Performance evaluation of reverse logistics in food supply chains in a circular economy using system dynamics

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Abstract

Supply chains are composed of multiple stakeholders who have complex inter-relationships. In addition, the forward and reverse flow of materials, information, human resources and finance occurs among different stakeholders in closing the loop of supply chains. Reverse logistics (RL) activities are gaining importance in terms of size and quantity due to both economic and environmental concerns. These flows in RL in supply chains are both dynamic and complex in nature. Further, the environmental impact of RL activities has barely been considered in holistic way in available literature. In this study, a system dynamics model has been developed to analyze and comprehend the green performance of RL activities by predicting the environmental impact of RL activities. The proposed model has been validated by a case study in the context of a food supply chain. In the company where the case study is carried out, the environmental effects of RL activities have been analyzed. These activities in a food supply chain in terms of CO_2 (carbon dioxide), NOx (nitrogen oxide), SO_2 (sulphur dioxide) and PM (particulate matter) emissions have been predicted through a system dynamics model for the years 2020 to 2024. The proposed methodology is applied in a food supply context, a major player in retail business, especially in emerging economies. According to our findings, the RL activities in a food supply chain can significantly contribute to green performance management by minimizing food waste and loss; hence, the environmental impacts of such activities should be closely examined from a managerial perspective.

Keywords: Reverse logistics, system dynamics, green business performance and environmental impact, food supply chain, circular economy.

List of abbreviations

CLSC closed-loop supply chain

SD system dynamics

RL reverse logistics

PM particulate matter

GHG greenhouse gas

1. Introduction

The concept of RL has been widely practised in many industries (e.g. manufacturing, electric and electronic, garments) (Tan and Kumar, 2006; Islam and Huda, 2018) gaining a legitimate popularity all over the world due to growing problems such as climate change, environmental protection, regulatory requirements, resource scarcity, sustainable business practices and social responsibilities (Agrawal et al. 2015; Govindan et al., 2015; Govindan and Soleimani, 2017). RL includes a series of processes associated with product return, collection and either recovery, repairing, refurbishing, recycling, remanufacturing or disposal of used or at end-of-life products (Ilgin and Gupta, 2010). RL play a significant role in achieving the sustainability goals of enterprises for greening their supply chains. The concept of RL covers not only profit and cost optimization, but also green (environmentally friendly) principles and laws. The main objectives of RL are primarily to focus on process operations that have an impact on environmental conditions at every stage of the supply chain such as waste minimization and optimized resource utilization (Mutingi, 2013). Therefore, environmental concerns can directly affect the financial performance of any organization (Le, 2020). There is an increasing interest in the relationship between environmental and economic performance due to the growing importance of environmental impacts (White 2005; Czerny and Letmathe, 2017). Capece et al., 2017, state that businesses which pay more attention to environmental policies and green vision achieve better working performance. Green business performance can be analyzed with the help of an examination of the environmental impacts of RL activities. Environmental concerns related to input measurements (environmental internalities) include energy, materials, water use or landfill area (Georgiadis and Besiou, 2008; Georgiadis and Besiou, 2009); output measurements (environmental externalities) include emissions containing liquid and solid pollutants as well as GHG such as CO_2, methane (CH_4) and NO (Abduaziz et al., 2015) that contribute to global warming. Improved environmental performance can be achieved by pollution prevention initiatives with a resulting positive impact on manufacturing and business performance (Kanashiro, 2020). Moreover, the modelling of environmental concerns including waste disposal, GHG and energy consumption etc. during production is regarded as the most pressing priority for the future of RL models (Bazan et al., 2016). In addition, environmental practices, and RL activities in particular, are reflected in the relationship between companies and the prior and subsequent links, especially in food supply chains (Gonzalez-Torre et al., 2004). Those practices require large amounts of data, which makes a RL system complex and dynamic (Zhao et al., 2017). Building an efficient big data system for managing used products can provide quality information on the returned devices in RL (Xu et al., 2019).

The food industry is a very suitable field for recycling in a circular economy (Heydari, Govindan and Sadeghi, 2018). RL activities are necessary to ensure high quality and food safety due to rapid damage and short shelf life (Vlachos, 2014). In addition, the food supply chain is more complex due to its short shelf life (Khalafi et al., 2019; Noya et al., 2016). RL activities in a food supply chain consisting of perishable products have become a valuable target in SC (Deng et al., 2019).

RL activities of food products are necessary to reduce food waste and ensure the efficient flow of logistics operations. Food waste and loss have many detrimental effects on the environment by increasing GHG and pollution (Sathiyagothai and Saravanan, 2017). These emissions can be reduced by avoiding unnecessary transport (Frei et al., 2020; Shamiss, 2018). RL activities can be implemented into the food supply chain to decrease food waste and loss. Besides, these activities in a food supply chain provide quality and safe food to consumers while considering the environment. Retailers can take responsibility to help reduce food waste as this has a significant effect in forward and reverse supply chains (Mena et al., 2011, Young et al., 2018). Analyzing the environmental impact of a company's activities, as well as reducing CO_2 emissions, gives an indication of a firm's performance (Capece et al., 2018). More studies are needed on green practices and to measure green performance (Pinto, 2020). In addition, many business decisions in RL and CLSC (closed-loop supply chain) have an environmental impact; however, literature is still scarce on the impact of business decisions on the performance of RL and CLSCM. Studies should be integrated into RL and CLSC studies. (Kazemi et al., 2019). Approximately one third of the foods produced annually in the world, in other words almost 1.3 billion tons, are lost or wasted (FAO, 2013). Food loss and waste also result in a devastating reduction in resources and have an adverse impact on the environment by producing unnecessary GHG emissions. Food waste and loss are increasing problems for emerging countries. The total edible food loss and waste is estimated at almost 26.04 million tons/year in Turkey (Salihoglu et al., 2018). Huge amounts of food are wasted because of the quality standards demanded, especially at the retail level. In 2013, FAO announced that almost 3.3 billion tons of CO_2 emissions were released as a result of the ineffective management of food waste; 10% of gas emissions are caused by food waste. There is a direct relationship between food waste and CO_2 emissions. Food supply chains are complex, continually changing systems, and include many participants (Kumar and Nigmatullin, 2011). Thanks to a system dynamics approach, relations among operations and partners involved in the entire food system can be managed effectively (Vanessa et al., 2015; Georgiadis, et al., 2005). This approach allows us to predict and also manage the multiple factors interacting in complex food systems (Vanessa et al., 2015). Therefore, this study aims to contribute to minimizing the negative impact on the environment by applying RL implementation in the food processing industry in a circular economy using system dynamics modelling. This paper makes a valuable contribution to current literature by focusing on value adding and non-value adding RL activities in the context of food supply chains. Existing RL models in food and beverage industries are scarce (Govindan et al., 2015; Islam and Huda, 2018); there is no study on SD modelling to measure the environmental aspects for RL in food supply chains.

Consequently, this study proposes the research question:

RQ1. What are the environmental impacts of RL activities in the food supply chain?

In this study, our aim is to explain the following research objectives:

- To analyze environmental impacts of RL activities due to its extensive complexity
- To create a model in order to handle the accumulated big data to estimate and forecast the environmental impacts of RL activities to analyze green business performance.
- To propose important implications for managers and policy makers

In this paper, a system dynamics model is proposed to evaluate the environmental impacts of RL activities for assessing green performance. Environmental impacts have been categorized as the emissions caused by value adding and non-value adding activities. The proposed SD model has been applied to the RL in a food supply chain to deal with its complex and dynamic nature and to forecast emission levels for the next five years. This research consisted of a single case study, analyzing the environmental impact of RL activities in a food supply chain in Turkey. The case study company is involved in defining the decision variables in building the model, formulating the relationships between decision factors and determining the relevant key decision makers (Alamerew and Brissaud, 2020). Finally, the results of the application have been discussed with guide managers and policy makers in their decision-making processes.
Following the introduction, the related literature review on environmental impacts of RL is presented in Section 2. Section 3 describes the system dynamics model to analyze the food supply chain. RL in the food supply chain and the need for them is discussed in Section 4.

Section 5 includes the case study based on the proposed system dynamics model, result of the applications and implications. Section 6 presents the conclusion.

2. Theoretical Background

RL provide companies with the opportunity to manage waste and to increase environmental efficiency. RL activities have various advantages such as reducing consumption of raw material resources, creating economic value by recovering waste, improving customer satisfaction, saving energy, reduction in landfills and reducing gas emissions. Therefore, RL activities have a positive impact on environmental issues, provide green benefits, and should be a considered in a holistic view due to the complex and dynamic nature of RL.

At present, there are a large number of publications covering RL and CLSC modelling employing various methodologies (Govindan et al., 2015). Some models use traditional techniques (e.g. goal programming) with specific aims to measure environmental impacts or carbon footprint (Agrawal et al. 2015; Govindan et al., 2015; Govindan and Soleimani, 2017); others use system thinking or system approach techniques (e.g. SD) to model RL or CLSC without considering environmental impacts.

Only a limited number of models deal with either RL or CLSC with the specific aims of measuring environmental aspects or carbon footprint (Govindan et al., 2015). Some examples include: Kannan et al., (2012) who presented a mixed integer-based model for RL to minimize climate change (specifically, the CO_2 footprint); Liao (2018) suggested a generic mixed integer nonlinear programming model for recycling bulk waste in Taiwan. The model aims to decrease the amount of incineration or landfill at disposal sites. Therefore, it will decrease CO_2 and the environmental impact. Bottani et al., (2019) carried out a study to analyze environmental issues in food supply chains using life cycle assessment methodology. Agrawal and Singh (2019) used Partial Least Squares Path Modelling to measure the Triple Bottom Line performance based on economic, environmental and social factors of RL in the Indian electronics industry. Dev et al. (2019) presented a bass diffusion model for RL to analyze economic and environmental performances.

According to the above-mentioned articles, it is difficult to analyze the environmental impact of RL with the methods suggested in current literature because they may not cover the dynamic complexity inherent in RL activities. For instance, due to a failure to embrace the complex structure of RL activities while analyzing environmental aspects, the existing literature concentrates only on carbon emissions; NO and PM were not considered in analyzing environmental aspects of RL activities as mentioned by Kannan (2012).

Therefore, SD is a powerful method to gain insights into the structure of complex and dynamic systems (Sterman, 2000; Georgiadis and Besiou, 2008; Franco 2019); it supports long-term, strategic decision-making (Rebs et al., 2019) to model, understand and discuss real-world problems. There is a gap in associated literature since no adequate research has been conducted on the environmental impact on RL considering value added and non-value activities with SD.

On the other hand, there are studies on RL that have used SD as a methodology. Past research has looked at developing RL models by using SD (Rebs et al., 2019) in order to measure financial impact (e.g. Abduaziz et al., 2015) or to support decision making (e.g. Tan and Kumar, 2006).

Georgiadis and Vlachos (2003) developed a SD model for reverse and forward logistics to analyze the system behaviour under external factors, including environmental legislation and investments on remanufacturing facilities. Georgiadis and Vlachos (2004) proposed a dynamic model that includes direct and reverse supply chain by using SD methodology; they studied long-term decision-making problems to analyze the effects of various RL capacity expansion policies on system behavior. Georgiadis et al. (2005) used SD modelling to determine optimal network configuration and to analyze the key issue of strategic supply chain management for long-term capacity planning. Tan and Kumar (2006) presented a decision-making model using SD and simulation for manufacturers of computers to understand the profitability of RL operations. Georgiadis and Besiou (2008) developed a system dynamic model for a single producer with recycling activities applied in real-world cases and analyzed the long-term behaviour of CLSC. Georgiadis and Besiou (2009) proposed another SD model for CLSC of the electronic industry to analyze and measure the effects of different legislative measures, CLSC activities and design-for-environment practices; these included availability of natural resources, landfill capacity and economic sustainability. Narayana et al. (2014) developed a SD model to determine a set of feedback loops operating in the system responsible for complexities in RL in the Indian pharmaceutical industry. Mutingi (2014) proposed a model based on SD to simulate and analyze the impact of RL in terms of capacity building for collection and remanufacturing operations. Golroudbary and Zahraee (2015) used a SD approach to assess the system behavior of an electrical manufacturing company in CLSC. Abduaziz et al. (2015) used a mixed model of SD and discrete event simulation to assess a proposed RL model by measuring its benefits in operational costs and green practices. Sudarto et al. (2017) proposed a SD model to optimize capacity-planning decision for efficient flexible control while identifying product lifecycle uncertainty in a CLSC with RL processes and social responsibility objectives. Miao et al. (2017) carried out research on third-party enterprise-dominating remanufacturing CLSC through a SD methodology. Ghisolfi et al. (2017) proposed a model on social inclusion of informal waste pickers into the environmental policy in CLSC in Brazil using SD methodology. Franco (2019) presented a SD model to analyze the systemic effects of combining multiple product design and business model strategies for CLSC in a circular economy, conducting a simulation of system behavior for different model variables. Cao et al. (2019) developed a SD model to observe the entire life cycle of an electric-coal supply chain with reference to a greening energy intensive supply chain. Cosenz et al. (2019) also used SD in examining social, environmental and economic drivers of a single company from a sustainability perspective. Subsequently, Alamerew and Brissaud (2020) worked on developing a model based on SD methodology to comprehend synergetic interaction between diverse disciplines and a variety of influencing indicators including economic, societal, managerial, regulatory and environmental factors for RL within the circular economy perspective.

These aforementioned studies have explored solely RL modelling using a SD model an investigation of green performance by considering environmental impacts caused by RL activities needs to be considered. Govindan (2015) mentioned that green and environmental objectives should be included in all RL studies.

In order to improve green performance and to deal with the challenges of environmental issues, studies must be properly conducted and evaluated by adapting green initiatives and RL activities (Marsillac, 2008). Excellence in logistics practices are strongly related to high quality business performance. According to Vlachos (2016), reserve logistics activities and capabilities have a direct impact on a firm's performance. Performance measures that indicate the influence of green practices on company performance need to be further investigated (Pinto, 2020). Previous studies have rarely explained which particular environmental management practices or strategies have more impact on improving a firm's performance (Singh and Trivedi, 2016). In existing literature there are many studies that have evaluated green performance directly (Lin et al., 2011; Lai and Wong, 2012; Ala-Harja and Helo, 2014; Lee and Wu, 2014; Singh and Trivedi,2016) but there is a lack of exploration of dynamic relationship environmental logistic performance indicators such as CO_2 emissions, GHG emissions and green business performance (Liu, 2018).

Table 1. Summary of Theoretical Background

Author(S)	*Aim of study*	*Method*	*Sector*
Georgiadis and Vlachos (2003)	to analyze the system behaviour under external influences, such as the environmental legislation and investments on remanufacturing facilities	System Dynamic Model	Manufacturing
Georgiadis and Vlachos (2004)	to analyze the effects of various RL capacity expansion policies	System Dynamic Model	Manufacturing
Georgiadis et al. (2005)	to determine optimal network configuration	System Dynamic Model	Food Industry
Tan and Kumar (2006)	to observe profitability of RL operations for both replacement parts to suppliers and refurbished parts to manufacturers	A Decision-Making Model Using System Dynamic Model	Computer Manufacturing
Georgiadis and Besiou (2008)	analyzed the long-term behaviour of CLSC	System Dynamic Model	Electrical and Electronic Equipment
Georgiadis and Besiou (2009)	to analyze and measure the impact of different legislative measures, CLSC activities and design-for-environment practices	System Dynamic Model	Electrical and Electronic Equipment
Kannan et al. (2012)	to minimize climate change and CO_2 footprint	Mixed Integer-Based Model	Plastic sector
Narayana et el. (2014)	to determine a set of feedback loops operating in the system responsible for complexities in RL	System Dynamic Model	Pharmaceutical Industry
Mutingi (2014)	to analyze the impact of RL in terms of capacity building for collection and remanufacturing operations	System Dynamic Model	Business
Golroudbary and Zahraee (2015)	to evaluate the system behaviour	System Dynamic Model	Electrical Manufacturing
Abduaziz et el. (2015)	to measure RL benefits in operational costs and green practices	System Dynamic Model and Discrete Event Simulation	Automotive Industry
Sudarto et el. (2017)	to optimize capacity-planning decision for efficient flexible control while identifying product lifecycle uncertainty in a CLSC with RL processes and social responsibility objectives	System Dynamic Model	Manufacturing
Miao et el. (2017)	to research on third-party enterprise-dominating remanufacturing CLSC	System Dynamic Model	Electronic information industry
Ghisolfi et el. (2017)	to analyze social inclusion of informal waste pickers into the environmental policy in CLSC	System Dynamic Model	Desktops and laptops supply chain
Liao (2018)	to decrease the amount of incineration or landfill at disposal sites	Mixed Integer Nonlinear Programming Model	Furniture Industry
Bottani et al., (2019)	to analyze environmental issues	Life Cycle Assessment	Food Industry
Agrawal and Singh (2019)	to measure the triple bottom line performance of RL	Partial Least Squares Path Modelling	Electronics Industry
Dev et al. (2019)	to analyze economic and environmental performances	A Bass Diffusion Model	Manufacturing
Franco (2019)	to analyze the systemic effects of combining multiple product design and business model strategies for CLSC in a circular economy	System Dynamic Model	Business sector
Cao et el. (2019)	to interact the whole life cycle supply chain with reference of greening energy intensive supply chain	System Dynamic Model	Electric-coal supply chain

Cosenz et el. (2019)	to examine social, environmental and economic drivers of a single company from sustainability perspective	System Dynamic Model	Business sector
Alamerew and Brissaud (2020)	to comprehend synergetic interaction between diverse disciplines and variety of influencing indicators including economic, societal, managerial, regulatory and environmental factors for RL within the circular economy perspective	System Dynamic Model	Electric Vehicle Batteries

Thus, there is still a need for assessment of green performance by considering the environmental impacts of RL by using a SD model. Therefore, the present study will aim to investigate the environmental impact of RL using SD methodology to analyze green business performance.

3. System Dynamics Modelling

Accelerating changes and new technologies give rise to unique and unforeseen challenges. Therefore, SD methodology is used in order to deal with problems of complexity and dynamic structure (Sterman, 2001). SD was first introduced by Jay Forrester (1961) as a modelling and simulation tool in management fields (Forrester, 1961). Afterwards, Meadows et al. (1972) presented the approach of "Limits to growth" which made use of system thinking and SD concepts to understand behaviors of complex socio-ecological problems. "Limits to growth" is considered as a precious resource for sustainability (Turner, 2012). Since then, the SD approach has been widely used for understanding and modelling real-world problems in a variety of fields such as business, social and ecology systems as well as socio-economic problems (Azar, 2012). The structure of the system is expressed by using causal-loop diagrams to indicate causal inter-relations among the variables. These variables and system boundaries are determined in accordance with the system objectives (Dekker et al., 2013). Systems consist of interacting components which operate in coordination to achieve a common goal. SD modelling provides a series of conceptual and quantitative methods to understand and simulate non-linear and complex interactions between system elements via feedback loops (Georgiadis and Besiou, 2008). A feedback loop is not only able to reinforce the system but also stabilize it. This means that there are two types of feedback loops. The reason for this is that feedback acts both as a positive (reinforcing) and a negative (balancing) loop. The structure of a system is explained through these feedback loop mechanisms.

Forrester (1961) states the advantages of a SD approach as follows;

- Investigating the behavior of constantly changing components of the system
- Analyzing the system with a holistic view and systems perspective
- Providing measures for the future effects of decision-making processes by presenting the possible effects in advance and explaining long-term results

Moreover, researchers can analyze the possible effects of long-term decisions at lower cost with the SD approach (Ekinci et al., 2020). This approach is important to comprehend the big picture and researchers can make effective decisions by seeing the big picture through SD modelling.

Besides, since the system can be divided into components, small changes can be seen due to the nonlinear behavior of the systems. However, different stakeholders and groups with various perspectives can develop different assumptions. Researchers can work with different variables and can propose system dynamics models with a different perspective. When dealing with real world problems using multivariables, a causal loop diagram and system dynamics model can become a very complex structure.

SD modelling enables us to design and control the dynamic and complex structure of supply chains that include various processes, information and strategies (Campuzano and Mula, 2011). In addition, the application of SD is a powerful tool for long-term analysis of supply chains. Forrester applied the SD methodology to supply chain management as the early example. There are many studies that handle SD simulation modelling on supply chains (Hafeez et al., 1996; Otto and Kotzab, 2003; Pierreval et al., 2007; Campuzano, 2010; Lie et al., 2016; Saavedra et al., 2018; Cao et al., 2019). Moreover, the SD approach is also a useful tool to model and analyze food supply chains because of the inclusion of dynamic and complex processes.

4. Reverse Logistics in Food Supply Chains

RL is necessary in the food industry to provide high quality and safe food to consumers without any damage to human life and the environment (Vlachos, 2014). RL in the food industry deals with a range of challenges such as food returns, food recalls, recycling, reuse and disposal (Vijayan, 2014). There are several reasons that require the use of RL in the food industry. These include shorter product lifecycles because of potential damage and product expiry, return of poor quality products and failure to comply with good manufacturing norms. The life span of the product causes customers to return low quality goods, especially meat and milk products that are vulnerable to spoilage. There are three important areas in the food industry where RL is essential; decreasing food waste, packaging and material waste.

The biggest challenge for RL processes within the food industry is that food is a perishable product, meaning that there is always a risk of returns to the manufacturer. Today, food loss and waste have become significant issues of public concern. Besides, the 2030 Agenda for Sustainable Development indicates that Sustainable Development Goals call for a reduction of one half per capita of global food waste at retail and consumer levels by 2030. There is also a call to reduce food losses and waste in food supply chains because of an increased global awareness of the food waste problem (FAO, 2011). FAO stated that food waste resulting from the failure to handle food waste properly caused 3.3 billion tons of carbon dioxide emission in 2013. Therefore, there is a direct relationship between food waste and CO_2 emission. It has been shown that 10% of GHG arise because of food waste (Sathiyagothai and Saravanan, 2017). The growing concern over food waste has encouraged a driving force for food manufacturers and distributors to adapt RL activities (Vlachos, 2014). Food waste can be reduced by introducing systems for reuse or recycling opportunities, managed in an efficient way through reverse supply chain networks (Waseem, 2020). The other important issues to be addressed in the food industry are packaging and transport material waste such as pallets and crates. However, RL activities have some disadvantages due to return and remanufacturing processes. Some activities may create gas emissions and pollutants during the reprocessing of products in remanufacturing processes.

5. Case study

5.1 Company Background and Data Collection

This company joined the sector as a brand for milk and dairy products 43 year ago, developing its activities into different fields of the food sector such as water, feeds and meat. This company has decided to focus on food, beverage and paint sectors, which it considers as its main activities in the 2000s. Thanks to an integrated structure, sectors can use each other's tools and materials in RL networks, producing a system that has been become very complex in nature. Having a 17.5% market share in the processed meat market, it is the leader in this market in Turkey. The company is one of Turkey's largest production facilities. It has an extensive network of distribution, operating through 98 dealers with 149 distribution points. The company has an aim of protecting the environment by using resources in an efficient way and reducing waste. TS EN ISO 14001 Environmental Management System is applied in milk factories in order to protect the environment and to minimize environmental damage. In this framework, environmental performance criteria have been determined in the company, plans for improvements have been created and targets have been developed. The company has its production facility based in Turkey. Case studies have been developed using in-depth interviews with six supply chain managers, business development managers and workers who work in different parts of the supply chain such as distribution and retailing in both milk and meat facilities. The participants identified decision variables and any interaction of these factors from their experience. Interviews are widely used to gather information that might be difficult to obtain with other techniques, entailing a basis for the comparison of participant responses to realize research objectives (Morali and Searcy, 2013; Kvale, 2007). Secondary data is collected from company reports and websites, including annual reports, databases and internal procedures provided by the company to increase the validity and reliability of the study. Moreover, secondary data is collected from governmental reports. A flow chart of methodology is presented in Figure 1.

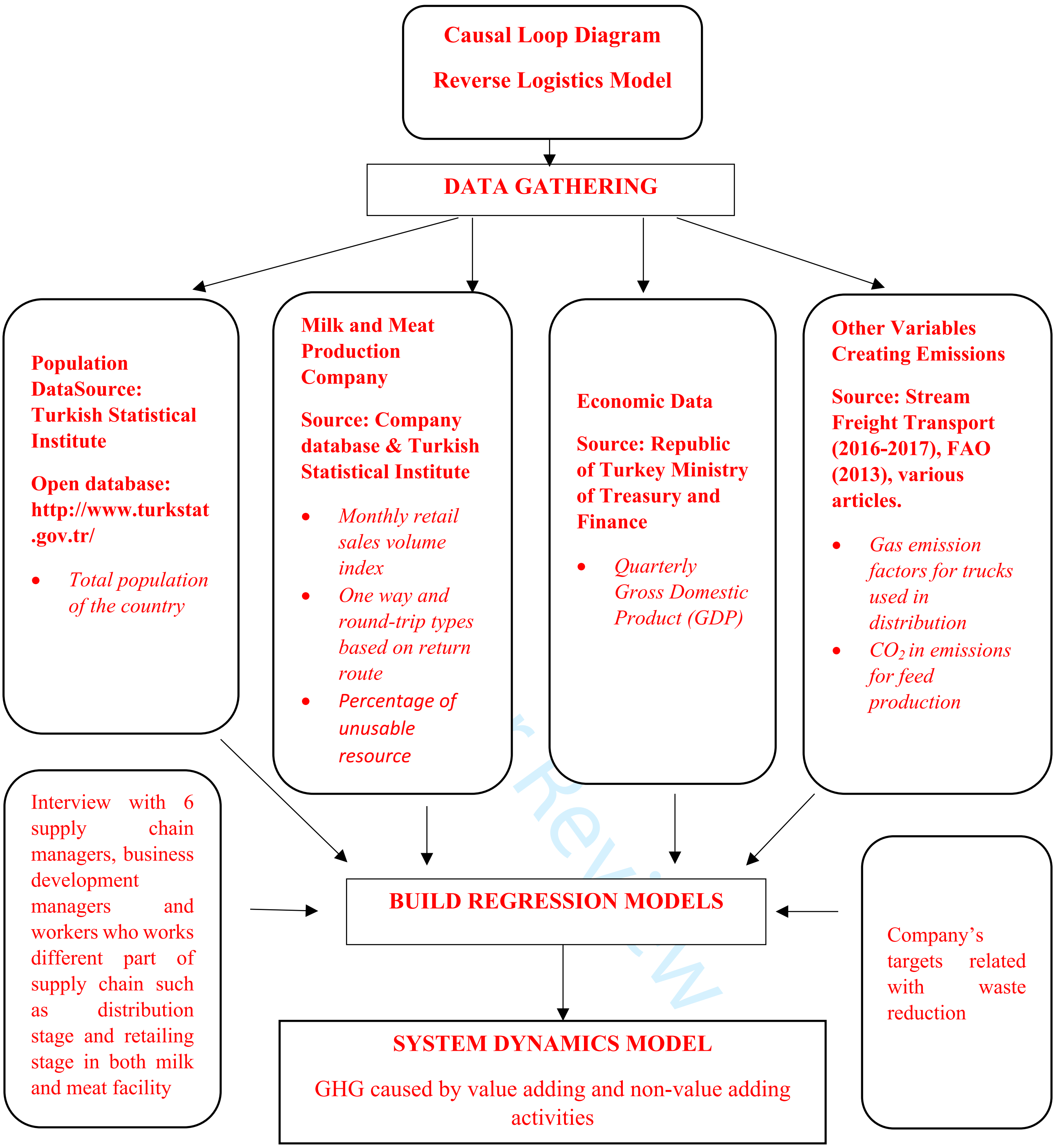
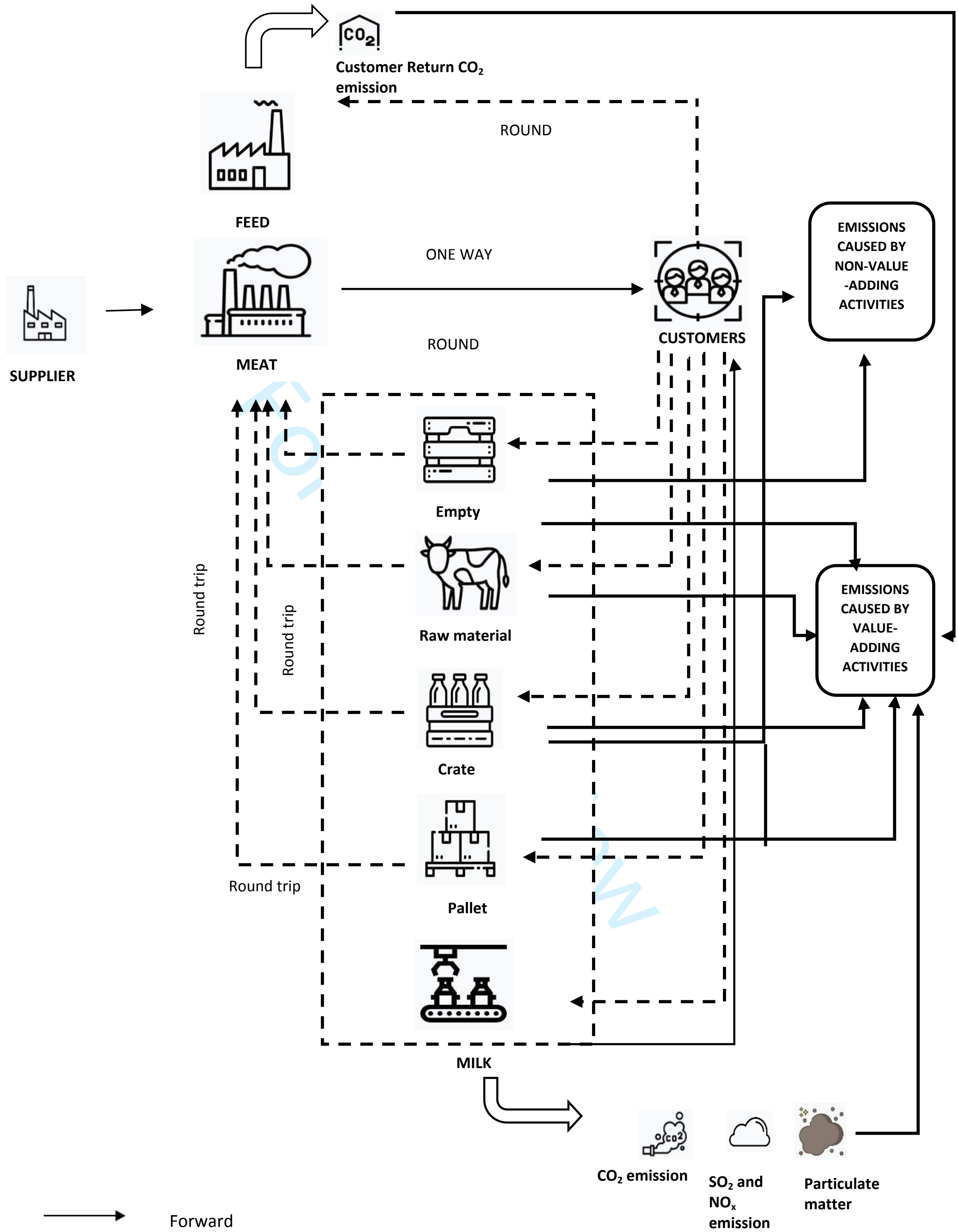


Figure 1. Flow chart of methodology

5.2 Reverse Logistics at the Case Company

The 'one-way' structure of traditional supply chain networks is transformed to CLSC networks with the help of the integration of reverse flow channels (Georgiadis and Vlachos, 2004). To illustrate this, the different forms of RL and forward logistics activities for the company, plus the main forward and RL networks are presented in Figure 2. The solid lines are used to demonstrate the forward channel while the dashed lines indicate the reverse channel of the company. The company has two different types of main logistics operations, the one-way trip and round trip. One-way trip is used for forward logistic activities, whereas round trip operates for RL activities. Round trip logistic activities provide several advantages by increasing network and transportation efficiency and decreasing CO_2, SO_2, NO_x emissions that arise with unnecessary transportation. As a result, emissions resulting from RL activities can be divided into two categories: emissions caused by value adding activities and non-value adding activities as adapted from the study of Steinhilper et al., 2013. The RL network system, presented in Figure 1, includes different actors: suppliers that provide raw material for the process, customers and the food and beverage group; this group incorporates the various companies that carry out dairy, meat and feed production. The company can therefore use materials in an effective way. On the one hand, forward logistics networks start from the supplier, go through meat production and finally to customers. On the other hand, RL activities of the company are carried out in four different ways; these are empty return, pallet and crate transportation, raw material transportation and customer return. Four different reverse loops indicate the structure of RL activities for the company. The first RL channel is provided by customer return because of spoilage. Due to quality problems and perishable food, the products that return as waste due to the expiration dates of milk and meat products go to the feed factory through the RL channel. CO_2, NO_X, SO_2 and PM emissions released during the recycling process from the feed factory are caused by value-adding activities. The second RL channel is an empty return. Emissions released during the return of trucks from customers to the meat production facility - without load - constitute non-value adding activities. The third RL channel is return of pallets and crates to the company. Pallet and crate transportation is crucial for the company since they are reusable. Thus, the emissions created can be considered as a consequence of value adding activities in the RL network. However, the remaining pallets are separated as scrap because of them becoming unusable; this creates CO_2, NO_X, SO_2 and PM caused by non-value adding activities. The last reverse channel within this logistics network is transportation of raw material to production facilities for manufacture. Semi-products, raw materials, additives, packaging products and other raw materials are included in the RL network without the need to allocate extra vehicles. Therefore, during this transportation CO_2, NO_X, SO_2 and PM are generated caused by value adding activities in this RL network. Due to the complex nature of the processes involved, RL networks are appropriate to take a holistic view with a systems perspective to reach greening targets (Mutingi, 2014).



Source: Icons are retrieved from https://www. flaticon.com/

Figure 2. The forward and RL processes of the case company

5.3 Case Analysis using SD

The SD model starts with a causal loop diagram provided in Figure 3. In the diagram, uncontrollable variables of the system have been shown within “<…>”, acting as inputs of the system. The main function of the model is to measure the emissions of the pollutants produced by the RL network of the company. Therefore, a forecast for the distribution volume has been created for the years between 2020 and 2024. Distribution plans can be impacted by the company’s strategy and targets as well as the economic conditions of the country. In the predictions, the following data is used:

- Total population of the country
- Quarterly Gross Domestic Product (GDP)
- Monthly retail sales volume index
- Company’s targets related with waste reduction

Population and GDP increase can support the model to explain the overall consumption increase in the retail sector. Another indicator showing growth in spending in the retail sector is the "Retail Sales Volume Index". These indicators on economic status and the retail sector have been obtained from the Turkish Statistical Institute (TSI), an open database on website http://www.turkstat.gov.tr/. To understand future expectancy in economy, the GDP forecasts in the "New Economic Program" of Ministry of Treasury and Finance have been used. In Table 2, actual data starting from the first quarter of 2015 to the third quarter of 2019 has been provided. Even though retail sales volume index derived from TSI is given monthly, quarterly averages have been used in the predictions to show consistency with GDP data. According to produced regression models used in the predictions, we expect retail sector growth in the coming years. An examination of the retail sector in Turkey shows that in the last seven years, two discount stores and one supermarket, based in Turkey, have entered into the top 250 global retailers list (Deloitte, 2019). These three retailers are major customers of our company of interest. As market leader in meat products in Turkey, the company sets its targets to support this sales growth. In order to use retail sales volume index in the model, forecasts have been converted to monthly by multiplying the quarterly data with seasonality factors, as shown in Table 3. Seasonality factors are calculated by using the averages of the past five years of data derived from TSI.

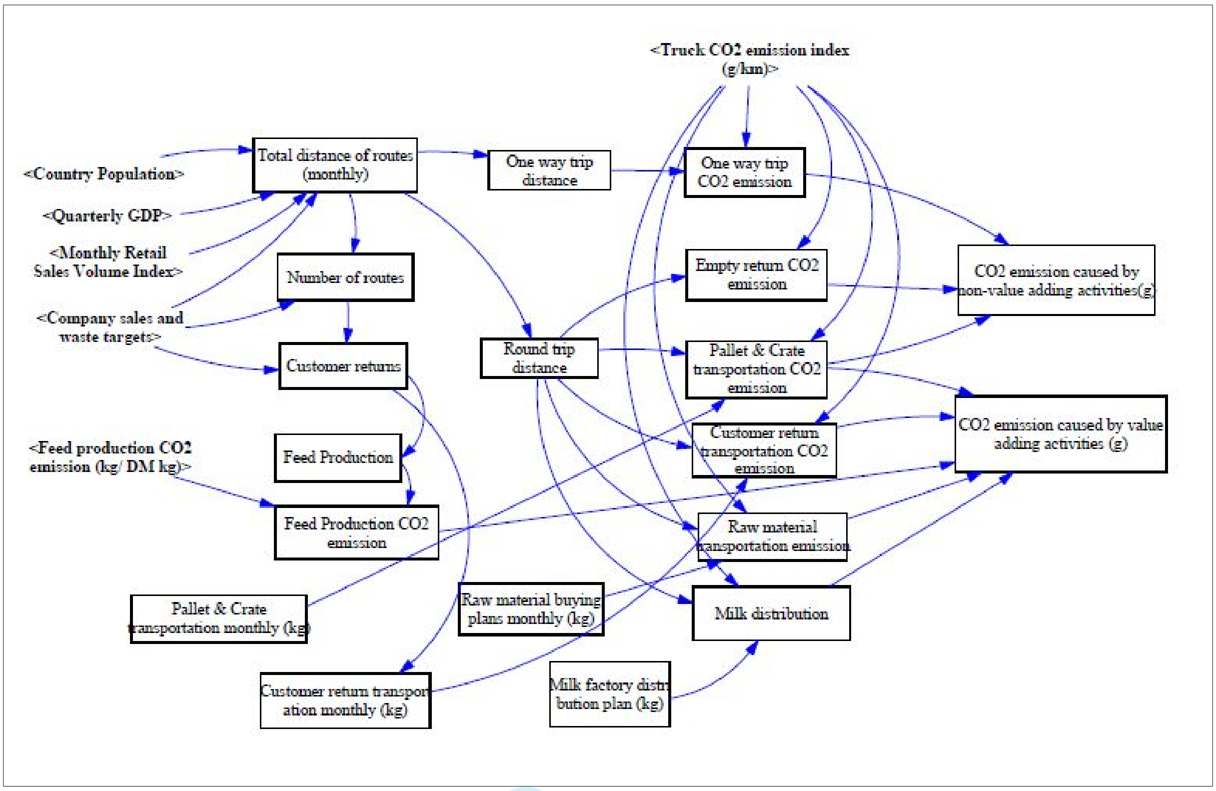


Figure 3 Causal loop diagram of the RL model

Table 2. Data predicted to estimate distribution plan

Year & Quarter	GDP (thousands Turkish Lira)	Population (Country total)	Retail Sales Volume Index
2015Q1	497,687,043	77,957,191	88.90
2015Q2	562,947,771	78,218,479	99.47
2015Q3	631,512,355	78,479,766	104.23
2015Q4	646,500,325	78,741,053	107.43
2016Q1	563,890,602	79,009,508	92.83
2016Q2	631,232,693	79,277,962	102.77
2016Q3	666,176,429	79,546,417	102.47
2016Q4	747,226,025	79,814,871	110.20
2017Q1	649,272,436	80,063,785	91.80
2017Q2	734,425,574	80,312,698	102.33
2017Q3	831,878,537	80,561,612	108.33
2017Q4	890,960,204	80,810,525	115.03
2018Q1	788,833,423	81,108,864	100.03
2018Q2	885,235,862	81,407,204	110.67
2018Q3	1,016,805,838	81,705,543	114.77
2018Q4	1,010,114,366	82,003,882	114.77
2019Q1	922,029,000	82,230,179	98.43
2019Q2	1,023,855,000	82,456,475	108.23
2019Q3	1,145,099,000	82,682,772	112.33
Predictions			
2019Q4	1,178,017,000	82,909,069	120.74

2020Q1	1,036,050,139	83,166,696	103.65
2020Q2	1,166,260,163	83,424,323	111.51
2020Q3	1,304,085,234	83,681,950	119.59
2020Q4	1,365,604,464	83,939,577	125.42
2021Q1	1,166,194,368	84,197,204	106.64
2021Q2	1,312,760,824	84,454,832	114.98
2021Q3	1,467,898,897	84,712,459	123.57
2021Q4	1,537,145,911	84,970,086	129.63
2022Q1	1,290,809,594	85,227,713	109.47
2022Q2	1,453,037,601	85,485,340	118.27
2022Q3	1,624,753,155	85,742,967	127.35
2022Q4	1,701,399,650	86,000,594	133.63
2023Q1	1,419,890,554	86,258,221	112.43
2023Q2	1,598,341,361	86,515,848	121.71
2023Q3	1,787,228,470	86,773,476	131.29
2023Q4	1,871,539,615	87,031,103	137.80
2024Q1	1,561,879,609	87,288,730	115.77
2024Q2	1,758,175,497	87,546,357	125.58
2024Q3	1,965,951,318	87,803,984	135.72
2024Q4	2,058,693,576	88,061,611	142.47

Table 3. Converting quarterly retail sales volume index to monthly

Year & Month	Retail Sales Volume Index (Quarterly)	Seasonality Factor	Retail Sales Volume Index (Monthly)
202001	103.65	0.97	101.02
202002		0.95	98.18
202003		1.08	111.75
202004	111.51	0.94	105.32
202005		1.02	113.30
202006		1.04	115.90
202007	119.59	1.00	119.91
202008		1.01	120.68
202009		0.99	118.17
202010	125.42	0.94	117.76
202011		0.93	116.28
202012		1.13	142.23
202101	106.64	0.97	103.93
202102		0.95	101.02
202103		1.08	114.98
202104	114.98	0.94	108.60
202105		1.02	116.83
202106		1.04	119.51
202107	123.57	1.00	123.91
202108		1.01	124.70
202109		0.99	122.11
202110	129.63	0.94	121.71
202111		0.93	120.19
202112		1.13	147.00
202201	109.47	0.97	106.69

202202		0.95	103.70
202203		1.08	118.03
202204		0.94	111.70
202205	118.27	1.02	120.18
202206		1.04	122.93
202207		1.00	127.69
202208	127.35	1.01	128.52
202209		0.99	125.84
202210		0.94	125.46
202211	133.63	0.93	123.89
202212		1.13	151.53
202301		0.97	109.57
202302	112.43	0.95	106.50
202303		1.08	121.22
202304		0.94	114.95
202305	121.71	1.02	123.67
202306		1.04	126.51
202307		1.00	131.65
202308	131.29	1.01	132.50
202309		0.99	129.74
202310		0.94	129.38
202311	137.80	0.93	127.76
202312		1.13	156.26
202401		0.97	112.83
202402	115.77	0.95	109.66
202403		1.08	124.82
202404		0.94	118.60
202405	125.58	1.02	127.60
202406		1.04	130.52
202407		1.00	136.08
202408	135.72	1.01	136.96
202409		0.99	134.11
202410		0.94	133.76
202411	142.47	0.93	132.09
202412		1.13	161.56

Customer distributions are planned using the trucks of a third party logistics company. They can be planned as one-way or round-trip. Currently, approximately 77% of the planned routes are round-trip; the company has set targets to increase round-trips to 90% by the end of year 2024; they plan transportation of various goods on the return journeys of trucks from customers.

In the model, pollutant gas emission factors generated by trucks are provided in Table 4 (Stream Freight Transport 2016, 2017). The first column provides the emission weight per km for an empty truck that weighs 15 tonnes; the second column presents the additional emissions created by a truck for each tonne loaded.

Table 4. Gas emission factors for trucks used in distribution

	Empty truck gas emission (per km)	Increase in emission per tonne load
CO_2 (gram / km)	791	13.25
SO2 (mg / km)	4.7	0.085
PMc (mg / km)	57	0.583
NOx (g / km)	6.5	0.031

The remainder of the model attempts to explain the classification of the emissions produced by RL activities. It has been assumed that if a one-way trip is planned, the return of that route is unplanned and creates emissions caused by non-value adding activities. On the other hand, round-trips can lead to emissions caused by both value adding or non-value adding activities; these are classified in Table 5. The company does makes efforts to reduce the number of one-way trips in order to minimize pollutant emission yet the planning activity of routes is a cumbersome manual task and inefficient; in some cases return routes for round-trips may remain unplanned; these account for approximately 4.89% of trips. Return routes for these round-trips can be regarded as non-value adding pollutant makers; whereas, return routes that transfer customer returns, raw material and milk products are value adding. The company also tries to collect empty pallets and milk crates from customers for re-use and repair if necessary. However, nearly 5% of the collected material is highly damaged and cannot be used. Re-usable and repairable material transfers are considered to be creating emissions because of value-adding activities, but transported not re-usable percentage generates emissions result of non-value adding activities. For all return routes, the weights of loads to be carried should be predicted and embedded into the model since the load affects the pollutant level created by the trucks. Since sales growth is expected in the coming years, this may possibly lead to an increase in customer returns due to expiration and shipment errors. Returned products are directly shipped to feed production factories. Feed production generates 3.6 kg CO_2 for each kg of dry input (FAO, 2013). Since returned products are not wasted but used in feed production, the resulting pollutant emission is regarded as the product of a value-adding activity.

Table 5. Round-trip types based on return route

Round-trip return route types	**Percentage**
Empty return	4.57 %
Pallet & crate transportation	8.90 %
Customer return	31.08%
Raw material transportation	14.03 %
Milk distribution	41.42 %
TOTAL	**100.00%**

The model will run on a monthly basis starting from January 2019 until December 2024 using STELLA software. 5705 routes in the year 2019 have been used to forecast the distribution distances for the next four years. Variables used in forecasting distribution distances are monthly retail sales volume index, number of routes in 2019 and month number. The number of routes and month number creates the seasonality throughout the monthly forecasts. In Table 6, actual and predicted distances can be seen. A one-way ANOVA test has been employed to 2019 data to test validity; it can be concluded that there is no evidence that simulation results are statistically different from the actual data (with 95% confidence level).

Table 6. Forecasts for the distribution distances

Year & Month	Retail Sales Volume Index (Monthly)	Month No	Number of routes in 2019	Distance (km)
201901	95.6	1	483	624,390
201902	92.9	2	458	561,665
201903	106.8	3	474	587,399
201904	103.2	4	436	558,481
201905	110.9	5	494	607,916
201906	110.6	6	389	549,975
201907	114.7	7	509	695,957
201908	110.8	8	428	573,660
201909	111.5	9	474	565,488
201910	108.1	10	490	600,860
201911	107.1	11	473	566,456
201912	136.9	12	597	747,275
Predictions				
202001	101.0	1	483	616,363
202002	98.2	2	458	583,092
202003	111.8	3	474	627,706
202004	105.3	4	436	574,095
202005	113.3	5	494	637,390
202006	115.9	6	389	554,336
202007	119.9	7	509	656,841
202008	120.7	8	428	588,184
202009	118.2	9	474	613,121
202010	117.8	10	490	619,567
202011	116.3	11	473	596,466
202012	142.2	12	597	761,770
202101	103.9	1	483	624,320
202102	101.0	2	458	590,826
202103	115.0	3	474	636,509
202104	108.6	4	436	583,048
202105	116.8	5	494	647,022
202106	119.5	6	389	564,189
202107	123.9	7	509	667,742
202108	124.7	8	428	599,155
202109	122.1	9	474	623,864

202110	121.7	10	490	630,357
202111	120.2	11	473	607,121
202112	147.0	12	597	774,802
202201	106.7	1	483	631,844
202202	103.7	2	458	598,139
202203	118.0	3	474	644,833
202204	111.7	4	436	591,529
202205	120.2	5	494	656,146
202206	122.9	6	389	573,522
202207	127.7	7	509	678,082
202208	128.5	8	428	609,561
202209	125.8	9	474	634,053
202210	125.5	10	490	640,597
202211	123.9	11	473	617,233
202212	151.5	12	597	787,170
202301	109.6	1	483	639,718
202302	106.5	2	458	605,792
202303	121.2	3	474	653,543
202304	115.0	4	436	600,391
202305	123.7	5	494	665,680
202306	126.5	6	389	583,275
202307	131.6	7	509	688,874
202308	132.5	8	428	620,423
202309	129.7	9	474	644,689
202310	129.4	10	490	651,281
202311	127.8	11	473	627,784
202312	156.3	12	597	800,075
202401	112.8	1	483	648,603
202402	109.7	2	458	614,428
202403	124.8	3	474	663,373
202404	118.6	4	436	610,357
202405	127.6	5	494	676,402
202406	130.5	6	389	594,243
202407	136.1	7	509	700,977
202408	137.0	8	428	632,604
202409	134.1	9	474	656,616
202410	133.8	10	490	663,250
202411	132.1	11	473	639,602
202412	161.6	12	597	814,530

5.4 Results and discussion

Using a STELLA model, CO_2, SO_2, PM_C and NO_X pollutant emissions for the RL distribution network have been calculated. In Figures 4 and 5, CO_2 emission of RL activities and feed production can be seen respectively. Output of the STELLA model can be seen in Table 7; yearly emission levels can be seen in Table 8. As indicated previously in the model explanation section, by decreasing planned one-way trip distance percentage from 23% to 10% until the end of 2024, emissions caused by non-value adding activities will be reduced by 40%; emissions caused by value adding activities will increase by 24%; these rates will also be valid for each individual CO_2, SO_2, PM_C and NO_X emission. In Table 9, total planned distances for each year have been shown. In terms of RL, if a one-way route has been planned, the return path would be a non-value adding activity; however, efforts for RL planning should be made for the return trip from customers, approximately half of the round-trip. Model results show that in the next five years, RL planning activities will increase from 2.7 million km to 3.5 million km, equivalent to an increase of approximately 26%.

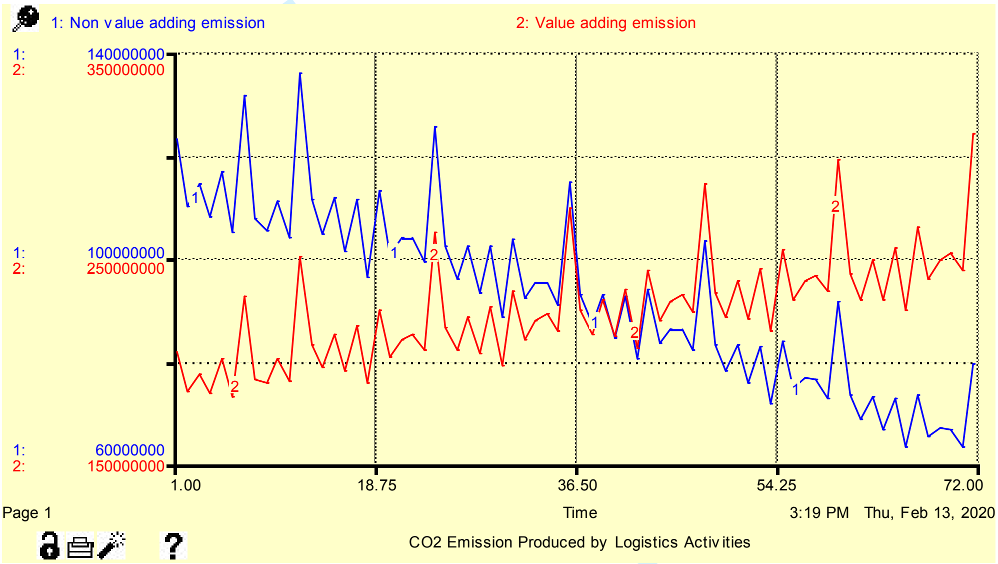


Figure 4. CO_2 emission (g) of RL activities between 2019 and 2024

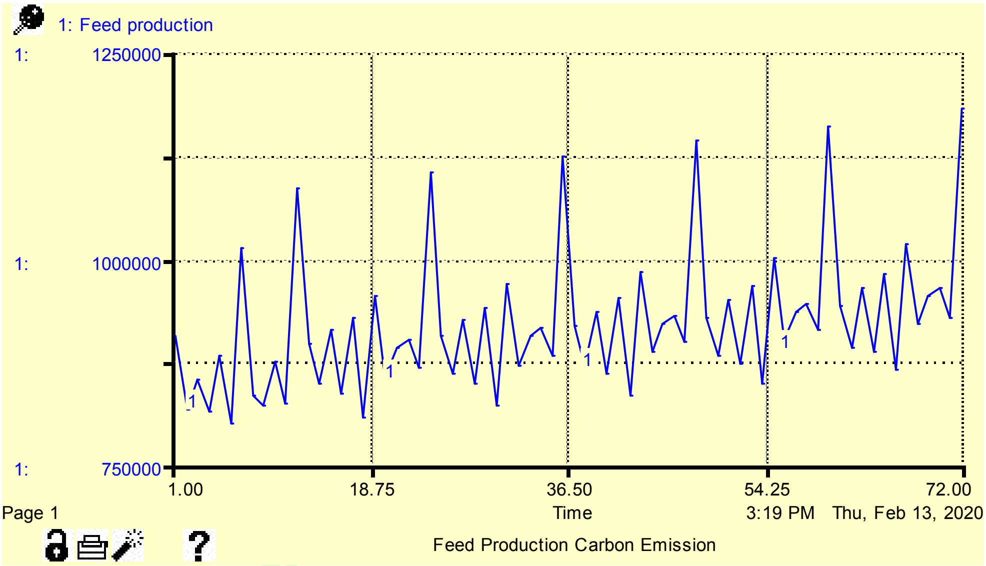


Figure 5. CO_2 emission (kg) of feed production between 2019 and 2024

Table 7. Output of the STELLA model showing CO_2, SO_2, PM_C and NO_X emissions

Year & Month	CO_2 Emission caused by non-value adding (Tonnes)	CO_2 Emission caused by value adding (Tonnes)	Feed Production CO_2 emission (Tonnes)	SO_2 Emission caused by non-value adding (kg)	SO_2 Emission caused by value adding (kg)	PM_c Emission caused by non-value adding (kg)	PM_c Emission caused by value adding (kg)	NO_x Emission caused by non-value adding (kg)	NO_x Emission caused by value adding (kg)
201901	123.23	204.06	905.33	0.73	1.22	8.88	14.06	1,012	1,542
201902	110.05	183.99	814.80	0.65	1.10	7.93	12.68	904	1,390
201903	114.27	192.87	851.75	0.68	1.16	8.23	13.29	939	1,457
201904	107.85	183.80	811.10	0.64	1.10	7.77	12.66	886	1,388
201905	116.54	200.53	881.31	0.69	1.20	8.40	13.82	957	1,515
201906	104.66	181.84	798.17	0.62	1.09	7.54	12.53	860	1,374
201907	131.45	230.64	1,010.64	0.78	1.38	9.47	15.89	1,080	1,742
201908	107.54	190.55	831.42	0.64	1.14	7.75	13.13	883	1,439
201909	105.21	188.27	820.34	0.63	1.13	7.58	12.97	864	1,422
201910	110.95	200.50	872.07	0.66	1.20	7.99	13.81	911	1,515
201911	103.79	189.45	822.19	0.62	1.14	7.48	13.05	853	1,431
201912	135.87	250.50	1,084.55	0.81	1.50	9.79	17.26	1,116	1,892
202001	111.20	207.09	894.24	0.66	1.24	8.01	14.27	913	1,564
202002	104.37	196.36	846.21	0.62	1.18	7.52	13.53	857	1,483
202003	111.47	211.86	910.87	0.66	1.27	8.03	14.60	916	1,600
202004	101.14	194.20	833.27	0.60	1.16	7.29	13.38	831	1,467
202005	111.39	216.10	925.65	0.66	1.30	8.02	14.89	915	1,632
202006	96.09	188.37	803.71	0.57	1.13	6.92	12.98	789	1,423
202007	112.93	223.70	953.37	0.67	1.34	8.14	15.41	928	1,690
202008	100.30	200.77	853.60	0.60	1.20	7.23	13.83	824	1,517
202009	103.68	209.75	888.70	0.62	1.26	7.47	14.45	852	1,585
202010	103.90	212.43	899.79	0.62	1.27	7.49	14.64	853	1,605
202011	99.18	204.96	864.68	0.59	1.23	7.15	14.12	815	1,548

202012	125.60	262.35	1,104.87	0.75	1.57	9.05	18.07	1,032	1,982
202101	102.05	215.49	905.33	0.61	1.29	7.35	14.85	838	1,628
202102	95.74	204.38	857.29	0.57	1.23	6.90	14.08	786	1,544
202103	102.25	220.67	923.81	0.61	1.32	7.37	15.20	840	1,667
202104	92.84	202.58	846.21	0.55	1.21	6.69	13.96	762	1,530
202105	102.11	225.30	938.59	0.61	1.35	7.36	15.52	839	1,702
202106	88.24	196.89	818.49	0.52	1.18	6.36	13.56	725	1,487
202107	103.49	233.54	968.15	0.61	1.40	7.46	16.09	850	1,764
202108	92.02	210.01	868.38	0.55	1.26	6.63	14.47	756	1,586
202109	94.93	219.15	905.33	0.56	1.31	6.84	15.10	780	1,656
202110	95.03	221.91	914.57	0.56	1.33	6.85	15.29	780	1,676
202111	90.67	214.19	881.31	0.54	1.28	6.53	14.76	745	1,618
202112	114.61	273.95	1,123.35	0.68	1.64	8.26	18.87	941	2,069
202201	92.57	223.88	916.41	0.55	1.34	6.67	15.42	760	1,691
202202	86.79	212.40	868.38	0.52	1.27	6.25	14.63	713	1,605
202203	92.66	229.47	934.89	0.55	1.38	6.67	15.81	761	1,733
202204	84.16	210.95	859.14	0.50	1.26	6.06	14.53	691	1,594
202205	92.43	234.50	951.52	0.55	1.41	6.66	16.16	759	1,771
202206	79.98	205.41	831.42	0.48	1.23	5.76	14.15	657	1,552
202207	93.60	243.38	982.93	0.56	1.46	6.74	16.77	769	1,839
202208	83.28	219.25	885.01	0.49	1.31	6.00	15.11	684	1,656
202209	85.73	228.54	920.11	0.51	1.37	6.18	15.75	704	1,726
202210	85.71	231.39	929.35	0.51	1.39	6.17	15.94	704	1,748
202211	81.72	223.42	896.09	0.49	1.34	5.89	15.39	671	1,688
202212	103.10	285.54	1,141.82	0.61	1.71	7.43	19.67	847	2,157
202301	82.89	232.54	927.50	0.49	1.39	5.97	16.02	681	1,757
202302	77.64	220.67	879.46	0.46	1.32	5.59	15.20	638	1,667
202303	82.83	238.57	947.82	0.49	1.43	5.97	16.44	680	1,802
202304	75.25	219.62	870.22	0.45	1.32	5.42	15.13	618	1,659
202305	82.49	244.02	966.30	0.49	1.46	5.94	16.81	677	1,843
202306	71.46	214.25	846.21	0.42	1.28	5.15	14.76	587	1,619
202307	83.42	253.57	999.56	0.50	1.52	6.01	17.47	685	1,916
202308	74.25	228.85	899.79	0.44	1.37	5.35	15.77	610	1,729
202309	76.25	238.29	934.89	0.45	1.43	5.49	16.42	626	1,800
202310	76.11	241.23	944.13	0.45	1.45	5.48	16.62	625	1,822
202311	72.47	233.00	910.87	0.43	1.40	5.22	16.05	595	1,760
202312	91.24	297.56	1,160.30	0.54	1.78	6.57	20.50	749	2,248
202401	73.05	241.72	940.43	0.43	1.45	5.26	16.65	600	1,826
202402	68.33	229.46	890.55	0.41	1.38	4.92	15.81	561	1,733
202403	72.84	248.24	962.61	0.43	1.49	5.25	17.10	598	1,875
202404	66.15	228.87	885.01	0.39	1.37	4.76	15.77	543	1,729
202405	72.36	254.15	981.08	0.43	1.52	5.21	17.51	594	1,920
202406	62.73	223.73	862.83	0.37	1.34	4.52	15.41	515	1,690
202407	73.01	264.46	1,016.19	0.43	1.59	5.26	18.22	599	1,998
202408	64.99	239.15	918.26	0.39	1.43	4.68	16.48	534	1,807
202409	66.53	248.72	953.37	0.40	1.49	4.79	17.14	546	1,879
202410	66.27	251.74	962.61	0.39	1.51	4.77	17.34	544	1,902
202411	63.00	243.26	927.50	0.37	1.46	4.54	16.76	517	1,838
202412	79.08	310.41	1,182.47	0.47	1.86	5.70	21.39	649	2,345

Table 8. Yearly output of the STELLA model showing CO_2, SO_2, PM_C and NO_X emissions

Year	CO_2 Emission caused by non-value adding (Tonnes)	CO_2 Emission caused by value adding (Tonnes)	Feed Production CO_2 emission (Tonnes)	SO_2 Emission caused by non-value adding (kg)	SO_2 Emission caused by value adding (kg)	PM_c Emission caused by non-value adding (kg)	PM_c Emission caused by value adding (kg)	NO_x Emission caused by non-value adding (kg)	NO_x Emission caused by value adding (kg)
2019	1,371.41	2,396.98	10,503.67	8.15	14.37	98.80	165.14	11,265	18,108
2020	1,281.25	2,527.93	10,778.96	7.61	15.16	92.30	174.16	10,523	19,097
2021	1,173.97	2,638.06	10,950.79	6.98	15.82	84.57	181.75	9,642	19,929
2022	1,061.75	2,748.14	11,117.07	6.31	16.48	76.48	189.33	8,719	20,760
2023	946.28	2,862.18	11,287.05	5.62	17.16	68.16	197.19	7,770	21,622
2024	828.32	2,983.91	11,482.90	4.92	17.89	59.66	205.58	6,801	22,541

Table 9. Total planned distribution distances and distances considered as part of RL

		Distances for Reverse Logistics	
Year	Total Planned Distance (km)	One way trip (km)	Round trip (km)
2019	7,239,523	1,665,090	2,787,216
2020	7,428,932	1,470,615	2,979,159
2021	7,548,955	1,328,510	3,110,223
2022	7,662,709	1,180,165	3,241,272
2023	7,781,526	1,027,490	3,377,018
2024	7,914,982	871,205	3,521,889

In line with this work, Georgiadis and Vlachos (2004) and Sudarto et al. (2017) aimed to analyze capacity-planning decisions for efficiency based on RL activities. Similarly, the proposed model in this study provides a basis for improvement in planning activities. The company should plan return trips better by improving current planning activities of routes; a decrease in one-way travel, minimizing pollution emissions, can be achieved with the help of this model. Abduaziz et al., 2015 and Kannan et al., 2012 state that RL benefits can be measured in green practices regarding CO_2 reduction. In a similar manner, this study involves analyzing environmental impacts of RL activities based on not only CO_2, NO_X and SO_2 emissions but PM as well. Based on the literature review, there are a limited number of studies (e.g. Bottani et al. 2019; Georgiadis et al., 2005) that focus on food supply chains in a holistic and dynamic approach. The main contribution of this study is the development of a holistic approach to analyze environmental impacts that have been categorized as the emissions caused by value adding and non-value adding activities of RL in the context of a food supply chain.

The results of the model can especially guide the company:

- **To measure how efficiently the distribution network has been designed and managed**: In this case, the empty truck percentage and one-way trip percentage leads the company in terms of inefficient management and non-value adding activity.
- **To discover the areas where the company can reduce environmental impact and costs to improve green business performance:** In this food supply chain, if the round-trip routes are put into practice in the future, as was predicted, it will mean that the company will be paying additional costs to the third party logistics company for collecting its pallets, crates and customer returns as well as transferring raw material and milk. In addition, extra efforts made to collect these items will mean doubling the emissions produced by non-value adding activities.

5.5 Implications of the research

For researchers, this study provides a novel insight into analyzing the environmental impacts of RL by considering the damage caused by value adding and non-value adding CO_2 emissions.

There are many managerial implications to be learned for minimizing the environmental impact of RL activities within food supply chain management. The managerial implications will be listed and then implications for policy makers will be suggested.

Initially, it should be asserted that the big data accumulated within food supply chains needs to be managed for the sake of sustainability. Digital solutions and data management tools and techniques should be used and improved, such as the systems dynamics used in this study. The sophisticated data management tools, IoT and RFID, are promising technologies to deal with the consequences of the rapidly growing population and increasing retail sector that elaborate the operations in food supply chains. Digital solutions can also be integrated with the managerial implications given below.

A group of managerial implications are based on operational research tools and techniques. Route optimization contributes significantly to RL by considering return trips and distances involved; increasing green performance will help to minimize the associated environmental impact and carbon emissions. Route optimization can help with the issue of perishable goods leading to food loss and waste; optimization can help to increase the number of circular actions. Vehicle utilization is another category where multiple loading and unloading activities are planned at an early stage. When vehicle utilization is maximized, this brings both economic and environmental improvements simultaneously. The proposed system dynamics model contributes to the company's efficiency by investigating how well the distribution network is designed. The company can explore other areas that can reduce environmental impact and costs by analyzing green business performance through the use of this system dynamics model.

Another category of implications is on developing innovative and environmental business models. One of the common problems of RL operations is related to the collection of empty pallets and crates. When companies are focused solely on economic objectives they may put pressure on the pallet and crate manufacturers to handle the reverse operations or a third party logistics provider can be hired. However, from an environmental point of view, this may have serious consequences in terms of additional and inefficient trips. Therefore, as indicated in this study, the collection of crates and pallets can be embedded into part of the overall reverse operations and can be managed by the main company. The resulting economic benefit can be shared among all parties.

In addition, another business model can be developed based on the concept of aggregation. As indicated in this study, conglomerates or holdings are composed of multiple companies that may turn out a range of products in the same sector, similar to the food industry.
The application of this study is conducted for meat and milk producing companies under the same holding. Thus, like the aggregation concept used in production planning, similar planning can be made for the reverse operations of multiple companies where common sales points are used. The scale of economy can bring significant contributions in every stage of RL. Actually, in order to implement this model, organizations may not even need to belong to a holding, but may come together to achieve environmental and economic benefits.

The rise of the retail sector is an important factor to be considered when considering the environmental impact of food supply chains. Large, central stores now face competition from discount stores and supermarkets, much smaller in size but with many more outlets and spread all over the cities. The smaller capacities of these discount stores or supermarkets necessitates the need for distributions with smaller quantities but higher frequencies. This brings in the problem of frequent deliveries as well as frequent reverse operations for manufacturers or logistics providers. This is a crucial phenomenon when analyzing green business performance, proving the need for the asserted managerial implications given above. This is a great problem, especially from an environmental point of view, and may not be solved only by management. Thus implications for policy makers need to be stated.

Policy makers should seriously consider the environmental concerns of food supply chains, especially for reverse operations. The digital and big data based solutions should be subsidized and promoted among those companies with tax-exemptions or favorable loan mechanisms for initial investment. In addition, similar privileges should be presented for companies who would like to implement innovative and environmental business models that go beyond the boundaries of competition and who strive for win-win for all parties concerning overall sustainability.

Policy makers should take remedies and actions towards the rapidly changing and evolving nature of the retail sector. As food supply chains constitute a significant portion, food supply chain operations and related reverse activities should be highlighted as one of the initial action points for policy makers. Local governments and municipalities should also involve themselves in this work as there is a direct, adverse effect on the logistics of towns and cities. The consequences are not only economic and environmental, but also social, due to resulting air pollution, noise, traffic congestion, accidents and a diminishing quality of life.

6 Conclusion

RL activities are gaining importance and increasing in terms of size and quantity due to both economic and environmental concerns in the circular economy. These activities involve reverse flow of materials, information, human resources and finance among various stakeholders. The environmental impact of RL activities are generally neglected in a holistic sense in related literature. The main contribution of this paper to existing literature is the development of a systematic approach to analyze environmental impacts that have been categorized as emissions caused by value adding and non-value adding activities of RL in the context of a food supply chain. Thus, a systems approach enables managers to understand the dynamic and complex nature of RL. Hence, SD is a suitable tool to analyze the environmental impacts of RL activities. Therefore, in this study, SD modelling has been implemented to analyze and predict the environmental impact in a food supply chain. Environmental impacts of RL activities have been examined in terms of CO_2, NO_X, SO_2 and PM emission to analyze green business performance. In the analysis, economic growth rates have been studied based on population, GDP and retail sales volume index to predict the future of retail business and corresponding forward and RL activities. There will be an expansion in retail business causing an inevitable increase in RL activities. As the food industry grows, CO_2 emissions will increase and studies aiming to reduce GHG emissions will be needed. It is necessary to highlight the need for such studies and to support them. Thus, the environmental impact of growing RL activities should be evaluated to assess green business performance. According to our study, it can be concluded that initially, companies should differentiate between value adding and non-value adding RL activities; they should then set their targets in order to minimize non-value adding activities. In that manner, if efficient and effective planning of forward and RL is achieved, then the resulting environmental impacts can be decreased to ensure better green performance.

In this study, the food supply chain that has been examined started its RL activities three years ago. RL planning activities are organized by different departments causing various data to be collected by different individuals; this brings problems in integration and reporting. Another limitation is that, only two sectors, meat and milk, have been considered and their RL have been merged. The inclusion of more than two sectors may contribute to revealing more precise and enriched results.

In future studies, the supply chains and their RL activities can be compared among various emerging economies or even with developed economies. This may contribute to enhancing the outcome of local and global solutions and implications that may be either generic or unique, according to the context of the analysis. In addition, the proposed methodology can be implemented in different sectors and supply chains. The proposed model can be improved using various indicators of environmental impact in RL activities. In addition, this study also ensures different perspectives by incorporating different gases such as NOX, SO2 and PM emissions into the investigation of the environmental impact of RL activities. This study proposes a dynamic model from factory to retail activities in food supply. This study can be further extended from farm to factory by considering the entire food supply chain. The driving and challenging aspects of digitization on RL activities and the environmental impact of these activities can also be scrutinized in future studies.

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REFERENCES

Abduaziz, O., Cheng, J.K., Tahar, R.M., Varma, R. (2015). A hybrid simulation model for green logistics assessment in automotive industry. *Procedia Engineering*, 100, 960-969.

Agrawal, S. and Singh, R.K. (2019) Analyzing disposition decisions for sustainable reverse logistics: Triple Bottom Line approach. *Resources, Conservation and Recycling*, 150, 104448.

Agrawal, S., Singh, R.K., Murtaza, Q. (2015). A literature review and perspectives in reverse logistics, Resources, *Conservation and Recycling*, 97, 76–92.

Ala-Harja, H., Helo, P. (2014). Green supply chain decisions- Case-based performance analysis from the food industry. *Transportation Research Part E: Logistics and Transportation Review*, 69, 97-107.

Alamerew, Y.A. and Brissaud, D. (2020). Modelling Reverse Supply Chain through System Dynamics for Realizing the Transition towards the Circular Economy: A Case Study on Electric Vehicle Batteries. *Journal of Cleaner Production*, 254.

Armendàriz, V., Armenia, S., Atzori, A. S., & Romano, A. (2015). Analyzing Food Supply and Distribution Systems using complex systems methodologies. *Proceedings in Food System Dynamics*, 36-58.

Azar, A. T. (2012). System dynamics as a useful technique for complex systems. *International Journal of Industrial and Systems Engineering*, *10*(4), 377-410.

Bazan, E., Jaber, M.Y. and Zanoni, S. (2016). A review of mathematical inventory models for reverse logistics and the future of its modeling: An environmental perspective. Applied Mathematical Modelling, 40, 4151–4178.

Bottani, E., Vignali, G., Mosna, D., & Montanari, R. (2019). Economic and environmental assessment of different reverse logistics scenarios for food waste recovery. *Sustainable Production and Consumption*, *20*, 289-303.

Campuzano, F., & Mula, J. (2011). *Supply chain simulation: A system dynamics approach for improving performance*. Springer Science & Business Media.

Cao, Y., Zhao,Y., Wen, L.,Li, Y., Li, H., Wang, S., Liu, Y., Shi, Q. and Weng, J. (2019). System dynamics simulation for CO_2 emission mitigation in green electric-coal supply chain. *Journal of Cleaner Production*, *232*,759-773.

Capece, G., Di Pillo, F., Gastaldi, M., Levialdi, N., & Miliacca, M. (2017). Examining the effect of managing GHG emissions on business performance. *Business Strategy and the*

Environment, 26(8), 1041-1060.

Cosenz, F., Rodrigues, V. P., & Rosati, F. (2019). Dynamic business modeling for sustainability: Exploring a system dynamics perspective to develop sustainable business models. *Business Strategy and the Environment*, *29*, 651–664.

Czerny, A., & Letmathe, P. (2017). Eco-efficiency: GHG reduction related environmental and economic performance. The case of the companies participating in the EU Emissions Trading Scheme. *Business Strategy and the Environment*, *26*(6), 791-806.

Dekker, R., Fleischmann, M., Inderfurth, K., & van Wassenhove, L. N. (Eds.). (2013). Reverse logistics: quantitative models for closed-loop supply chains. *Springer Science & Business Media*.

Deng, X., Yang, X., Zhang, Y., Li, Y., & Lu, Z. (2019). Risk propagation mechanisms and risk management strategies for a sustainable perishable products supply chain. *Computers & Industrial Engineering*, *135*, 1175-1187.

Dev, N.K., Shankar, R., Swami, S. (2019). Diffusion of green products in industry 4.0: Reverse logistics issues during design of inventory and production planning system. *International Journal of Production Economics*, 107519.

Ekinci, E., Kazancoglu, Y., & Mangla, S. K. (2020). Using system dynamics to assess the environmental management of cement industry in streaming data context. *Science of The Total Environment*, *715*, 136948.

FAO (2011), Global Food Losses and Food Waste – Extent, Causes and Prevention, Food and Agriculture Organization of the United Nations, Rome, available at: www.fao.org/docrep/014/mb060e/mb060e.pdf (accessed January 9, 2020).

FAO (2013), “Food wastage footprint: impacts on natural resources – summary report”, Rome, available at: www.fao.org/docrep/018/i3347e/i3347e.pdf (accessed January 11, 2020).

Forrester, J.W. (1961). *Industrial Dynamics* (1st ed.). Cambridge: England.

Franco, M.A. (2019). A system dynamics approach to product design and business model strategies for the circular economy. *Journal of Cleaner Production*, 241.

Frei, R., Jack, L., & Krzyzaniak, S. A. (2020). Sustainable reverse supply chains and circular economy in multichannel retail returns. *Business Strategy and the Environment*, 1-16.

Georgiadis, P. and Besiou, M. (2009). Environmental strategies for electrical and electronic equipment supply chains: which to choose? *Sustainability*, *1*, 722-733.

Georgiadis, P., & Besiou, M. (2008). Sustainability in electrical and electronic equipment closed-loop supply chains: a system dynamics approach. *Journal of cleaner production*, *16*(15), 1665-1678.

Georgiadis, P., & Vlachos, D. (2003). Analysis of the dynamic impact of environmental policies on reverse logistics. *Operational Research*, *3*(2), 123.

Georgiadis, P., & Vlachos, D. (2004). Decision making in reverse logistics using system dynamics. *Yugoslav Journal of Operations Research*, *14*(2), 259-272.

Georgiadis, P., Vlachos, D., & Iakovou, E. (2005). A system dynamics modeling framework for the strategic supply chain management of food chains. *Journal of food engineering, 70*(3), 351-364.

Ghisolfi, V., Chaves, G.L.D., Siman, R.R. and Xavier, L.H. (2017). System dynamics applied to closed loop supply chains of desktops and laptops in Brazil: A perspective for social inclusion of waste pickers. *Waste Management*, *60*, 14-31.

Golroudbary, S. R., Zahraee, S.M. (2015). System dynamics model for optimizing the recycling and collection of waste material in a closed-loop supply chain, *Simulation Modelling Practice and Theory*, *53*, 88–102.

Gonzalez-Torre, P.L., Adenso-Diaz, B., Artiba, H. (2004). Environmental and reverse logistics policies in European bottling and packaging firms. *International Journal of Production Economics*, *88*, 95–104.

Govindan, K., Soleimani, H. (2017). A review of reverse logistics and closed-loop supply chains: a journal of cleaner production focus, *Journal of Cleaner Production*, *142*, 371–384.

Govindan, K., Soleimani, H. and Kannan, D. (2015). Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European Journal of Operational Research*, *240*(3), 603-626.

Greenhouse gas emissions from pig and chicken supply chains, (2013). http://www.fao.org/3/i3460e/i3460e.pdf (accessed December 12, 2019).

Hafeez, K., Griffiths, M., Griffiths, J., and Naim, M. (1996). System design of a two-echelon steel industry supply chain", *International Journal of Production Economics*, *45*, 121-130.

Hazen, B. T., Mollenkopf, D. A., & Wang, Y. (2017). Remanufacturing for the circular economy: An examination of consumer switching behavior. Business Strategy and the Environment, *26*, 451–464.

Heydari, J., Govindan, K., & Sadeghi, R. (2018). Reverse supply chain coordination under stochastic remanufacturing capacity. *International Journal of Production Economics, 202*, 1-11.

Ilgin, M.A. and Gupta, S.M. (2010). Environmentally conscious manufacturing and product recovery (ECMPRO): A review of the state of the art. *Journal of Environmental Management*, *91*, 563–591.

Islam, M.T. and Huda, N. (2018). Reverse logistics and closed-loop supply chain of Waste Electrical and Electronic Equipment (WEEE)/E-waste: A comprehensive literature review. *Resources, Conservation & Recycling*, *137*, 48–75.

Kanashiro, P. (2020). Can environmental governance lower toxic emissions? A panel study of US high-polluting industries. *Business Strategy and the Environment*, 1-13.

Kannan, D., Diabat, A., Alrefaei, M., Govindan, K., & Yong, G. (2012). A carbon footprint based reverse logistics network design model. *Resources, conservation and recycling*, *67*, 75-79.

Kannan, G., Noorul Haq, A., & Devika, M. (2009). Analysis of closed loop supply chain using genetic algorithm and particle swarm optimisation. *International Journal of Production Research*, *47*(5), 1175-1200.

Kazemi, N., Modak, N. M., & Govindan, K. (2019). A review of reverse logistics and closed loop supply chain management studies published in IJPR: a bibliometric and content analysis. *International Journal of Production Research*, *57*(15-16), 4937-4960.

Khalafi, S., Hafezalkotob, A., Mohamaditabar, D., & Sayadi, M. K. (2020). A novel model for a network of a closed-loop supply chain with recycling of returned perishable goods: A case study of dairy industry. *Journal of Industrial and Systems Engineering*, *12*(4), 136-153.

Kumar, S., & Nigmatullin, A. (2011). A system dynamics analysis of food supply chains–Case study with non-perishable products. *Simulation Modelling Practice and Theory*, *19*(10), 2151-2168.

Kvale, S. (2007). Doing Interviews. Thousand Oaks: SAGE.

Lai, K. H., & Wong, C. W. (2012). Green logistics management and performance: Some empirical evidence from Chinese manufacturing exporters. *Omega*, *40*(3), 267-282.

Le, T.T. (2020) Performance measures and metrics in a supply chain environment. *Uncertain Supply Chain Management*, 8, 93-104.

Lee, K. H., & Wu, Y. (2014). Integrating sustainability performance measurement into logistics and supply networks: A multi-methodological approach. *The British Accounting Review*, *46*(4), 361-378.

Li, C., Ren, J., & Wang, H. (2016). A system dynamics simulation model of chemical supply chain transportation risk management systems. *Computers & Chemical Engineering*, *89*, 71-83.

Liao, T-Y. (2018). Reverse logistics network design for product recovery and remanufacturing. *Applied Mathematical Modelling*, 60, 145–163.

Lin, R. J., Chen, R. H., & Nguyen, T. H. (2011). Green supply chain management performance in automobile manufacturing industry under uncertainty. *Procedia-Social and Behavioral Sciences*, *25*, 233-245.

Liu, J., Yuan, C., Hafeez, M., & Yuan, Q. (2018). The relationship between environment and logistics performance: evidence from Asian countries. *Journal of cleaner production*, 204, 282-291.

Marsillac, E. L. (2008). Environmental impacts on reverse logistics and green supply chains: similarities and integration. *International Journal of Logistics Systems and Management*, 4(4), 411-422.

Meadows, D., Meadows, D., Randers, J. (1972). *The Limits to Growth*. Universe Books, New York.

Mena, C., Adenso-Diaz, B., & Yurt, O. (2011). The causes of food waste in the supplier–retailer interface: Evidences from the UK and Spain. *Resources, Conservation and Recycling*, *55*(6), 648-658.

Miao, S., Wang, T. and Chen, D. (2017). System dynamics research of remanufacturing closed-loop supply chain dominated by the third party. *Waste Management & Research*, 35(4), 379-386.

Minegishi, S., and Thiel, D. (2000). "System dynamics modeling and simulation of a particular food supply chain". *Simulation – Practice and Theory*, 8, 321-339.

Morali, O., & Searcy, C. (2013). A review of sustainable supply chain management practices in Canada. *Journal of business ethics*, *117*(3), 635-658.

Mutingi M. (2013). Developing green supply chain management strategies: A taxonomic approach. *Journal of Industrial Engineering and Management*, *6*(2), 525–546.

Mutingi, M. (2014). The impact of reverse logistics in green supply chain management: a system dynamics analysis. *International Journal of Industrial and Systems Engineering*, *17*(2), 186-201.

Narayana, S.A., Elias, A.A. and Pati, R.K. (2014). Reverse logistics in the pharmaceuticals industry: a systemic analysis. *The International Journal of Logistics Management*, *252*(2), 379-398.

Noya I., Aldea X., & Gasol C. M., et al.(2016) .Carbon and water footprint of pork supply chain in Catalonia: From feed to final products. *Journal of Environmental Management*, *171*,133-143.

Pinto, L. (2020). Green supply chain practices and company performance in Portuguese manufacturing sector. *Business Strategy and the Environment*, 1-18.

Rebs, T., Brandenburg, M. and Seuring, S. (2019). System dynamics modeling for sustainable supply chain management: A literature review and systems thinking approach. *Journal of Cleaner Production*, *208*, 1265-1280.

Saavedra M, M. R.; de O. Fontes, C. H.; Freires, F. G. M. (2018). Sustainable and Renewable Energy Supply Chain: A System Dynamics Overview. *Renewable Sustainable Energy Review*, *82*, 247−259.

Salihoglu, G., Salihoglu, N. K., Ucaroglu, S., & Banar, M. (2018). Food loss and waste management in Turkey. *Bioresource technology*, *248*, 88-99.

Sathiyagothai, B., & Saravanan, S. (2017). Reverse logistics in food processing industries in India. *International Journal of Economics & Management Sciences*, *408*(6).

Shamiss, S. (2018). goTRG uses technology to embrace the circular economy. *Reverse Logistics Magazine, 91*, 10-12.

Singh, A., & Trivedi, A. (2016). Sustainable green supply chain management: trends and current practices. *Competitiveness Review*,*26*(3), 265-288

Steinhilper R, Kruse A, Drews T. (2013).Ecological analysis of manufacturing systems focusing on the identification of variety induced non-value adding emission. In: Seliger G (ed). *Proceedings of the 11th global conference on sustainable manufacturing—innovative solutions*, Berlin, 66–71.

Sterman JD. *Business dynamics: systems thinking and modelling for a complex world*. McGraw-Hill; 2000.

Sterman, J.D. (2001). System dynamics modeling: tools for learning in a complex. *California Management Review*, *43* (4), 8-25.

Stream Freight Transport 2016 (2017), https://www.cedelft.eu/publicatie/stream_freight_transport_2016/1855 (accessed December 27, 2019).

Sudarto, S., Takahashi, K. and Morikawa, K. (2017). Efficient flexible long-term capacity planning for optimal sustainability dimensions performance of reverse logistics social responsibility: A system dynamics approach. *International Journal of Production Economics*, *184*, 179–192.

Tan, A.W.K. and Kumar, A. (2006). A decision-making model for reverse logistics in the computer industry. *The International Journal of Logistics Management*, *17*(3), 331-354.

Turner, G.M. (2012). On the Cusp of Global Collapse? Updated Comparison of The Limits to Growth with Historical Data. *Ecological Perspectives for Science and Society*, *21*(2), 116-124.

Vijayan, G., Kamarulzaman, N. H., Mohamed, Z. A., & Abdullah, A. M. (2014). Sustainability in food retail industry through reverse logistics. *International Journal of Supply Chain Management*, *3*(2), 11-23.

Vlachos, I. P. (2014). Reverse food logistics during the product life cycle. *International Journal of Integrated Supply Management*, *9*(1-2), 49-73.

Vlachos, I. P. (2016). Reverse logistics capabilities and firm performance: the mediating role of business strategy. *International Journal of Logistics Research and Applications*, *19*(5), 424-442.

Waseem, M. (2020). Adoption of Reverse Logistics in Food Companies: A Case of Pakistan. *Sukkur IBA Journal of Management and Business*, *6*(2), 24-57.

White, G. B. (2005). How to report a company's sustainability activities. *Management Accounting Quarterly*, *7*(1), 36-44.

Xu, F., Li, Y., Feng, L. (2019). The influence of big data system for used product management on manufacturing remanufacturing operations. *Journal of Cleaner Production*, 209, 782-794.

Young, C. W., Russell, S. V., Robinson, C. A., & Chintakayala, P. K. (2018). Sustainable retailing–influencing consumer behaviour on food waste. *Business Strategy and the Environment*, *27*(1), 1-15.

Zhao, R., Liu, Y., Zhang, N., Huang, T. (2017). An optimization model for green supply chain management by using a big data analytic approach, *Journal of Cleaner Production*, 142, 1085-1097.