and output rates)

Transportation cost = (total km for waste disposal + total km for material purchasing transportation)*average extra cost for transportation per Km + total fuel cost

Frequency of transportation for material purchasing = number of material supplier*(total material consumption in production/truck capacity)

Fuel consumption per km for material supplying = 48L/100KM

Fuel consumption per km for waste disposal = 32L/100kM

Iteration rate = iteration for first project + iteration for second project + iteration for third project.

Skill gap = acceptable skill level-operator skill

Average material consumption per assemble part = 0.3 kg

Number of material supplier = DELAY1 (1/5*total of assemble parts, 52)

Supplier lead time = average order lead time*number of material supplier

Design = IF THEN ELSE (New designs released > 0, discover-iteration rate, 0)

Frequency of transportation for waste disposal = waste generation in material processing during production/truck capacity 2

Total distance (km) for waste disposal = frequency of transportation for waste disposal*distance to the disposal site

Total material consumption in production = DELAY1 (total of assemble parts*production number*average material consumption per assemble part, 53)

Decrease rate = reduction per project in first year + DELAY1 (reduction per other project, 53)

Total repair cost = total of assemble parts*production number*average repair cost per unit

Total tool cost = total of assemble parts*average tooling cost per unit

Total waste in material processing during production = total material consumption in production*waste

Training cost = training requirement*cost per training duration*personnel

Training requirement = skill gap/adj time

Material purchasing cost = average cost per one kg material*total material consumption in production

Operator skill = INTEG (increase through iterations + increase through training,

Total cost = redesign cost + carbon penalty cost + material purchasing cost + total tool cost + training cost + transportation cost + inventory cost

Total fuel cost = total fuel consumption*fuel cost per liter

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