MATHEMATICAL MODELING APPROACHES IN SUSTAINABLE FOOD SUPPLY CHAINS

by

AMIN GHAREHYAKHEH

Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT ARLINGTON

May 2020

Supervising Committee:

Dr. Jamie Rogers

Dr. Caroline Krejci

Dr. Jaime Cantu

Abstract

Access to high quality and safe food is vital for sustainable development in societies. Perishable foods lose a major portion of their quality after harvesting until the consumption point due to poor storage and distribution conditions. Thus, improvements in food supply chain operations are very critical in the sustainable development of society and the industry. The first part of this dissertation seeks to find a cost-effective and reliable tool to monitor the quality loss and implementation of the least shelf life first-out inventory management policy in food banks. Application of the Gompertz model and Arrhenius equation based on time-temperature data collected from donated foods provides an accurate and reliable estimation for the shelf life through the inbound operations. As a result of applying this methodology, perishable products which have the least shelf life are selected first to distribute among the people in need. Furthermore, as the role of food distribution is highlighted in the literature, the next two sections of this dissertation discuss how to increase efficiency and improve sustainability in the distribution of perishable food products. In chapter 3, temperature abuses and long delivery routes are identified as the main reasons that foods lose a considerable portion of their quality during distribution. Energy equations are applied to predict temperature increases when the container door is open to unload part of the cargo in the location of a customer. These temperature estimates are used as the input of the Gompertz model and the Arrhenius equation to predict the remaining shelf life of foods when they are delivered at their destination. Loss in the shelf life of the delivered products can be transformed into the revenue loss and discarding cost which can be integrated with other distribution costs in the objective function of the perishable food distribution model. Simulated Annealing algorithm is developed to solve the proposed mathematical model. The results of comparing the proposed quality dependent perishable food distribution model with the conventional food distribution model

show that the total distribution costs in the proposed model are lower than the conventional model, and this gap goes up as the size of the problem increases. In chapter 4, the main influential elements in the sustainability of perishable food distribution networks are identified as distribution costs, CO_2 emission which comes from the diesel engine of the refrigerated vehicle, and freshness of foods. A novel multi-objective mathematical model is developed to consider each of these impactful factors as an objective of the model. The freshness of the products are measured by integration of the temperature and shelf life prediction models, the CO_2 emission is calculated based on the energy consumed to transport and refrigerate the perishable foods, and the distribution costs are the combination of the fixed dispatching costs and variable costs of transporting products between two locations. Non-dominated sorting genetic algorithm II is developed to solve the multi-objective model. The performance of the solution algorithm is verified by comparing it with a weighted Simulated Annealing algorithm. The analysis over the results illustrates that the sustainability goals are conflicting in nature, and optimizing any of these goals leads to the optimality gap in other objectives. The results show that the sustainability goals of perishable food distribution are sensible to the shelf life of the foods, and foods with lower shelf life imply higher distribution costs, CO_2 emission, and lower freshness. Also, the results show that when temperature sets for higher degrees inside the container of refrigerated vehicles, although CO_2 emission is lower the freshness of perishable foods is getting worse.

Acknowledgment

I would like to thank all the people who helped and supported me in this significant achievement of my life. My sincere appreciation is for my supervising committee, Dr. Jamie Rogers, Dr. Caroline Krejci, and Dr. Jaime Cantu, for providing the incredible support and encouragement through this long journey. Their knowledge, expertise, and experience in different fields of engineering assist me to improve the quality of this dissertation in various aspects. I want to be grateful for their time and resources to help me making progress in this dissertation. I especially want to thank Dr. Caroline Krejci who introduced me to the challenges in the food supply chain, and her passion and perseverance is a great example for me to follow my curiosity, explore new ideas, and achieve my goals through my life.

I am thankful to my father, Adel Gharehyakheh, and my deeply missed mother, Jila Ghorbanalizadeh, who provided their warmest and endless love and support in my entire life. I also appreciate my older sister, Sepideh Gharehyakheh, who always cares and pays attention to my education. The last but not the least, I am grateful for all dedication, support, friendship, and counseling of my wife, Farnoosh Sharbafi.

Table of Contents

List of Illustrations

List of Tables

Chapter 1 INTRODUCTION

1.1. Background

Food quality is a major influence on a community's health and safety, which are critical to sustainable development in society. Access to safe and high-quality food is necessary to achieve zero hunger, which is one of the United Nations' 17 Sustainable Development Goals (Goal 2), in support of peace and prosperity around the world (United Nations, 2019).

Loss of quality in food products leads to wastage, which is a major challenge for sustainable development: according to the United Nations Food and Agriculture Organization, 1.3 billion tons of food products, accounting for one-third of the entire global food supply, is wasted (FAO- Food and Agriculture Organization of the United Nations, 2011). The economic impact of food waste is estimated to be $218 billion annually in the US (Young, 2012).

Food distribution is responsible for 8-23% of food quality loss (Osvald & Stirn, 2008), which is the result of non-optimized supply chain processes (Jedermann et al., 2014). Thus preserving food quality across the FSC is a widely accepted strategy for reducing food waste (Aung & Chang, 2014; Göransson et al., 2018; Huis In't Veld, 1996). However, maintaining the quality of perishable foods depends on optimal temperature control throughout the distribution process (Mercier et al., 2017). The quality of perishable products degrades over time, but the rate of degradation mainly depends on their temperature (Bruckner et al., 2013; Kreyenschmidt et al., 2010). Lower temperature slows the growth rate of microorganisms inside the food, and wherefore, loss in quality happens at a slower rate (Bruckner et al., 2013; Kreyenschmidt et al., 2010). In particular, the limited shelf life of perishable foods is significantly reduced when a distribution is delayed, or when storage temperatures rise, even for a short duration (Hsu et al., 2007). Reduced shelf life increases the probability that perishable food is wasted, which results in wasted energy and money across the FSC, as well as reduced availability of high-quality food for consumers.

Nonetheless, keeping the food temperature in the lowest possible level consumes a high level of energy since the cooling equipment needs to compensate for the heat exchange between the cold inside air and the hot ambient air especially when the refrigerated truck needs to unload a portion of its load in a delivery location. 9% and 14% of CO_2 emissions respectively in the European Union and the US are produced by transportation trucks (Stellingwerf et al., 2018), in which perishable food transportation with vapor compression refrigeration system and an enormous volume of transportation has a huge share in this emission. Adekomaya et al. (2016) show that 15% of fossil fuels and 40% of global greenhouse effects are results of food refrigeration. Even though the advantage of reducing the environmental impact of the food distribution network is promising, the relation of reducing the emission and the loss in the quality of food urge a deeper analysis.

Therefore, a route with a lengthy transport time and frequent unloading stops challenges food temperature control (Hsu et al., 2007) and thereby food quality. Although dividing the route into shorter travel distances and fewer deliveries make it more possible to maintain a lower temperature and food quality, this routing alternative does not have the least cost and emission results. Consequently, the optimum balance between maintaining food quality, and minimizing the operation costs and emissions in food distribution networks can lead to an overall improvement in sustainability indices.

1.2 Mathematical modeling in food supply chain

The conflicting nature of sustainability goals and the necessity to accurate predictions urge to implementation of a proper method and tool in the planning phase. The integration of the prediction and optimization mathematical modeling approach can provide a unique opportunity to accurately predict the impactful parameters such as food temperature and shelf life and to measure the sustainability objectives in a constrained food distribution problem.

Mathematical modeling provides the capability to optimize a single or multi-objective function such that the constraint of a problem is satisfied. Therefore, sustainability goals can be defined as the objectives of the problem, and distribution limitations are the constraints of the mathematical model. Gharehyakheh et al. (2017) illustrate that the mathematical modeling approach has been applied in sustainable supply chain problems more than any other approach. Furthermore, the dynamic of parameters in perishable food distribution network urge to have an approach to estimate their value in the model. Hence, the relations between the model parameters are defined in a set of equations to predict the value of dynamic parameters under specific conditions. Nevertheless, the predictive model is a proper approach to integrate with the mathematical model.

Despite the wide application of the mathematical models in the sustainability of food supply chains, the proposed models often assume some constant values for the model dynamic parameters which are not the case in the real world. Therefore, the integration of predictive and mathematical models makes the results of the study closer to reality. Additionally, sustainability objectives are often defined as a single integrated objective function that blurs the consequence of a decision on each of the sustainability perspectives. Thus, chapter 4 of this dissertation provides a novel multi-objective model in which each of the sustainability goals is defined as a separate objective in the model.

1.3 Research Questions and Contribution

In this dissertation, finding the answers to the following questions are targeted.

1) How can we accurately measure the shelf life of perishable food products in the food supply chain operations?

2) Which inventory management policy is suitable for managing the perishable food inventory, and how to implement it?
3) How can we predict the temperature fluctuations inside the container of a refrigerated vehicle in the food distribution process?
4) How can a food shelf life prediction model be integrated with a perishable food distribution model?
5) How can we integrate the impact of influential elements in sustainability, including the freshness of food, distribution costs, and CO_2 emissions, in a perishable food distribution model?

Sustainability contains a wide range of subjects and challenges in a food supply chain. This dissertation only studies the sustainability in food banks, chapter 2, and distribution of perishable foods, chapters 3 and 4. The contribution of this dissertation in each of the following chapters is as follows, see Table 1.

Table 1-1. Contribution of dissertation in each chapter

Chapter 2	Providing a shelf life prediction model as a proper tool to implement least shelf life first out inventory management policy
	Providing a reliable and accurate tool to reduce food waste and improve inbound operations in food banks
	Verifying the results of the proposed approach over a local food bank as a case study
Chapter 3	Extending the vehicle routing problem by integrating the shelf life prediction model in the objective function
	Predicting the temperature inside the container of the refrigerated vehicle using energy balance equations
	Adapting the simulated annealing algorithm to efficiently solve the proposed model
Chapter 3	Extending the vehicle routing problem by integrating freshness and CO_2 emissions as the separate objectives of the model
	Predicting the energy required for food refrigeration in the refrigerated vehicles by applying energy balance equations
	Adapting non-dominated sorting genetic algorithm II to efficiently provide a set of Pareto solutions

1.4 Dissertation Organization

Chapter 2 provides a deeper overview of the food quality and safety in food banks. Technology limitations and dependency on volunteers challenge the capability of food banks to distribute high quality and safe foods. This study recommends that predicting food shelf life depending on time-temperature data is a cheap and reliable tool to implement a proper inventory management policy based on the least shelf life first out rule. The strategy can improve sustainability goals such as reducing food waste and serving more people in need with high quality and safe foods in food banks.

The impact of temperature fluctuations in a food distribution network on the quality of perishable foods is highlighted in chapter 3. A prediction of temperature dynamic using energy balance equations provides an opportunity to have an estimation on the quality of delivered foods using the predicted time-temperature data in a shelf life estimation model. The integration of these prediction models with vehicle routing problems with the time window model gives an accurate estimation of quality loss if the food delivery process which set to be minimized. Simulated annealing as an efficient and reliable solution procedure is applied to find the optimum solution to the proposed model.

In chapter 4, the tradeoff between cost, CO_2 emission, and food quality are studied as the main sustainability objectives in a food distribution process. The impact of temperature on the food shelf life and CO_2 emission in refrigerated vehicles is presented in a novel multi-objective sustainable vehicle routing problem. Non-dominated sorting algorithm II is adapted to provide sustainable solutions to the proposed model over a series of Solomon's test problems.

The conclusion of this research is presented in chapter 5.

References

Adekomaya, O., Jamiru, T., Sadiku, R., & Huan, Z. (2016). Sustaining the shelf life of fresh food in cold chain–A burden on the environment. *Alexandria Engineering Journal*, *55*(2), 1359–1365.

Aung, M. M., & Chang, Y. S. (2014). Temperature management for the quality assurance of a perishable food supply chain. *Food Control*, *40*, 198–207.

Bruckner, S., Albrecht, A., Petersen, B., & Kreyenschmidt, J. (2013). A predictive shelf life model as a tool for the improvement of quality management in pork and poultry chains. *Food Control*, *29*(2), 451–460.

FAO- Food and Agriculture Organization of the United Nations. (2011). Global food losses and food waste: extent, causes and prevention. *Save Food! Global Food Losses and Food Waste*. https://doi.org/10.1098/rstb.2010.0126

Gharehyakheh, A., Cantu, J., & Rogers, K. J. (2017). Sustainable supply chain management: a modeling perspective. *American Society for Engineering Management*.

Göransson, M., Jevinger, & Nilsson, J. (2018). Shelf-life variations in pallet unit loads during perishable food supply chain distribution. *Food Control*. https://doi.org/10.1016/j.foodcont.2017.08.027

Hsu, C. I., Hung, S. F., & Li, H. C. (2007). Vehicle routing problem with time-windows for perishable food delivery. *Journal of Food Engineering*. https://doi.org/10.1016/j.jfoodeng.2006.05.029

Huis In't Veld, J. H. J. H. I. (1996). Microbial and biochemical spoilage of foods: An overview. *International Journal of Food Microbiology*. https://doi.org/10.1016/0168-1605(96)01139-7

Jedermann, R., Nicometo, M., Uysal, I., & Lang, W. (2014). Reducing food losses by intelligent food logistics. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*. https://doi.org/10.1098/rsta.2013.0302

Kreyenschmidt, J., Hübner, A., Beierle, E., Chonsch, L., Scherer, A., & Petersen, B. (2010). Determination of the shelf life of sliced cooked ham based on the growth of lactic acid bacteria in different steps of the chain. *Journal of Applied Microbiology*, *108*(2), 510–520.

Mercier, S., Villeneuve, S., Mondor, M., & Uysal, I. (2017). Time–Temperature Management Along the Food Cold Chain: A Review of Recent Developments. *Comprehensive Reviews in Food Science and Food Safety*. https://doi.org/10.1111/1541-4337.12269

Osvald, A., & Stirn, L. Z. (2008). A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. *Journal of Food Engineering*. https://doi.org/10.1016/j.jfoodeng.2007.07.008

Stellingwerf, H. M., Kanellopoulos, A., van der Vorst, J. G. A. J., & Bloemhof, J. M. (2018). Reducing CO 2 emissions in temperature-controlled road transportation using the LDVRP model. *Transportation Research Part D: Transport and Environment*, *58*, 80–93.

United Nations. (2019). *17 goals to transform the world for persons with disabilities*. The United Nations. https://www.un.org/development/desa/disabilities/envision2030.html

Young, L. (2012). *Our biggest problem? We're wasting food*. Canadian Grocer. http://www.canadiangrocer.com/top-stories/what-a-waste-19736

Chapter 2 Dynamic Shelf-Life Prediction System to Improve Sustainability in Food Banks

Amin Gharehyakheh, Caroline Krejci, Jaime Cantu, Jamie Rogers

The University of Texas at Arlington

Arlington, TX, 76019, USA

Abstract

Because food banks receive primarily surplus foods with limited shelf-life, inaccurate quality monitoring can lead to increased food safety risk and waste. A lack of information about the quality and condition of donated food, dependence on volunteer workers, and inadequate inspection equipment can limit a food bank's ability to safely distribute food to people in need. In lieu of expensive lab equipment and technicians, historical data and visual inspections provide a reasonable estimate of the initial quality of donated food, and bacterial growth models can be used to project spoilage rates during storage. Since spoilage rates are highly dependent on food temperature, this paper considers the effect of temperature in a kinetic model to estimate the number of specific spoilage organisms and to predict the remaining shelf-life of perishable foods in food banks. This method can be integrated with warehouse management systems to develop a sustainable inventory management system that reduces food waste and improves food safety, thereby enabling food banks to serve more people in need.

Keywords

Shelf-life prediction, cold chain, food bank, food waste, specific spoilage organism, time-temperature data

1. Introduction and Background

Fifteen million American families (nearly twelve percent of U.S. households) did not have access to sufficient nutritious food at some time in 2017 [1]. In the U.S., food banks alleviate hunger by collecting surplus food and distributing it through a network of charitable organizations [2]. Feeding America, the largest hunger-relief organization in the US [2], manages a nationwide network of food banks that provide 3.5 billion pounds of food to people in need [3]. Although public funding covers some of their operational costs, food banks depend on donations from farms, food manufacturers, retailers, and distributors [4]. In most cases, food is donated to a food bank when it loses its market value due to poor storage conditions, manufacturing errors, damages occurring during shipping and handling, or expiration date [4].

Although Feeding America has made strides in addressing hunger in the U.S., the problem persists. In fact, there has been a steady increase in the gap between food banks' supply and the demand for food assistance [5]. One reason for this gap is spoilage. Donated food typically has a very limited shelf-life, i.e., the time during which it can be consumed safely by the end customer [6]. Therefore, it is important for food banks to monitor the condition and remaining shelf-life of perishable foods via a systematic and unambiguous inventory management policy.

The food industry commonly uses a Least Shelf-life First Out (LSFO) inventory management strategy [7], where shelf-life is determined using the expiration date provided by the food manufacturers. The manufacturers determine expiration dates based on their expectation of the conditions under which the food will likely be stored. These estimates tend to be conservative [8], which increases the chance that buyers dispose of food that is still nutritious and safe to use. On the other hand, if storage conditions are worse than expected, this method can endanger consumers' safety.

More reliable methods for estimating remaining shelf-life exist, including evaluating whether 1) the number of Specific Spoilage Organisms (SSOs) exceeds the standard acceptable level, and/or 2) there is a significant change in the sensible quality of the item such as color, texture, and/or odor [9]. While changes in sensible quality can be detected through observation, counting the number of SSOs requires expertise and expensive lab equipment. This paper proposes a dynamic shelf-life prediction model that estimates the number of SSOs using time-temperature data, which can be captured with an inexpensive temperature logger. Model outputs can be easily integrated with a food bank's warehouse management system to facilitate accurate shelf-life prediction for more effective inventory management, thereby reducing waste and increasing the food bank's capacity to serve those in need.

2. Methodology

The most important factor affecting shelf-life of food is its temperature as it traverses the cold chain [10]. High temperature accelerates the growth of SSOs, which causes the quality of food to decline [11, 12]. Ahumada and Villalobos modeled the decline of food quality as a linear function over time [13]. Rong et al. predicted a non-linear quality decline for foods using the first-order reaction method [14]. These methods are reliable for an isothermal process, in which the temperature of the system remains constant. However, they will yield misleading results in a non-isothermal environment. The handling and storage of perishable items in a food bank is a non-isothermal process: food is loaded and unloaded, inspected, repacked, and stored in different temperature zones inside the warehouse.

Kreyenschmidt et al. [9] and Bruckner et al. [15] suggest a more appropriate method of estimating SSO growth over time for non-isothermal conditions, by combining the Gompertz model and the Arrhenius equation. The Arrhenius equation, given in Equation (1), evaluates the influence of temperature (T) on the SSO growth rate (B).

$$ln(B) = \ln(F) - \frac{E_a}{R}.(\frac{1}{T}) \quad (1)$$

B: relative growth rate,
F: pre-exponential factor,
E_a: activation energy for bacterial growth (J/mol),
R: gas constant (8.314 J/mol K),
T: absolute temperature (K).

Bruckner et al. [15] used non-linear regression to estimate the value of B for five different temperature scenarios (Table 1), and these data points were used to fit a linear regression to predict the value of B ($\hat{B}$) at any temperature (Equation (2)).

$$ln(\hat{B}) = 40.70 - 12361.99.\left(\frac{1}{T}\right), \quad R^2 = 0.99 \quad (2)$$

Table 2-1: Growth parameter predicted by applying nonlinear regression, and M values in temperature scenarios [15].

Temperature (°F)	Temperature (°K)	B	R^2	M (h)
36	275	0.014	0.941	65
39	277	0.020	0.971	58
45	280	0.033	0.940	42
50	283	0.058	0.960	28
59	288	0.103	0.961	18

B=relative growth rate, R^2 = adjusted coefficient of determination, M=time when maximum growth rate is obtained.

Bruckner et al. derived the value of M for the first time interval (i.e., the first duration of time in which the temperature is recorded) in the non-isothermal temperature condition from the linear regression of M (h) against temperature (°K) in isothermal conditions [15], given in Equation (3).

$$\widehat{M} = 1102.71 - 3.78.(T), \quad R^2 = 0.96 \quad (3)$$

Once the value of $\widehat{M}$ and $\hat{B}$ are determined, the predicted number of SSOs at the first-time interval (t_0) can be calculated using the Gompertz model (Equation (4)).

$$N(t_0) = A + C.e^{-e^{-\hat{B}(t_0-\widehat{M})}} \quad (4)$$

N(t): microbial count ($\log_{10}$ cfu/g] at time t_0,
A: initial bacterial count constant value ($\log_{10}$ cfu/g),
C: the difference between maximum population level and the initial bacterial count constant value ($\log_{10}$ cfu/g),
$\hat{B}$*:* relative growth rate,
t_0*:* length of the first time interval (h),
$\widehat{M}$*:* estimated time at which maximum growth rate is obtained (h).

Microbial count at time t_0 can be used to derive M from the Gompertz model using the Equation (5).

$$M = \frac{\ln\left(-\ln\left(\frac{N(t_{e-1})-A}{C}\right)\right)}{\hat{B}} + t \quad (5)$$

After the first time interval, the value of M calculated by Equation (5) replaces the $\widehat{M}$ in Equation (4) to predict the growth of SSOs in the next time intervals, given in Equation (6).

$$N(t) = A + C.e^{-e^{-\hat{B}(t-M)}} \quad (6)$$

Figure 1 shows the relationship between SSO growth, shelf-life, and food quality. The shelf-life of a product begins immediately after harvest and continues until the SSO count reaches its maximum allowable value. Food manufacturers divide the maximum shelf-life into three zones. Products that are the first shelf-life zone have the highest quality level and quality of product declines as the number of SSOs increases over time. Food industry actors typically donate products at the lowest quality level to the food banks.

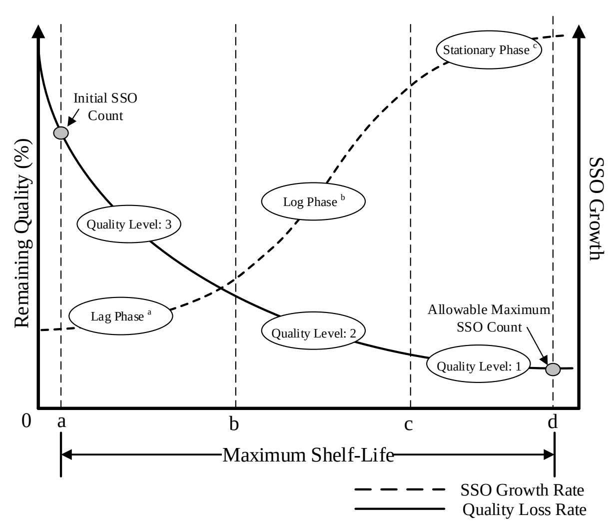

Figure 2-1: The relation of quality loss and growth of SSOs in perishable foods (adapted from [8]).
[a] Bacteria are metabolically active but not dividing, [b] A time of exponential growth, and [c] Growth reaches a plateau.

To determine how time-temperature data could be used to improve food quality and reduce waste at a food bank, time-temperature data was collected and analyzed for pallets of poultry at a local food bank. The proposed method is employed to analyze the time-temperature data in two scenarios: 1) actual time-temperature data collected from real food bank's operations, and 2) proposed time-temperature data for the improved food bank's operation.

3. Case Study Application and Results

The food assistance cold chain begins with the collection of donated items from the donor's location using refrigerated vehicles, which then deliver the donated food to the food bank's warehouse [16]. Because there is not any information available about the donor's storage conditions, it is assumed that products have been stored in a clean storage area which is free from any sort of contamination, and the moisture and the temperature level have been at the standard level. The food is usually received on pallets, which are unloaded in the warehouse receiving area before being moved to temporary storage for quality and safety inspection. Typically, volunteer workers with rudimentary training on inspection procedures decide whether the food meets the minimum acceptable quality level for safe consumption. Food that does not pass this quality inspection is either composted or sent to the landfill. Food that passes the quality inspection is put into refrigerated storage or freezers at 0 °F based on United States Department of Agriculture (USDA) recommendations [17]. Each pallet is labeled with information about its contents, including the supplier, received date, and product name. This information, along with the appearance of the items, is used to determine storage locations and picking prioritization. Based on this policy, food is pulled from storage as needed, loaded into refrigerated vehicles, and distributed to food assistance agencies, such as churches, soup kitchens, and shelters, throughout the region served by the food bank [18].

Time-temperature data for a sample of pallets containing poultry were collected from the moment the pallets were unloaded at the food bank's dock, until the time that these pallets were loaded into a refrigerated truck for distribution. *Quality Blue Cargo Data* was the brand of data recorder that was used to collect the data, which has the capability to store temperature data in 15-minute time intervals.

The collected data indicated that the pallets are sometimes staged in an unrefrigerated receiving area for a long time while waiting to be inspected or moved into storage. Exposing the poultry to these temperatures sharply accelerates the growth of SSOs and shelf-life is rapidly lost accordingly. The collected time-temperature data for a food pallet that waited 18 hours at room temperature (280 °K, or 44 °F) to be stored in the freezer and a prediction of the growth of SSOs in the food is shown in Figure. 2. In this figure, the red line represents the time-temperature data collected from the poultry pallets, and the blue line, which shows the growth of SSOs inside the poultry, is predicted by a combination of the Gompertz model and Arrhenius equation. The blue line is a representative of the log phase and then the stationary phase of SSO growth that are shown in Figure 1. At first, the blue line has exponential growth while the temperature is high, followed by a gradual increase in the number of SSOs over the time as temperature decreases. The maximum allowable number of SSOs, by which food can be consumed safely, is defined by food scientists to be 7.5 ($\log_{10}$ cfu/g) for poultry [15]. As shown in Figure 1, food shelf-life ends when the SSO count reaches its max allowable amount. In this example, a prediction of the number of SSOs reaches 7.5 ($\log_{10}$ cfu/g) after 82 hours.

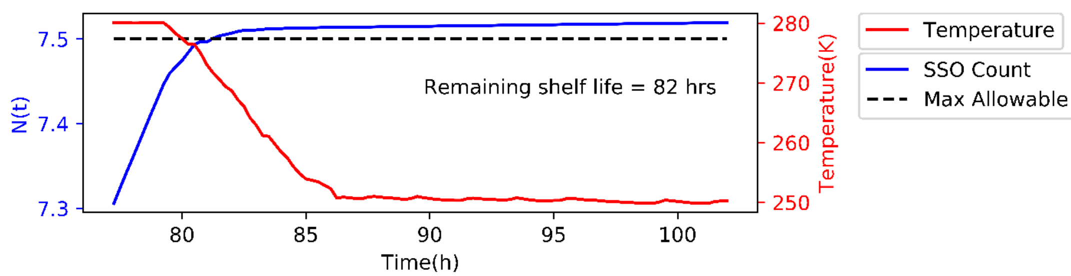

Figure 2-2: Effect of long staging time on the growth of SSOs and the remaining shelf-life of the products.

The results shown in Figure 2 suggest that there is significant potential for increasing the shelf-life of this food by reducing the staging time of the pallets. To determine the value of reducing staging time at the food bank's warehouse, the model was applied to a hypothetical situation in which the pallets only waited 4 hours to be moved to the freezer. Figure 3 shows the resulting output, which indicates that reducing staging time from 18 to 4 hours can prolong the shelf-life by about 5 days.

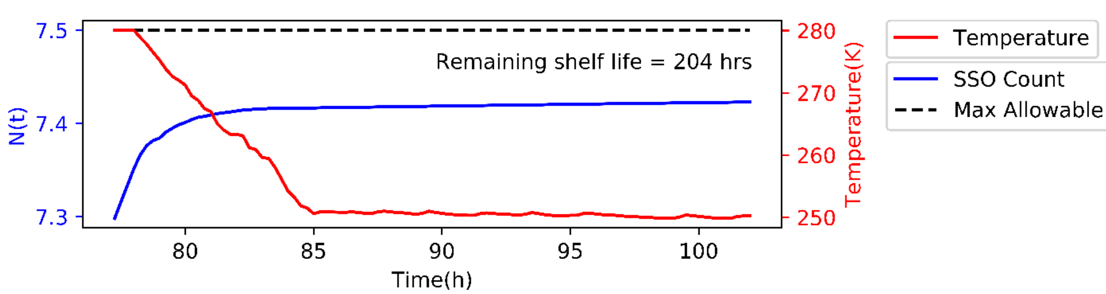

Figure 2-3: Effect of shortening staging time on the growth of SSOs and the remaining shelf-life of the products.

Additionally, the collected data shows an increase in the temperature of a food pallet inside the freezer, which can affect the remaining shelf-life of the products. Moving the food pallet to another cold storage with a higher temperature, malfunctioning cooling equipment, or human error in setting the temperature level can cause this sort of undesirable change in temperature. The red line in Figure 4 shows the actual temperature of a food pallet inside a freezer over time, which rose sharply from 250 °K (-10 °F) to 260 °K (8 °F) after 60 hours of storage. The impact of this temperature increase is shown by the rapid growth of SSOs inside the food pallet (represented by the blue line). The shelf-life of the poultry food pallet under this time-temperature condition is approximately 79 hours.

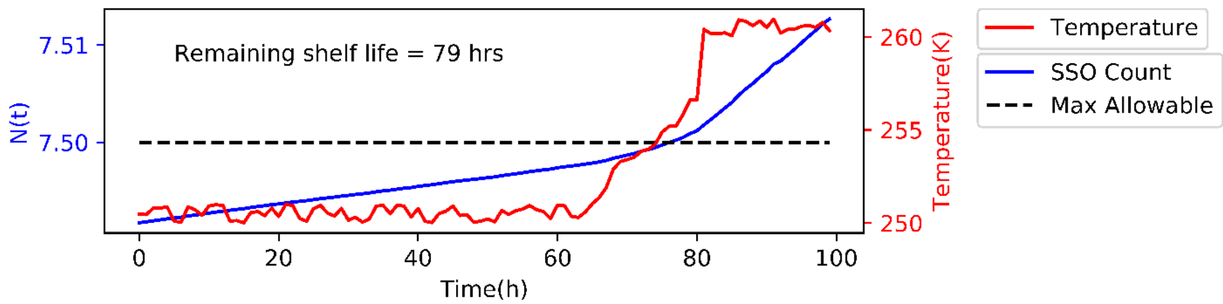

Figure 2-4: Effects of an increase in temperature on the growth of SSOs and the remaining shelf-life of the products.

To determine the impact of holding the freezer temperature steady, the model was applied to a simulated time-temperature dataset in which the temperature fluctuates slightly around 250 °K (-10 °F). Figure 5 shows that the rate of growth in SSOs will be nearly constant when the temperature inside the freezer remains around 250 °K (-10 °F). A comparison of the two time-temperature data sets given in Figures 4 and 5 shows that poultry can lose 3 days of shelf-life if the temperature of the freezer increases 10 °K for 20 hours.

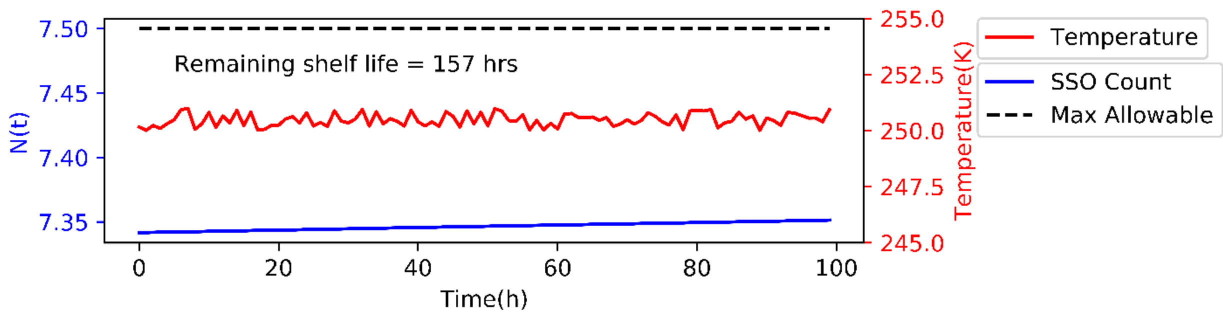

Figure 2-5: Effects of low steady temperature on the growth of SSOs and the remaining shelf-life of the products.

4. Discussion and Conclusion

The combination of the kinetic equation and growth model can deliver a reliable estimation of the dynamic shelf-life of perishable food products in a non-isothermal environment by predicting the growth of SSOs in food products. This approach helps to more effectively implement an LSFO inventory management strategy and find potential improvements in inbound logistics activities, particularly receiving and cold storage operations, to increase shelf-life and reduce waste.

Food banks' inbound logistics activities are highly dependent on volunteer workers, which adds uncertainty and complexity to labor scheduling. The analysis presented in this paper suggests that better labor management in the staging area has the potential to expand the shelf-life of the products by 5 days. Additionally, the analysis indicates that a 10 °K increase in the storage temperature for 20 hours can result in 3 days of shelf-life loss. Computational analysis of available data can help to identify and prevent such quality loss in a food bank's warehouse.

Food banks are struggling to preserve the quality of the donated foods. A simple, reliable, and inexpensive method to control and monitor the quality of products in the food bank's warehouse is essential. Integrating the method presented in this paper with a food bank's WMS can potentially prevent tons of foods from being wasted every year, and thereby reducing the number of people who are suffering from food insecurity.

One of the biggest obstacles to accurately predicting the shelf-life of perishable foods in food banks is the lack of information about the temperature and conditions in which the donated foods are stored in the previous stages of the cold chain. Food donors should take more responsibility on recording and sharing the information about their donations. Presenting a framework, a tool, or a strategy which can build a structure for sharing data between food donors and food banks is a promising area of research. Additionally, before making a major decision at any level of the cold chain, it is recommended to couple the dynamic shelf-life prediction model with simulation or mathematical models to obtain more reliable results [19].

References

1. 2017, "Food security in the U.S.: Key statistics and graphics." https://www.ers.usda.gov/ topics/food-nutrition-assistance/food-security-in-the-us/key-statistics-graphics.aspx. Accessed January 16, 2019.
2. "Our history," https://www.feedingamerica.org/about-us/our-history. Accessed January 10, 2019.
3. 2018, "annual report-solving hunger," https://www.feedingamerica.org/sites/default/files/ 2018-12/2018%20 Feeding %20America%20Annual %20Report_0.pdf. Accessed January 14, 2019.

4. Tarasuk V, Eakin JM., 2005, “Food assistance through “surplus” food: Insights from an ethnographic study of food bank work,” Agriculture and Human Values, 22(2): 177-186.
5. Gödecke T, Stein AJ, Qaim M., 2018, “The global burden of chronic and hidden hunger: Trends and determinants,” Global food security, 17, 21-29.
6. Schneider F., 2013, “The evolution of food donation with respect to waste prevention,” Waste Manage, 33(3), 755-763.
7. Qi L, Xu M, Fu Z, Mira T, Zhang X., 2014, “A WSN-based perishable food shelf-life prediction and LSFO strategy decision support system in cold chain logistics,” Food Control, 38, 19-29.
8. Gunders D., 2012 “Wasted: How America is losing up to 40 percent of its food from farm to fork to landfill,” Natural Resources Defense Council, 26.
9. Kreyenschmidt J, Hübner A, Beierle E, Chonsch L, Scherer A, Petersen B., 2010 “Determination of the shelf life of sliced cooked ham based on the growth of lactic acid bacteria in different steps of the chain,” J Appl Microbiol, 108(2), 510-520.
10. Gharehyakheh A, Cantu J, Krejci C, Rogers J., 2018, “Sustainable delivery system in a temperature controlled supply chain,” Institute of Industrial and Systems Engineers Conference, May 19-22, Orlando, Florida.
11. Nychas GE, Skandamis PN, Tassou CC, Koutsoumanis KP., 2008, “Meat spoilage during distribution,” Meat Science, 78(1-2), 77-89.
12. Gram L, Ravn L, Rasch M, Bruhn JB, Christensen AB, Givskov M., 2002, “Food spoilage—interactions between food spoilage bacteria,” Int J Food Microbiol, 78(1-2), 79-97.
13. Ahumada O, Villalobos J., 2011, ‘A tactical model for planning the production and distribution of fresh produce,” Ann Oper Res, 190(1), 339-358.
14. Rong A, Akkerman R, Grunow M., 2011, “An optimization approach for managing fresh food quality throughout the supply chain,” Int J Prod Econ, 131(1), 421-429.
15. Bruckner S, Albrecht A, Petersen B, Kreyenschmidt J., 2013, “A predictive shelf life model as a tool for the improvement of quality management in pork and poultry chains,” Food control, 29(2), 451-460.
16. Gharehyakheh A, Tavakkoli-Moghaddam R., 2012, “A fuzzy solution approach for a multi-objective integrated production-distribution model with multi products and multi periods under uncertainty,” Management Science Letters, 2(7), 2425-2434.
17. 2013, “How Temperatures Affect Food,” https://www.fsis.usda.gov/wps/portal/fsis/ topics/food-safety-education/get-answers/food-safety-fact-sheets/safe-food-handling/how-temperatures-affect-food/ct_index, Accessed January 16, 2019.
18. Gharehyakheh A, Sadeghiamirshahidi N., 2018, “A sustainable approach in food bank logistics,” American Society for Engineering Management Conference, October 17-20, Coeur d'Alene, Idaho.
19. Gharehyakheh A, Cantu J, Rogers KJ., 2017, “A systematic review of quantitative modeling approach in sustainable supply chain under uncertainty,” American Society for Engineering Management Conference, October 18-21, Huntsville, Alabama.

Chapter 3 Optimizing Distribution of Perishable Food Products Considering Temperature Variability and Food Quality Deterioration

Amin Gharehyakheh, Caroline Krejci, Jaime Cantu, Jamie Rogers

The University of Texas at Arlington

Arlington, TX, 76019, USA

Abstract

Perishable products lose a considerable part of their quality during distribution. As a result, the narrow profit margin of food supply chain actors is cut, and the environmental problems associated with food waste emerge. Thus, the need for measuring and minimizing the quality loss in the distribution of products is inevitable. In this paper, the dependency of the distribution problem to the quality loss of perishable products is integrated with Vehicle Routing Problem with Time Window (VRPTW). In the presented approach, energy balance equation is formulated to estimate the temperature of the products when the container door is open to deliver part of the load, and when the products are maintained in the isolated container during the transportation, which then is used to predict the quality loss in the distribution of the products. The integrated mathematical model is solved by an efficient simulated annealing algorithm. The results compare the application of Quality Dependent (QD)-VRPTW and conventional VRPTW to demonstrate that this new approach improves distribution costs up to 16% especially when the size of the problem increases. Optimizing the delivery sequence and vehicle routing decisions integrally can significantly increase the quality of delivered products, and accordingly, reduce costs and environmental effects associated with quality loss in the distribution of perishable products.

Keywords: Perishable food; Vehicle Routing Problem; Quality Prediction; Food Waste; Temperature Prediction; Food Supply Chain

1. Introduction

The Food and Agriculture Organization of the United Nations estimates that as much as 60% of perishable food produced worldwide is wasted because of quality degradation (FAO, 2011). Loss of quality decreases the likelihood that a food product will be sold, due to consumer preference for freshness and concerns about safety (Tekin & Erol, 2017). Unsold products become part of the waste stream and represent lost revenue for the food supply chain (FSC) actors, cutting into their already narrow profit margins (Goodman, 2004). Food waste is also a serious environmental concern; it is the largest component of all landfilled municipal solid waste in the U.S. and accounts for nearly 18% percent of anthropogenic methane emissions in the U.S. (U.S. EPA, 2017).

A significant percentage (8-23%) of quality loss in food products occurs during distribution (Osvald & Stirn, 2008), due to non-optimized supply chain processes (Jedermann, Nicometo, Uysal, & Lang, 2014), and is therefore a major contributor to FSC distribution cost (Blackburn & Scudder, 2009; Rong, Akkerman, & Grunow, 2011; Yu & Nagurney, 2013). Factors that impact the quality of food products during distribution include temperature, humidity, packaging, and handling (Novaes, Lima Jr, Carvalho, & Bez, 2015). However, the temperature is the primary contributor to food quality degradation and safety issues (James, James, & Evans, 2006; & Kiranoudis, 2002). Thus, refrigerated vehicles are used to deliver perishable food products to retailers. The products are stored in an isolated container that maintains a pre-specified temperature while traversing the supply chain (S. Wang, Tao, & Shi, 2018).

However, even with refrigeration, the quality of products in transit begins to degrade as soon as the load is dispatched from the point of origin. In particular, the temperature inside the refrigerated container is highly dependent on the frequency with which the container door is opened. Because customer demand is usually less than a full truckload and delivering multiple orders in a single route is cost-effective, each route typically includes multiple deliveries to different locations. These delivery points are critical to temperature control: when the doors of a refrigerated container are opened to unload a customer's order, the hot outside air causes a rapid temperature increase inside the container (James et al., 2006; Novaes et al., 2015). The food products degrade over time at any temperature, and temperature fluctuations only affect the rate of degradation. Therefore, lengthy transport times and frequent delivery stops in hot weather make temperature control particularly challenging (Hsu, Hung, & Li, 2007). By contrast, a route with few deliveries and shorter travel distance is more capable of maintaining pre-specified food product temperatures during distribution, thereby maintaining product shelf life and retailer revenues. However, reducing the number of delivery points and traveling distances in each route will necessitate an increase in the number of routes, which increases transportation costs (Hsu et al., 2007).

Designing optimal distribution systems for perishable foods is, therefore, a complex task that requires consideration of multiple interdependent factors. Distribution cost is not only a function of transport distances but is also a function of food quality degradation during transport. The rate of perishable food product degradation mostly depends on the temperature in which they are stored during the distribution. Although cooling equipment tries to keep the temperature at the desired level, the routing decisions such as the vehicles' sequence of delivery and frequency of stops highly impact the temperature variations inside the container. While many existing models of perishable food distribution incorporate shelf-life prediction models, most assume a linear relationship between shelf-life and transport time, which neglects the significant nonlinear impacts of refrigerated container door opening on temperature increase and therefore shelf life loss during deliveries. Furthermore, to the best of our knowledge, none of the perishable food distribution models are integrated with a temperature prediction model to accurately predict the shelf life of the delivered products.

This paper describes a modeling approach in which the Vehicle Routing Problem with Time Windows (VRPTW) is integrated with a food quality degradation prediction model in order to consider and accurately account for the cost of quality loss when planning distribution for perishable food products. Determining the cost of quality loss for a given routing requires an estimate of the cargo's remaining shelf life upon delivery to retailers, which is highly impacted by variations of temperature. The integrated model described in this paper uses the Arrhenius equation and the Gompertz model to precisely predict the remaining shelf life of food products. In addition, a set of energy balance equations are developed to estimate the temperature inside the container based on the refrigerated vehicles cooling unit performance and convective heat transfer between the ambient hot air and cold air inside the container when the container door is open. Dependency on quality loss makes Quality Dependent Vehicle Routing Problem with Time Window (QD-VRPTW) very difficult to solve. Thus, a Simulated Annealing (SA) algorithm is used to evaluate the assignment of loads and routes to vehicles, such that overall transportation cost, including food quality degradation costs, is minimized.

The paper is organized as follows: Section 2 describes the importance of considering the quality loss in perishable food distribution network which follows with a summary of the literature. Section 3 demonstrates the application of energy balance equations to predict the temperature inside a vehicle's refrigerated container while the vehicle is in transit and during unloading. In addition, this section explains the mathematical model used to predict the remaining shelf life of perishable products under dynamic temperature conditions and describes a method of translating quality loss into the cost. Section 4 and section 5 respectively present the integrated QD-VRPTW model and the SA algorithm as a solution method. Section 6 demonstrates an application of the model, and the results are discussed. Section 7 concludes the paper with a summary of key findings, as well as a discussion of the model's limitations and future work.

2. Quality considerations in food distribution optimization

The quality dependent food distribution system allocates customer orders for perishable food products to multiple refrigerated vehicles and then creates delivery sequences for each vehicle. The model described in this paper optimizes the distribution plan by minimizing costs associated with both operations and quality loss. An example of the relationship between the delivery sequence and product quality is illustrated in Fig. 1. In this simplified example, customer B's demand is twice that of customer A. A single refrigerated vehicle is loaded with both customers' orders at the depot. In Fig. 1a, customer B's order is delivered before customer A's order, while in Fig. 1b the delivery sequence is reversed. In both scenarios, the vehicle's cooling system maintains a temperature of 273 °K in the storage container during transportation from the depot to the first customer, such that the products' shelf life decreases very gradually. Assuming that the ambient temperature and travel time are the same for the first delivery, at this stage, the products have 278 days of remaining shelf life for both scenarios. However, when the cooling system is turned off and the container door is opened for unloading at the first stop, ambient air enters the container. The resulting energy exchange causes the temperature inside the container to rise above 280 °K, which corresponds to a nonlinear sharp decline in product shelf life. The container door is then closed, and the cooling system is turned on, such that the container returns to 273 °K during travel between the first and the second deliveries.

The important difference between these two scenarios is the unloading time for the first delivery. Since the demand for customer B is twice that of customer A, the unloading time for customer B is assumed to also be twice the time required for customer A. Hence, the duration of the second delivery's exposure to increased temperatures is longer in Fig. 1a, which results in a greater loss of shelf life for customer A's order (236 days remaining), compared with customer B's order in Fig. 1b (259 days remaining). This example demonstrates the importance of delivery sequence in the shelf life of delivered products. The sequence changes the duration in which the rest of the cargo faces the higher temperature when the container door is open.

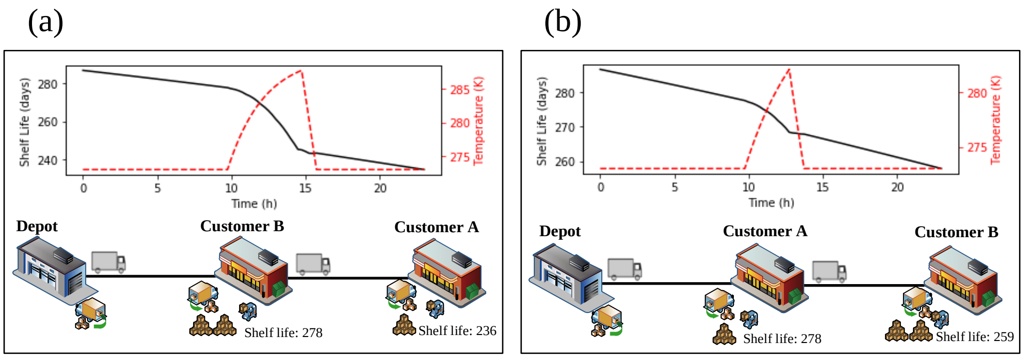

Figure 3-1. Comparing the effects of delivery sequence on the temperature of the container and remaining product shelf life, (a) delivery sequence is B-A (b) delivery sequence A-B.

A wide range of models has been developed to address food perishability and quality loss during distribution. Estimating quality loss in models of perishable food distribution is challenging. For simplicity, most models assume linear degradation of product quality over time and disregard the effect of temperature fluctuations on the rate of quality loss. For example, Osvald and Stirn (2008) included the impact of linear quality degradation during transport as a component of food distribution cost in their VRPTW model. Chen, Hsueh, and Chang (2009) developed a mathematical model that integrates linear deterioration of product quality with production and distribution decisions to determine optimal production quantities, production start times, and vehicle routes. Rahbari, Nasiri, Werner, Musavi, and Jolai (2019) developed a routing and scheduling model in which product quality is assumed to degrade linearly during unloading and transportation. Ghezavati, Hooshyar, and Tavakkoli-Moghaddam (2017) incorporated a triangular ripeness function in their model, in which product value increases linearly over time, reaches a maximum level, and then decreases at a constant rate. Haass, Dittmer, Veigt, and Lütjen (2015) conducted a simulation study in which intelligent containers select routes and customers to minimize food losses and transportation costs. The rate of product ripening during transport is assumed to occur linearly over time, with a slope that increases at higher temperatures. Rong and Grunow (2010) developed a production and distribution model to minimize the operation costs and to determine a constraint in which the product quality level which degrades linearly after production does not exceed customers' minimum quality threshold. Devapriya, Ferrell, and Geismar (2017) and Nakandala et al. (2016) used the same approach to present a cost optimization model that guarantees the delivery of food products at or above a minimum acceptable level of quality. They both used a linear quality degradation function and prohibit solutions that do not satisfy customers' quality requirements. Although simplifying the degradation of quality enables food quality loss considerations in more complicated problems, but it can result in a huge economic and environmental loss in food distribution network. Therefore, Blackburn & Scudder (2009) studied the nonlinearity of the effect of temperature on quality loss. They developed a model to optimize the size of batches, subject to the tradeoff between batch size and loss of product value. They assumed that product value decays exponentially over time, and the rate of decay depends on storage temperature.

Researchers took different approaches on how to integrate the effect of quality loss in the food distribution network. Quality loss leads to lost revenue and increased lateral costs associated with food waste; therefore, deterioration of food quality is sometimes translated into the cost (Hsiao, Chen, & Chin, 2017; S. Wang et al., 2018; Yan, Banerjee, & Yang, 2011). Because minimizing delivery time always improves the quality of the delivered products, minimizing delivery time is equivalent to maximizing product freshness. Thus, Bortolini et al. (2016) included three objective functions in their distribution model to minimize delivery time, operating cost, and carbon footprint. In another study, Albrecht and Steinrücke (2018) modeled the tradeoff between reducing the delivery lead time and the associated increase in distribution cost. In their model, product quality is represented by discrete quality grades (low, medium, and high), which deteriorate during distribution after exceeding specific shelf life thresholds. Therefore, they were seeking to find a solution in which the combination of revenue from sales of more fresh products and its associated operating costs is optimized. Other models seek to directly maximize freshness or minimize quality loss (Ahumada & Villalobos, 2011; Amorim & Almada-Lobo, 2014; Amorim, Günther, & Almada-Lobo, 2012; Farahani, Grunow, & Günther, 2012; X. Wang, Wang, Ruan, & Zhan, 2016). Gallo, Accorsi, Baruffaldi, & Manzini (2017) developed a model that minimizes total energy consumption across the entire food distribution network, including the energy required to maintain a certain temperature level, the required energy to process, package, and transport products, and energy associated with any food waste that results from quality loss during distribution. The results show that delivering food products with a longer shelf life saves energy overall. Regardless of the modeling approach, the results of all the studies show that combining the food quality loss in modeling food distribution problems is inevitable.

Most of the studies fail to address the effect of temperature variations which are a result of transferring heat from hot ambient air to inside the container when the door is open to unload part of the load in a customer's location. Hsu et al. (2007) considered the effect of opening container doors on increased product temperature and spoilage rate. They assumed that spoilage occurs at a constant rate during distribution, which then changes during unloading based on differences in temperatures inside and outside the container. Novaes et al. (2015) used commercial software to predict the temperature inside the container for feasible routes in a traveling salesman problem model. They demonstrated that having an estimation of the temperature inside the container provides the capability to increase the quality of delivered products.

Perishable food distribution is a complex problem since several interdependent factors impact the quality of the products and the operating cost of the distribution. Even though it is difficult to estimate and integrate the effects temperature dynamics and quality loss in distribution problem, this research presents a simple and accurate method to predict temperature increases as a result of the door opening and temperature decrease based on the capacity of cooling equipment which is then used to predict the nonlinear loss of quality. A combination of the distribution model with the prediction of the quality loss accounts for a more accurate representation of the real cost in the food distribution problem.

3. Predicting temperature, quality, and market value in the food distribution problem

The presented QD-VRPTW consists of two main connected modules, see Fig. 2. VRPTW module generates a feasible routing option with the associated transportation costs. The quality dependent module uses the routing information to predict the temperature inside the container. An accurate estimation of the temperature is used to estimate the shelf life of the delivered products which then transformed into the quality cost of the distribution. The quality cost and transportation cost add up at the end to calculate the total distribution costs.

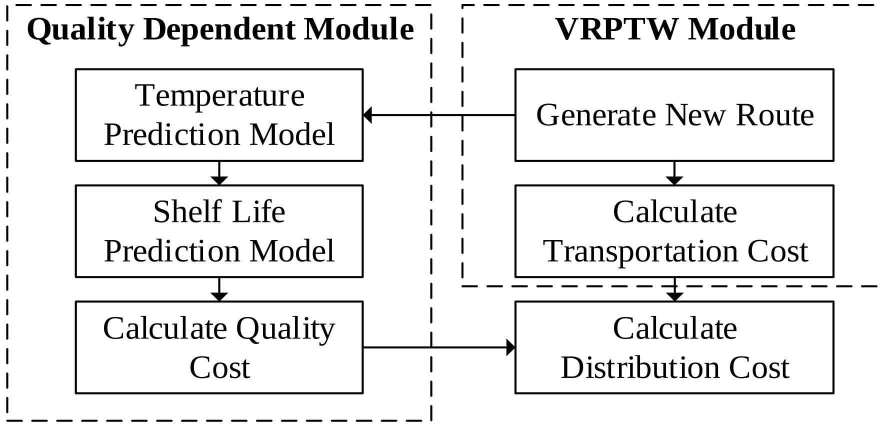

Figure 3-2. Schematic of QD-VRPTW structure

3.1 Temperature prediction in the food distribution system

Increases in food product temperature during distribution can sharply raise the rate of microbial growth, leading to quality loss and increased food safety risk (Zhou, Xu, & Liu, 2010). Thus, the ability to predict product temperature during distribution, which enables the prediction of remaining product shelf life upon delivery to the customer, is critical to effective distribution planning. Most existing studies of time-temperature behavior in refrigerated vehicles have focused on predicting temperature fluctuations when the container door is open since the heat exchange through cracks and gaps in the walls, floor, and roof of a closed shipping container is comparatively negligible. Survey results indicate that the container door can be opened as many as 50 times a day, whereupon heat enters the container via airflow from the higher-temperature exterior, as well as material handling activities during unloading (James et al., 2006). A single opening of the container door in eight hours of delivery requires 25% more cooling capacity, and this number increases to 200% when the refrigerated vehicle needs to stop and open the container door 31-35 times (Novaes et al., 2015). As a result, maintaining the temperature of refrigerated food is very difficult for a delivery route with frequent stops (James et al., 2006).

The time-temperature behavior of a refrigerated vehicle during distribution can be evaluated using information collected from lab experiments; however, this is expensive and time-consuming. By contrast, implementing thermodynamic models in a steady-state environment can provide rapid and reliable temperature prediction (Moureh, Menia, & Flick, 2002; Spence, Doran, & Artt, 2004). Thermodynamic models, such as computational fluid dynamics simulations, have been used to evaluate the effect of door opening on the air temperature inside refrigerated vehicles (Artuso et al., 2019; Lafaye De Micheaux, Ducoulombier, Moureh, Sartre, & Bonjour, 2015; Moureh et al., 2002; Rai, Sun, & Tassou, 2019; Tso, Yu, Poh, & Jolly, 2002). In the model described in this paper, mathematical equations derived from the energy balance equation are used to predict the temperature inside the container during distribution.

The temperature of a vehicle's refrigerated container is predicted for two distinct delivery phases: unloading, and transportation. During the unloading phase, the container door is open, and heat is transferred through the open door into the container. It is assumed that the vehicle's cooling system is turned off during the unloading phase to protect the engine and to avoid polluting the air around unloading docks. During the transportation phase, the container door is closed, and the vehicle's cooling system is running to maintain the container temperature at a predetermined level (T_d). A thermostat turns the cooling system off when the container temperature reaches T_d.

3.1.1 Temperature prediction during unloading

The amount of energy transferred into the container while unloading product at customer *j* (TE_j, in joules) is a function of the air mass inside the container (m_a, in kg), the air transfer ratio (r_o), the specific heat of the air (c_a, in J/kg K), the temperature difference between the inside of the container and the ambient external temperature (ΔT_j, in degrees K), and the duration of unloading time (u_j):

$$TE_j = m_a . r_o . c_a . \Delta T_j . u_j \tag{1}$$

The accumulated heat inside the container while unloading at customer *j* (AE_j, in joules) is a function of the air mass (m_a), the specific heat of air (c_a), cargo mass (m_{c_j}, in kg), the specific heat of the cargo (c_c in J/kg K), and the rate of change in temperature ($\frac{dT}{dt}$):

$$AE_j = \left(m_{c_j} c_c + m_a c_a\right) \frac{dT}{dt} \tag{2}$$

The overall rate of heat transfer into the container is equal to the rate of accumulation of heat inside the container (Holdsworth, Simpson, & Barbosa-Cánovas, 2008). The energy balance model is established by equating the overall rate of heat transferred into the container (TE_j) with the rate of accumulation of heat inside the container (AE_j). This relationship can be used to predict the temperature inside the container at customer *j* (T_j) when the door is open for duration t ($t \leq u_j$), given an initial temperature T_0, and an outside temperature T_{out}.

$$m_a . r_o . c_a . \Delta T_j . t = \left(m_{c_j} c_c + m_a c_a\right) \frac{dT}{dt} \tag{3}$$

$$\int_0^t \frac{m_a.r_o.c_a}{\left(m_{c_j}c_c+m_ac_a\right)}dt = \int_{T_0}^{T_j} \frac{dT}{(T_{out}-T)} \tag{4}$$

$$\frac{m_a.r_o.c_a}{\left(m_{c_j}c_c+m_ac_a\right)}(t-0) = -(\ln\left(T_{out}-T_j\right) - ln(T_{out}-T_0))\ ) \tag{5}$$

$$-\frac{m_a.r_o.c_a}{\left(m_{c_j}c_c+m_ac_a\right)}.t = \ln\frac{\left(T_{out}-T_j\right)}{(T_{out}-T_0)} \tag{6}$$

$$T_j = T_{out} - (T_{out} - T_0).e^{-\frac{m_a.r_o.c_a}{\left(m_{c_j}c_c+m_ac_a\right)}.t} \tag{7}$$

3.1.2 Temperature prediction during transportation

The heat absorbed by the container during unloading must be removed during the transportation phase. The vehicle's cooling equipment compensates for the transferred heat by blowing cold air inside the container during transportation, which lowers the temperature. The amount of heat that can be removed from the inside of the container by the cooling equipment is denoted by Q_C. Again, the energy balance model can be used to predict the temperature drop (T_p) inside the container during transportation by equating the rate of heat that can be removed by the cooling equipment to the rate of accumulation of heat inside the container:

$$Q_C = AE \tag{8}$$

$$Q_C = (m_cc_c + m_ac_a)\frac{dT}{dt} \tag{9}$$

$$\int_0^t \frac{Q_c}{(m_cc_c+m_ac_a)}dt = \int_{T_0}^{T_p} dT \tag{10}$$

$$\frac{Q_c}{(m_cc_c+m_ac_a)}(t-0) = (T_p - T_0) \tag{11}$$

$$T_p = \frac{Q_c}{(m_cc_c+m_ac_a)}.t + T_0 \tag{12}$$

Eq. 12 shows that the cooling equipment removes $\frac{Q_c}{(m_cc_c+m_ac_a)}$ heat in each unit of time. However, because the cooling system does not operate while the temperature is at or below the desired temperature (T_d), the actual temperature during transportation is:

$$T = Max\{T_p\ , T_d\} \tag{13}$$

3.2 Modeling the effect of temperature on food quality

To deliver high-quality and safe products to customers, a refrigerated vehicle's storage must maintain a low-temperature environment during distribution. Microbial growth, which is a primary contributor to perishable food spoilage and quality loss, is inhibited at low temperatures (Jedermann, Ruiz-Garcia, & Lang, 2009). Food scientists have defined specific temperature ranges at which food products can be stored to minimize food safety risks and maximize product shelf life (Aung & Chang, 2014). Any temperature fluctuation outside the target range can stimulate the growth of pathogens and Specific Spoilage Organisms (SSOs) in perishable food products (Mercier, Villeneuve, Mondor, & Uysal, 2017). The growth rate of SSOs is a function of storage temperature and time, where higher temperatures result in more rapid quality degradation (Bruckner, Albrecht, Petersen, & Kreyenschmidt, 2013), and temperature abuses over extended periods of time can cause considerable quality loss (Ashby & of Agriculture. Office of Transportation, 2004). A perishable food product reaches the end of its shelf-life when the number of SSOs reaches a maximum acceptable level, or when major changes in the texture, odor, color, and/or shape of the product occur (Borch, Kant-Muermans, & Blixt, 1996; Huis In't Veld, 1996; Kreyenschmidt et al., 2010; Nychas, Marshall, & Sofos, 2007). At this point, the products should no longer be consumed. Almonacid-Merino & Torres (1993) described a model that predicts the effects of temperature abuses and packaging characteristics on product shelf life. They demonstrated that even small deviations in temperature can result in a significant loss of shelf life during distribution. Gill & Phillips (1993) collected temperature data from the surface of hanging beef in refrigerated railway wagons and road trailers. They used this data to model the growth of bacteria during distribution, demonstrating that refrigerated railway wagons' cooling capabilities result in longer shelf life.

In most existing studies, quality loss is assumed to decline linearly over time (Gram et al., 2002; Nychas, Skandamis, Tassou, & Koutsoumanis, 2008). Several studies combine temperature history and kinetic spoilage models to predict microbial growth in food products. The kinetic modeling approach aims to predict the spoilage of the food products based on an understanding of chemical reactions within the products. In these studies, food product temperature is continuously monitored to ensure that it remains in the desired range, and the resulting time-temperature data are used to predict the products' remaining shelf life (Giannakourou, Koutsoumanis, Nychas, & Taoukis, 2001; Taoukis, 2010). Zanoni & Zavanella (2012) used the kinetic model to determine optimal FSC temperatures for different constant temperature scenarios, given the tradeoff between maintaining product quality and saving energy. To relax the assumption of constant temperature, Van Impe, Nicolai, Martens, De Baerdemaeker, and Vandewalle (1992) applied a first-order differential equation over the entire biokinetic temperature range of bacterial growth and inactivation to predict bacterial population as a function of time and temperature.

Since the temperature of the refrigerated vehicle's storage container dynamically changes throughout a delivery route with frequent stops, it is more accurate to use a model that captures nonlinear quality degradation for non-isothermal conditions. Therefore, the approach described in this paper applies the modeling methods of Bruckner et al. (2013) and Kreyenschmidt et al. (2010) which is also used by Gharehyakheh, Krejci, Cantu, & Rogers (2019) to provide a shelf life prediction model as a reliable and non-expensive tool to manage the perishable inventory of the food banks, in which the growth of SSOs over time is estimated using the Gompertz model (Gibson, Bratchell, & Roberts, 1987), and temperature-dependent parameters of the model are predicted by the Arrhenius equation (Arrhenius, 1889) at each time step.

The Gompertz model is used to describe the growth of SSOs with time (Eq. 14):

$$N(t) = A + C * e^{-e^{-B(t-M)}} \tag{14}$$

N(t): SSO count ($\log_{10}$ cfu/g) at time *t*,
A: initial SSO count of the food product at the time it is loaded into a refrigerated vehicle (log10 cfu/g)
C: the difference between the maximum SSO population level (a constant defined for each type of food product) and the initial SSO count *A* ($\log_{10}$ cfu/g)
M: time at which the maximum growth rate is obtained (h)
B: relative growth rate at time *M* (h^{-1})

The Arrhenius equation (Eq. 15) assesses the impact of temperature (T) on the relative SSO growth rate (*B*):

$$ln(B) = \ln(F) - \frac{E_a}{R}.(\frac{1}{T}) \tag{15}$$

F: pre-exponential factor describing the number of times two molecules collide
E_a*:* activation energy for growth of SSOs (J/mol)
R: gas constant (8.314 J/mol K)
T: absolute temperature (K)

The growth rate *B* for any temperature value can be estimated as $\hat{B}$ by evaluating the Gompertz model for different temperature scenarios. The accuracy of the estimated values has been demonstrated for many different types of food products (for pork and poultry, see Bruckner et al. (2013), and for ham, see Kreyenschmidt et al. (2010)).

The parameter *M*, which is the time at which the maximum SSO growth rate occurs, changes according to changes in temperature. The value of *M* can be calculated by rearranging Eq. 14 and can be initialized using values derived from an empirically defined linear regression model of M against temperature (Bruckner et al., 2013). The value of M at current time t_e depends on the SSO count at the previous time, $N(t_{e-1})$, and the estimated value of relative growth rate at the current temperature, $\hat{B}$.

$$M = \frac{\ln\left(-\ln\left(\frac{N(t_{e-1})-A}{C}\right)\right)}{\hat{B}} + t_e \tag{16}$$

Eq. 14 and Eq. 15 can be integrated to predict the growth of SSOs under non-isothermal conditions (Kreyenschmidt et al., 2010).

3.3 Modeling the effect of food quality on market value

Because consumers prefer to purchase fresh products, quality loss reduces the likelihood that a retailer will be able to sell a product. Therefore, if distribution times are long, or if products face frequent temperature abuses during distribution, they are less likely to be sold and more likely to become waste.

The loss of market value due to quality loss in food products has been incorporated into existing models of food distribution. Mirzaei and Seifi (2015) considered the impact of perishable inventory age on lost sales when optimizing inventory and routing plans for perishable products. Hsiao, Chen, and Chin (2017) assumed that the market values for different levels of quality are known, such that temperature during distribution and routing can be optimized to meet customers' expectations as closely as possible. In their model, the difference between the actual value of the delivered products and customers' expected value is considered as a cost in the objective function.

The model described in this paper incorporates the effect of food quality on its market value by using the concept of a Quality Reduction Point (QRP). Bortolini, Faccio, Ferrari, Gamberi, and Pilati (2016) and Osvald and Stirn (2008) define the QRP for a particular product as the percentage of its shelf life at which the retailer no longer expects to sell it at its full price, because observable changes in product shape, color, texture, or odor discourage customers from purchasing it at full price. It is assumed that consumers are willing to pay full price for products that have not passed their QRP because their observable quality is still acceptable. Beyond the QRP, the retailer will discount the price of the product according to its loss in quality. If the product surpasses its maximum shelf life, the retailer will discard it (i.e., it becomes food waste), which incurs a disposal cost.

An example of the relationship between food quality and market value over time with respect to the QRP and maximum shelf life is illustrated in Fig. 3. While the loss of quality for perishable products is often modeled as a linear function of time (Osvald & Stirn 2008), in reality, the functions are nonlinear. Applying the Gompertz model and Arrhenius equation (as described below) to more accurately estimate SSO growth rate and quality loss yields a more realistic nonlinear pattern of quality loss.

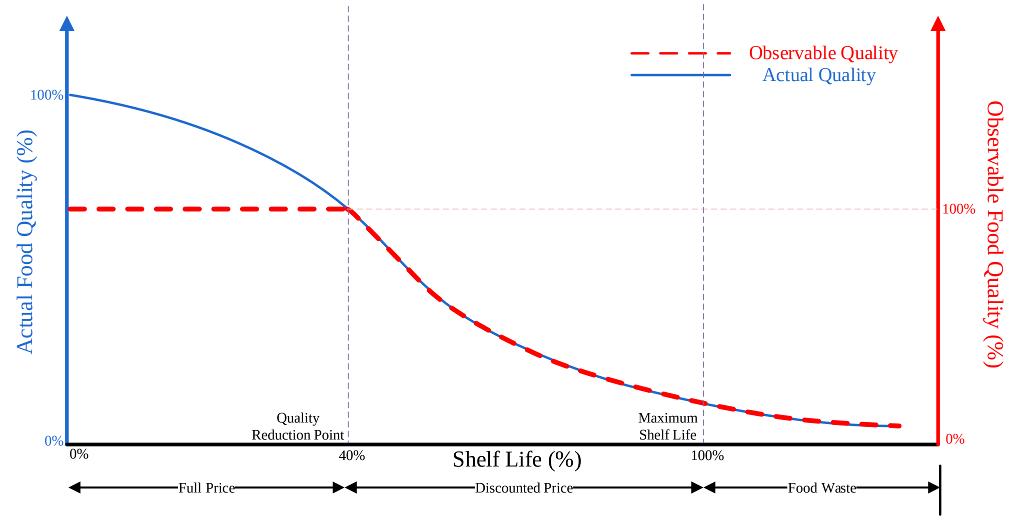

Figure 3-3. Example of the relationship between food quality and market value over time (Adapted from Osvald & Stirn (2008))

The model described in this paper evaluates the cost of quality loss for an item by first quantifying its purchase probability ∅ when it arrives at a retailer's location with a known shelf life, using the method of Osvald & Stirn (2008):

$$\emptyset = Min\left\{\frac{1-SL}{1-QRP}, 1\right\} \tag{17}$$

If the product's shelf life loss (*SL)* is less than its QRP, it is assumed that the delivered products will be sold at the highest possible price, Pr. If the loss in the shelf life is greater than the QRP, there is a probability ∅ that the retailer will be able to sell the product; otherwise, with probability *1-∅,* it will reach the end of its shelf life before it is sold and therefore must be discarded. Hence, the retailer loses the potential revenue of selling the product and must also pay for disposal with probability *1-∅*:

$$(1-\emptyset).(Pr + Dis) \tag{18}$$

1-∅: the probability of not being able to sell the product,
Pr*:* highest market price of the product,
Dis*:* disposal cost of the product

4. QD-VRPTW model

In this section, it is illustrated how the VRPTW module is connected to the quality dependent module. The quality costs represented by the Eq. 18 is added to the transportation cost of the conventional VRPTW in the objective function. Now, the objective function of the QD-VRPTW is an accurate representation of the distribution costs of perishable food products.

The food distribution problem is defined as a directed graph, where G = (N, A) is a graph in which N= {0, 1, …, n} is the set of nodes, with node 0 representing the depot, C = {1, …, n} representing the set of customers, and A = {(i, j): i, j ∈ N, and i ≠ j} is the set of arcs representing the possible transportation paths between nodes. A fleet of homogenous vehicles V = {1, …, v}, each with capacity Q, deliver food from the depot to the customers. Customer i requests delivery of d_i products in the interval between times a_i and b_i. It is assumed that each customer's demand is less than the capacity of a vehicle to deliver with a single visit. Further, it is assumed that deliveries are only allowed during the customers' requested time intervals; if a vehicle arrives early at the location of customer i, it must wait until time a_i to begin unloading its cargo. For ease of reference, all notations are as follows:

Sets

C = {1, …, n} set of customers
V = {1, …, v} set of vehicles
N = {0} ∪ C set of depot and customers

Parameters

c_{ij}	cost of traveling from node i to node j
$\emptyset_i$	probability of being able to sell the product
Pr	price of an item
Dis	disposal cost of an item
t_{ij}	travel time from customer i to customer j
Q	capacity of a vehicle
d_i	demand of customer i
$[a_i, b_i]$	required time window for delivery to customer i
ut	average unloading time for one unit of product
u_i	unloading time at customer i, where $u_i = \frac{d_i}{ut}$ and $u_i \leq b_i - a_i$

Decision variables

y_{ik}	the time that vehicle k arrives at node i

x_{ijk} equals 1 if vehicle k travels from node i to node j, 0 otherwise
l_{ijk} amount of load carried by vehicle k between nodes i and j, in units of products

The mathematical formulation of the QD-VRPTW is as follows:

$$Minimize\ Z = \sum_{k\epsilon V}\sum_{i\epsilon N}\sum_{j\epsilon N} c_{ij}\, x_{ijk} + \sum_{i\epsilon N}(1-\emptyset_i)(Pr + Dis)\, d_i \qquad (19)$$

$$\sum_{k\epsilon V}\sum_{j\epsilon N} x_{ijk} = 1 \qquad \forall\ i \in C,\ i \neq j \qquad (20)$$

$$\sum_{i\epsilon C} d_i \sum_{j\epsilon N} x_{ijk} \leq Q \qquad \forall\ k \in V,\ i \neq j \qquad (21)$$

$$\sum_{j\in C} x_{0jk} \leq 1 \qquad \forall\ k \in V \qquad (22)$$

$$\sum_{i\epsilon N} x_{ihk} - \sum_{j\epsilon N} x_{hjk} = 0 \qquad \forall\ h \in N,\ k \in V \qquad (23)$$

$$\sum_{j\in N}\sum_{k\in V} l_{jik} - \sum_{j\in N}\sum_{k\in V} l_{ijk} = d_i \qquad \forall\ i \in C \qquad (24)$$

$$y_{ik} + u_i + t_{ij} - M\left(1 - x_{ijk}\right) \leq y_{jk} \qquad \forall\ i \in C,\ j \in N,\ k \in V \qquad (25)$$

$$t_{0j} \leq y_{jk} + M\left(1 - x_{0jk}\right) \qquad \forall\ j \in C,\ k \in V \qquad (26)$$

$$a_i \leq y_{ik} \leq b_i \qquad \forall\ i \in C,\ k \in V \qquad (27)$$

$$l_{ijk} \leq (Q - d_i)x_{ijk} \qquad \forall\ i \in N,\ j \in N,\ k \in V \qquad (28)$$

$$d_j x_{ijk} \leq l_{ijk} \qquad \forall\ i \in N,\ j \in C,\ k \in V \qquad (29)$$

$$y_{ik} \geq 0 \qquad \forall\ i \in C,\ k \in V \qquad (30)$$

$$l_{ijk} \geq 0 \qquad \forall\ i \in N,\ j \in C,\ k \in V \qquad (31)$$

$$x_{ik} \in \{0,1\} \qquad \forall\ i \in C,\ k \in V \qquad (32)$$

The objective (19) minimizes both transportation costs and the cost of food waste (adapted from Eq. (5)). If customer j receives a product with a shelf life that has exceeded the quality reduction point (QRP), the probability that customer j will not be able to sell the product is $(1-\emptyset_i)$, where $0 \leq \emptyset_i < 1$. Therefore, customer i loses the sales revenue for that product and must also pay for disposal. Constraint (20) shows that only one vehicle can visit each node. A vehicle cannot carry loads greater than its capacity, constraint (21). Constraint (22) implies that a vehicle can only depart from the depot at most one time. If a vehicle enters a node, it should leave the node to maintain the flow of delivery, constraint (23). The amount of unloaded cargo at each location should be equal to the demand at that location, constraint (24). Constraint (25) shows that the next customer cannot be visited earlier than the arrival time at the previous customer plus unloading time and the time it takes to travel between those two customers. In constraint (26), the time that the first customer is visited cannot be earlier than the time it takes to travel between the depot and the customer. Customers must be visited at the time requested by the customer, constraint (27). The load carried by a vehicle between two nodes cannot be greater than the capacity of the vehicle, minus the previous customer's demand, and it should be at least equal to the demand of the next customer, constraints (28-29). Constraints (30-32) provide the nonnegativity and integrality constraints on the decision variables.

5. Solution approach

With the inclusion of the quality loss component, the objective function of the QD-VRPTW model (Eq. 19) becomes nonlinear. Metaheuristic algorithms are appropriate and efficient search tools to find globally optimized solutions to nonlinear models (Gandomi, Yang, Talatahari, & Alavi, 2013). SA is a powerful metaheuristic search technique that is used to solve the QD-VRPTW model. The SA optimization algorithm is an iterative algorithm that begins each iteration by evaluating a candidate solution. The algorithm explores the neighborhood of this candidate solution by making small changes to its structure. If a neighboring solution improves the value of the objective function, it will become the new best candidate solution. However, even if the neighboring solution does not improve the objective function, it can still potentially be chosen as the new best solution, according to a probability that decreases as the number of SA iterations increases. The purpose of this randomness is to explore the solution space to find a globally optimal solution by preventing stagnation at a locally optimal solution.

SA is based on the concept of annealing, in which metal is heated to a high temperature and is then slowly cooled in a controlled environment to achieve desired physical properties (e.g., strength, ductility). Similarly, a "temperature" parameter is used in the SA algorithm to control the rate of exploration and exploitation of the solution space. The value of this "temperature" parameter is set high initially (i.e., high rate of exploration), and it slowly decreases as the algorithm runs (i.e., less exploration and more exploitation of high-quality solutions).

The elements of the SA algorithm are as follows:

Temperature (T): a parameter that defines the size of the search space to be explored in a given iteration.
Fitness value (f): the value of the objective function for a given solution.
Neighbor search: the process of randomly selecting a solution that is close to the current one.
Best solution: the best possible neighboring solution found in each iteration.
$\Delta f = f(x_{new}) - f(x_{current})$: the difference between the fitness values associated with the new and current solutions.
Probability (P(Δf, T)): determines whether the new solution is selected as the new best solution, based on the current value of T and the difference between the new and current solutions' fitness values:

$$P(\Delta f, T) = \begin{cases} 1 & f(x_{new}) \leq f(x_{current}) \\ e^{-\frac{\Delta f}{T}} & f(x_{new}) > f(x_{current}) \end{cases} \tag{33}$$

Termination criterion: the condition that determines when the algorithm stops running.

5.1 Proposed SA algorithm

The key decision is how to assign *n* customers to *v* vehicles. To accomplish this, a one-dimensional array is first created to store the current solution. This array is divided into *v* sections that are separated by *v*-1 special characters (see Fig. 5 for an example, where *v* = 3 and the special characters are "*"), and customer numbers are grouped in the array according to their assigned vehicles. In the example shown in Fig. 4, the demand of seven customers is allocated to three vehicles: customers 5 and 3 are assigned to vehicle 1, customers 1, 4, and 2 are assigned to vehicle 2, and customers 7 and 6 are assigned to vehicle 3. Note that the order of the customer numbers in the array designates the order in which these customers are visited by their assigned vehicle, i.e., the routing.

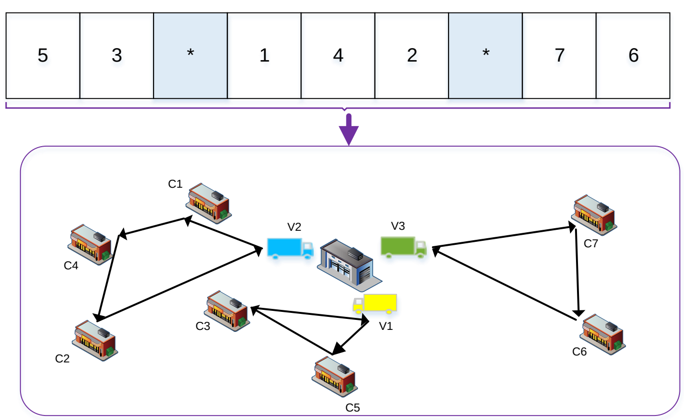

Figure 3-4. SA solution encoded as a vehicle routing schedule.

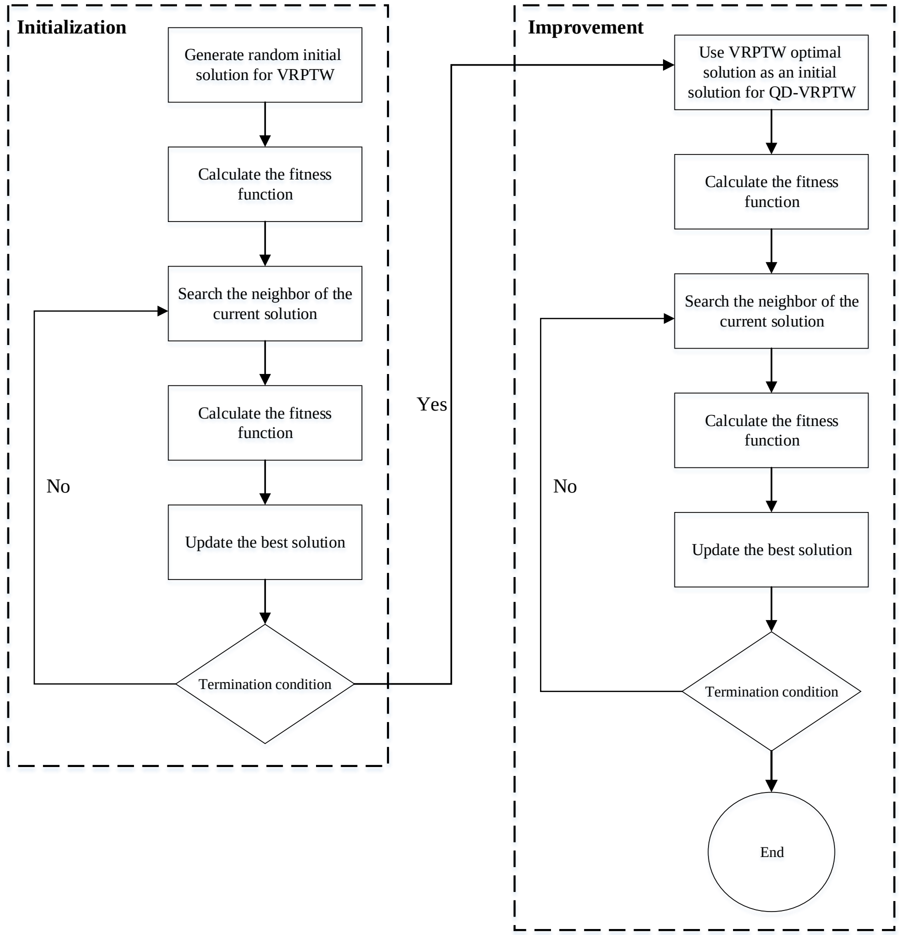

Figure 3-5. Proposed SA algorithm.

The main difference between the VRPTW and QD-VRPTW models is the fitness function. The VRPTW objective is to minimize the transportation cost, while the QD-VRPTW objective function includes both transportation and quality losses. In order to save computational time, the corresponding VRPTW is first solved using the SA algorithm to generate an initial solution to the original QD-VRPTW. A flowchart representing the SA algorithm is shown in Fig. 5.

The steps of the SA algorithm to solve the VRPTW problem are summarized as follows:

1. Generate a random initial solution.

Randomly assign customers and *v*-1 special characters to a one-dimensional array.

2. Calculate the fitness value.

The current solution matrix is decoded as a routing schedule, and the objective function value associated with this schedule is calculated using Eq. (19). In addition, penalties for capacity and time window violations are added to the objective function value to obtain the fitness value:

$$\text{Fitness value} = (\text{objective value}).(1 + \overline{CapV}.M_1 + \overline{TWV}.M_2) \qquad (34)$$

$\overline{CapV}$: average capacity violation for all vehicles.

$\overline{TWV}$: average time window violation for all vehicles.

M_1, M_2: sufficiently large number to generate feasible solutions.

3. Search the neighbors of the current solution.

Either swap, reversion, or insertion operators are randomly selected to find a new neighbor for the current solution. Fig. 6 shows how these three operators work.

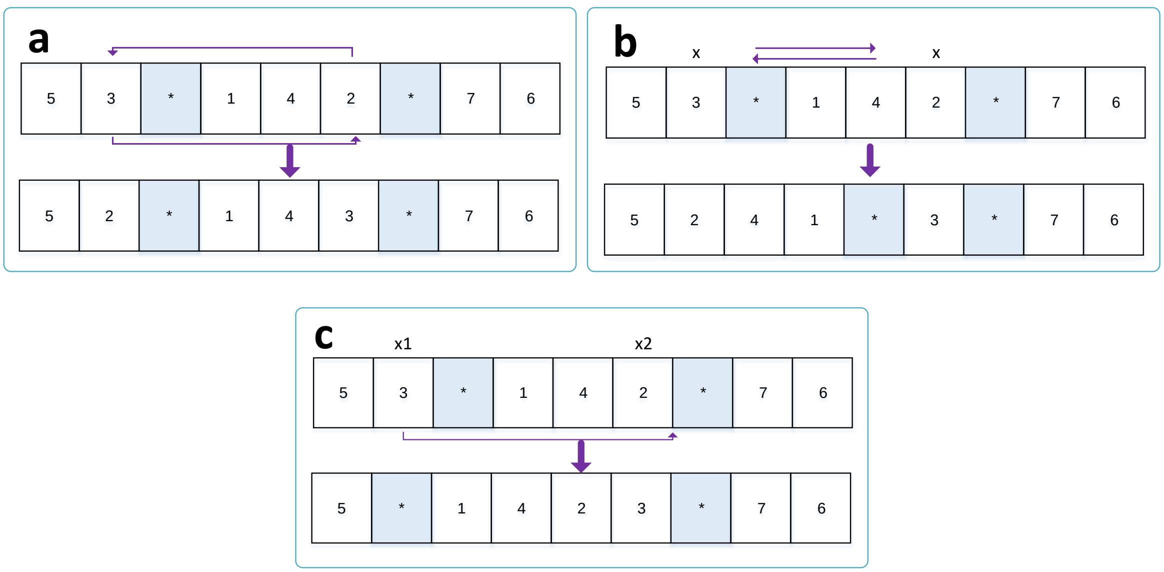

Figure 3-6. Swap, reversion, and insertion operators to create a new neighbor.

Swap operator (Fig. 6a)*:* two elements are randomly selected, and their locations are exchanged.

Reversion operator (Fig. 6b)*:* the order of any elements in between two randomly selected elements is reversed.

Insertion operator (Fig. 6c)*:* the first randomly selected element is moved to the right of the second randomly selected element.

4. Update the best solution.

The new solution is stored as the new best solution with a probability of P(Δf, T), per Eq. (33).

5. Evaluate termination criterion.

The algorithm terminates when the fitness value stops improving. Specifically, the algorithm terminates when it is unable to find a better solution in 10*(*v***n*) consecutive iterations; otherwise, it returns to the third step.

The same steps are followed to solve the QD-VRPTW, except that the corresponding VRPTW solution is used as the initial solution.

6. Results and discussion

In this section, the performance of the proposed QD-VRPTW model is compared with the VRPTW model, using frozen poultry distribution as an example. Both models are solved using the SA algorithm for small, medium, and large-scale test problems. Because VRPTW does not consider quality loss, only the initialization part of the algorithm is applied to find the optimal solutions for VRPTW.

Five test problems were created for each of the three problem size categories. For each of these test problems, the following model parameters were defined: number of customers, customer demand, customer locations (i.e., x- and y-coordinates), ambient temperature at each customer location, customer delivery time windows, number of available vehicles, and vehicle capacity. Euclidean distance is assumed as the travel distance between two customers.

Table 1 summarizes the results, which indicate that for frozen poultry, including the cost of quality when determining delivery vehicle routings can reduce total distribution costs by as much as 16%. Furthermore, the results show that the transportation costs that result from using the VRPTW model are always less than or equal to QD-VRPTW transportation costs. This is unsurprising, given that the objective of the VRPTW model focuses strictly on minimizing transportation costs. Similarly, quality costs in the QD-VRPWT model are always less than or equal to the quality costs in the VRPTW model. However, as the size of the problem increases, the differences in cost of quality between these two models increase. Because there are more feasible alternative solutions in the search space of larger-scale problems, the algorithm has a greater opportunity to find better-quality solutions. As a result, QD-VRPTW performance always dominates VRPTW (see Fig. 7).

Table 3-1. Comparison of VRPTW and QD-VRPTW performance for frozen poultry distribution

Problem Size	Example	No. of customers	No. of vehicles	VRPTW Costs ($)			QVRPTW Costs ($)			PD*
				Transportation	Quality	Total	Transportation	Quality	Total	
Small	1	3	1	766	75	841	766	75	841	0.00%
	2	4	2	527	14	541	527	14	541	0.00%
	3	5	2	710	69	779	710	69	779	0.00%
	4	7	3	776	219	995	776	219	995	0.00%
	5	8	3	930	130	1060	930	130	1060	0.00%
Medium	6	12	4	1141	494	1635	1141	494	1635	0.00%
	7	13	5	1233	556	1789	1242	452	1694	5.61%
	8	15	5	1457	567	2024	1468	423	1891	7.03%
	9	17	5	1553	789	2342	1594	610	2204	6.26%
	10	19	6	1711	852	2563	1723	634	2357	8.74%
Large	11	20	6	1642	873	2515	1682	623	2305	9.11%
	12	30	5	1727	812	2539	1820	468	2288	10.97%
	13	35	7	2036	1038	3074	2120	523	2643	16.31%
	14	40	6	2098	1205	3303	2156	748	2904	13.74%
	15	50	7	2513	1426	3939	2564	852	3416	15.31%

* Percentage Difference (PD) = ($VRPTW_{\text{Total costs}}$ – $QD\text{-}VRPTW_{\text{Total costs}}$) / ($VRPTW_{\text{Total costs}}$)

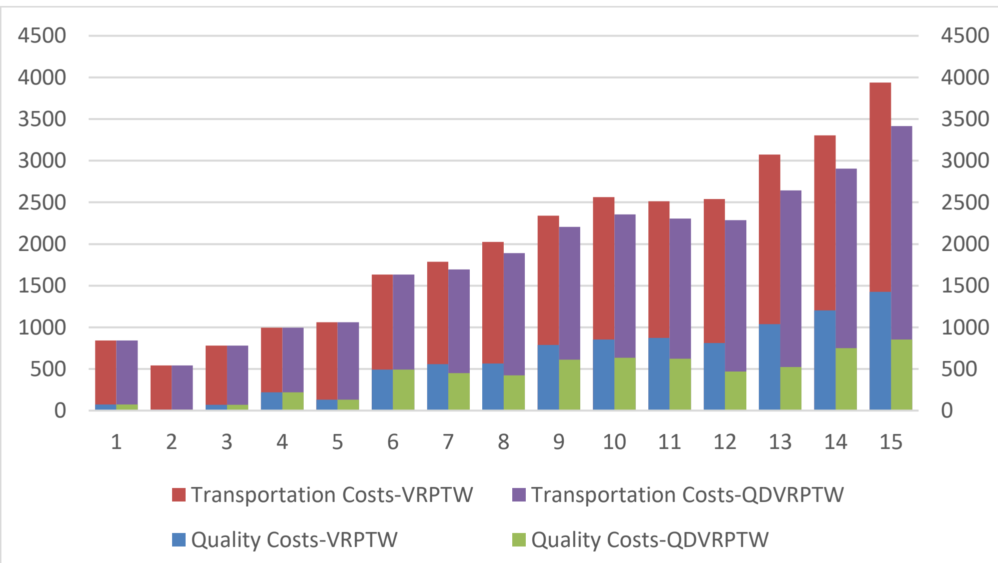

Figure 3-7. Comparison of delivery costs in QD-VRPTW and VRPTW for each test problem

To demonstrate the impact of quality cost inclusion on the delivery sequence and routing decisions, the optimal routings generated by VRPTW and QD-VRPTW for two test problems are compared. Figs 8a and 8b illustrate a test problem in which a single vehicle delivers to customer 1 (c_1) and customer 2 (c_2), which demand 20 and 50 units of frozen poultry, respectively. Both customers are located the same distance from the depot. The VRPTW objective function yields the same value for either delivery sequence because this approach only considers transportation cost, which is the same for both sequences. Therefore, when VRPTW recommends that customer 2 (which has greater demand and longer unloading time) should be visited first (as in Fig. 8a), customer 1's order is exposed to higher temperatures for a longer time than in the alternative sequence (shown in Fig. 8b). Since QD-VRPTW differentiates the sequences based on the cost of quality loss, it recommends the sequence shown in Fig. 8b, in which products are first delivered to the customer with lower demand. Table 2 summarizes the results generated by each approach.

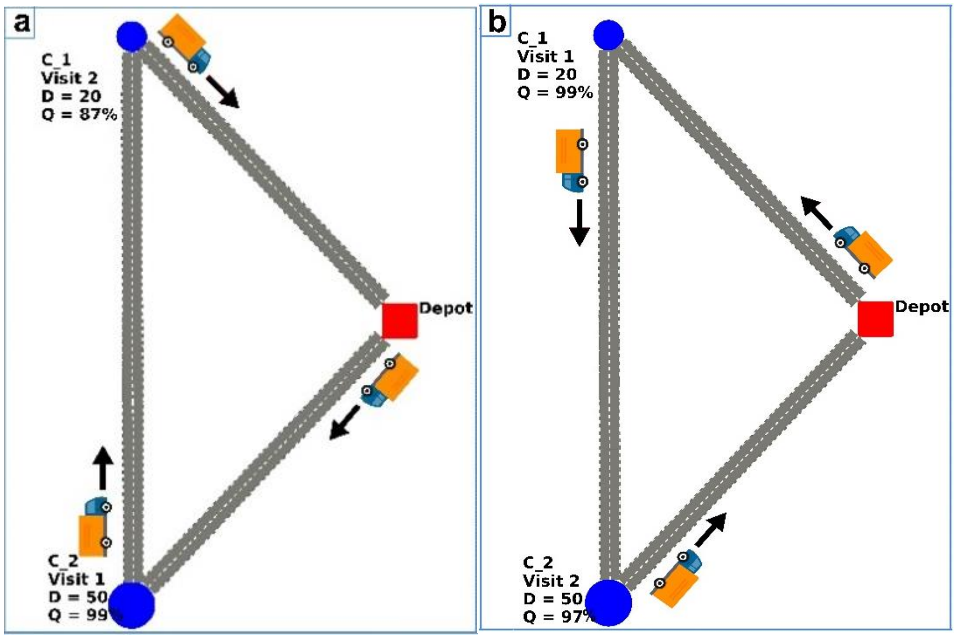

Figure 3-8. The optimal vehicle routing for 2 customers and 1 vehicle; Fig. a is VRPTW solution, Fig. b is QD-VRPTW solution

Table 3-2. Comparison of the VRPTW and QD-VRPTW optimal solutions for 2 customers and 1 vehicle

Model	C	V	Visit	Delivered Quality (%)	Quality Cost ($)	Transportation Cost ($)	Total Cost ($)
VRPTW	1	1	2	87	208	618	826
	2	1	1	99			
QD-VRPTW	1	1	1	99	170	618	788
	2	1	2	97			

Figs 9a and 9b illustrate results generated by VRPTW and QD-VRPTW, respectively, for a test problem with three customers and two vehicles. VRPTW recommends the use of one vehicle, which causes customer 1's order to experience longer and more frequent temperature abuses than in the QD-VRPTW solution, which recommends the use of two vehicles. The use of a single vehicle yields lower transportation costs; however, Table 3 shows that the total cost is lower for the QD-VRPTW solution since its higher transportation cost is compensated by reducing the quality cost.

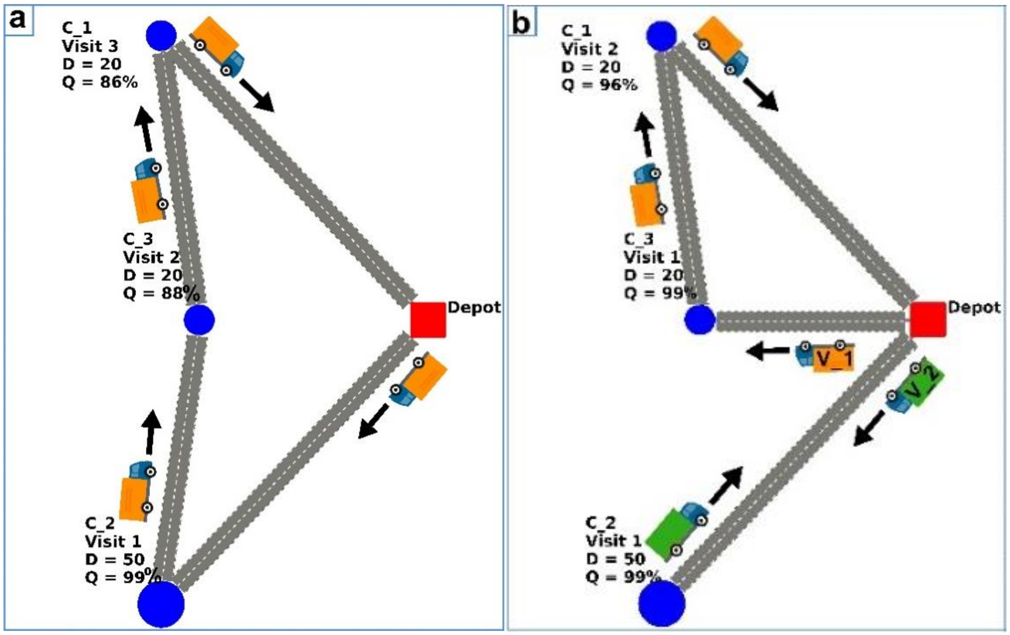

Figure 3-9. The optimal vehicle routing for 3 customers and 2 vehicles; Fig. a is VRPTW solution, Fig. b is QD-VRPTW

Table 3-3. Comparison of VRPTW and QD-VRPTW optimal solutions for 3 customers and 2 vehicles

Model	C	V	Visit	Delivered Quality (%)	Quality Cost ($)	Transportation Cost ($)	Total Cost ($)
	1	1	3	86			
VRPTW	2	1	1	88	300	634	934
	3	1	2	99			
	1	1	2	96			
QD-VRPTW	2	2	2	99	80	765	845
	3	1	1	99			

Different perishable food products will have different sensitivity to temperature abuses, as well as different market values, which will influence the optimal delivery sequence and routing generated by QD-VRPTW. High-value products that are highly sensitive to temperature variation (e.g., fresh produce) will be more likely to result in a solution in which orders are shipped directly to customers. In contrast, lower-value products with lower temperature sensitivity (e.g., frozen foods) will allow for greater flexibility, such that fewer and fuller vehicles will deliver to multiple locations. To demonstrate this, Table 4 compares the QD-VRPTW quality costs and transportation costs of a food distribution system with 35 customers and 7 vehicles for three different products. In this example, fresh-cut salad has the highest sensitivity to temperature abuses. As a result, the transportation cost for fresh-cut salad is 37% higher than for frozen poultry. Following the same logic, gouda cheese and frozen poultry meat have the second and the third highest transportation costs, respectively.

Table 3-4. Results of QD-VRPTW for different types of perishable food products

Product	Relative Level of Temperature Sensitivity*	Market Price (per lb.)	Quality Costs ($)	Transportation Costs ($)
Poultry frozen meat**	Low	$2	2035	1171
Fresh cut salad***	High	$4	2336	1610
Gouda Cheese****	Medium	$7	2036	1494

* It is assumed that a higher SSOs growth rate and lower shelf life for a product at a specific temperature corresponds to a higher sensitivity to the temperature.
** Data is collected from Bruckner et al. (2013).
*** Data is collected from Tsironi et al. (2017).
**** Data is collected from Weiss, Stangierski, Baranowska, & Rezler (2018).

Conclusion

The sensitivity of perishable food products to the temperature significantly increases the complexity of FSC distribution problems. The frequency and duration of vehicle stops elevate the growth rate of SSOs since the products frequently face temperature abuses before they are delivered to customers. The resulting loss of shelf life and quality can significantly reduce retailer revenue and increase food waste. Hence, increasing the number of vehicles and reducing the frequency of stops can improve the quality of perishable food products, but it can also result in higher transportation costs. Therefore, the quality loss must be quantified to measure its effect on the efficiency of routing decisions.

This paper presents a new modeling approach that integrates VRPTW with a food quality prediction model to accurately capture the cost of quality loss in the perishable food routing problem. The cost of quality loss of a route is highly impacted by the temperature rises resulted from transferring the heat of hot ambient air to the cold environment inside the container when its door is open to unload part of the load. The temperature fluctuations are predicted by a set of energy balance equations which helps to provide an accurate prediction of quality loss using a combination of Arrhenius equation and Gompertz model. The integration of quality loss in the form of cost with transportation cost in the QD-VRPTW model provides a novel way to predict food quality based on the estimation of temperature during distribution. A metaheuristic SA algorithm is developed to find optimized solutions that minimize the summation of quality and transportation costs in the complex perishable food distribution model.

The importance of accurately modeling the relationship between perishable food distribution decisions and product quality is illustrated in a set of small, medium, and large-scale test problems for frozen poultry meat products. Additionally, a set of descriptive examples demonstrate how the QD-VRPTW modeling approach can prevent quality loss in the FSC by changing the optimal delivery sequence and routing solutions. To demonstrate how temperature sensitivity and market value affect optimal routing solutions, the proposed approach is applied to frozen poultry meat, fresh-cut salad, and gouda cheese.

A limitation of the model described in this paper is the assumption of a single type of food product. This assumption ignores interactions between multiple products, as well as their different temperature requirements. Finding optimal temperature settings for the delivery of multiple products with interaction constraints is a valuable potential direction for future research. In addition, the energy balance equation used in this model only predicts the temperature inside the vehicle's container. This equation could be modified to accurately measure the energy consumed to maintain the temperature in the desired range during distribution.

The results of this study indicate that implementing QD-VRPTW in planning for perishable food distribution has the potential to yield significant economic and environmental savings, especially for large-scale problems, by increasing the quality of delivered products, thereby increasing the likelihood that they will be sold before the end of their shelf life. This benefits actors at every level of the food supply chain.

References:

Ahumada, O., & Villalobos, J. (2011). A tactical model for planning the production and distribution of fresh produce. *Annals of Operations Research*, *190*(1), 339–358. https://doi.org/10.1007/s10479-009-0614-4

Albrecht, W., & Steinrücke, M. (2018). Coordinating continuous-time distribution and sales planning of perishable goods with quality grades. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2017.1384584

Almonacid-Merino, S. F., & Torres, J. A. (1993). Mathematical models to evaluate temperature abuse effects during distribution of refrigerated solid foods. *Journal of Food Engineering*. https://doi.org/10.1016/0260-8774(93)90066-S

Amorim, P., & Almada-Lobo, B. (2014). The impact of food perishability issues in the vehicle routing problem. *Computers and Industrial Engineering*. https://doi.org/10.1016/j.cie.2013.11.006

Amorim, P., Günther, H. O., & Almada-Lobo, B. (2012). Multi-objective integrated production and distribution planning of perishable products. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2012.03.005

Arrhenius, S. (1889). Über die Reaktionsgeschwindigkeit bei der Inversion von Rohrzucker durch Säuren. *Zeitschrift Für Physikalische Chemie*, *4*(1), 226–248.

Artuso, P., Rossetti, A., Minetto, S., Marinetti, S., Moro, L., & Col, D. Del. (2019). Dynamic modeling and thermal performance analysis of a refrigerated truck body during operation. *International Journal of Refrigeration*, *99*, 288–299. https://doi.org/10.1016/J.IJREFRIG.2018.12.014

Ashby, B. H., & of Agriculture. Office of Transportation, U. S. D. (2004). *Protecting Perishable Foods During Transport by Truck*. U.S. Department of Agriculture, Agricultural Marketing Service, Transportation and Marketing Programs. Retrieved from https://books.google.com/books?id=WnAjwgEACAAJ

Aung, M. M., & Chang, Y. S. (2014). Temperature management for the quality assurance of a perishable food supply chain. *Food Control*, *40*, 198–207.

Blackburn, J., & Scudder, G. (2009). Supply chain strategies for perishable products: The case of fresh produce. *Production and Operations Management*. https://doi.org/10.1111/j.1937-5956.2009.01016.x

Borch, E., Kant-Muermans, M. L., & Blixt, Y. (1996). Bacterial spoilage of meat and cured meat products. *International Journal of Food Microbiology*. https://doi.org/10.1016/0168-1605(96)01135-X

Bortolini, M., Faccio, M., Ferrari, E., Gamberi, M., & Pilati, F. (2016). Fresh food sustainable distribution: Cost, delivery time and carbon footprint three-objective optimization. *Journal of Food Engineering*. https://doi.org/10.1016/j.jfoodeng.2015.11.014

Bruckner, S., Albrecht, A., Petersen, B., & Kreyenschmidt, J. (2013). A predictive shelf life model as a tool for the improvement of quality management in pork and poultry chains. *Food Control*, *29*(2), 451–460.

Chen, H. K., Hsueh, C. F., & Chang, M. S. (2009). Production scheduling and vehicle routing with time windows for perishable food products. *Computers and Operations Research*. https://doi.org/10.1016/j.cor.2008.09.010

Devapriya, P., Ferrell, W., & Geismar, N. (2017). Integrated production and distribution scheduling with a perishable product. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2016.09.019

FAO- Food and Agriculture Organization of the United Nations. (2011). Global food losses and food waste: extent, causes and prevention. In *Save Food! Global Food Losses and Food Waste*. https://doi.org/10.1098/rstb.2010.0126

Farahani, P., Grunow, M., & Günther, H. O. (2012). Integrated production and distribution planning for perishable food products. *Flexible Services and Manufacturing Journal*. https://doi.org/10.1007/s10696-011-9125-0

Gallo, A., Accorsi, R., Baruffaldi, G., & Manzini, R. (2017). Designing sustainable cold chains for long-range food distribution: Energy-effective corridors on the Silk Road Belt. *Sustainability (Switzerland)*. https://doi.org/10.3390/su9112044

Gandomi, A. H., Yang, X.-S., Talatahari, S., & Alavi, A. H. (2013). Metaheuristic applications in structures and infrastructures. In *Metaheuristic Applications in Structures and Infrastructures* (pp. 1–24). London: Elsevier Science. Retrieved from https://books.google.com/books?hl=en&lr=&id=fKKcI4uVTvcC&oi=fnd&pg=PA1&ots=2JEfGhXOci&sig=rfHq6nv9oNsjfR5hnSH4SgHuOTg#v=onepage&q&f=false

Gharehyakheh, A., Krejci, C., Cantu, J., & Rogers, J. (2019). Dynamic Shelf-Life Prediction System to Improve Sustainability in Food Banks. In *IISE Annual Conference and Expo*.

Ghezavati, V. R., Hooshyar, S., & Tavakkoli-Moghaddam, R. (2017). A Benders' decomposition algorithm for optimizing distribution of perishable products considering postharvest biological behavior in agri-food supply chain: a case study of tomato. *Central European Journal of Operations Research*, *25*(1), 29–54. https://doi.org/10.1007/s10100-015-0418-3

Giannakourou, M. C., Koutsoumanis, K., Nychas, G. J. E., & Taoukis, P. S. (2001). Development and assessment of an intelligent shelf life decision system for quality optimization of the food chill chain. *Journal of Food Protection*, *64*(7), 1051–1057.

Gibson, A. M., Bratchell, N., & Roberts, T. A. (1987). The effect of sodium chloride and temperature on the rate and extent of growth of Clostridium botulinum type A in pasteurized pork slurry. *Journal of Applied Bacteriology*, *62*(6), 479–490.

Gill, C. O., & Phillips, D. M. (1993). The efficiency of storage during distant continental transportation of beef sides and quarters. *Food Research International*. https://doi.org/10.1016/0963-9969(93)90026-F

Goodman, D. (2004). Rural Europe Redux? Reflections on alternative agro-food networks and paradigm change. *Sociologia Ruralis*. https://doi.org/10.1111/j.1467-9523.2004.00258.x

Gram, L., Ravn, L., Rasch, M., Bruhn, J. B., Christensen, A. B., & Givskov, M. (2002). Food spoilage—interactions between food spoilage bacteria. *International Journal of Food Microbiology*, *78*(1–2), 79–97.

Haass, R., Dittmer, P., Veigt, M., & Lütjen, M. (2015). Reducing food losses and carbon emission by using autonomous control - A simulation study of the intelligent container. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2014.12.013

Holdsworth, S. D., Simpson, R., & Barbosa-Cánovas, G. V. (2008). *Thermal processing of packaged foods* (Vol. 284). Springer.

Hsiao, Y.-H., Chen, M.-C., & Chin, C.-L. (2017). Distribution planning for perishable foods in cold chains with quality concerns: Formulation and solution procedure. *Trends in Food Science & Technology*, *61*, 80–93.

Hsu, C. I., Hung, S. F., & Li, H. C. (2007). Vehicle routing problem with time-windows for perishable food delivery. *Journal of Food Engineering*. https://doi.org/10.1016/j.jfoodeng.2006.05.029

Huis In't Veld, J. H. J. H. I. (1996). Microbial and biochemical spoilage of foods: An overview. *International Journal of Food Microbiology*. https://doi.org/10.1016/0168-1605(96)01139-7

James, S. J., James, C., & Evans, J. A. (2006). Modelling of food transportation systems - a review. *International Journal of Refrigeration*. https://doi.org/10.1016/j.ijrefrig.2006.03.017

Jedermann, R., Nicometo, M., Uysal, I., & Lang, W. (2014). Reducing food losses by intelligent food logistics. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*. https://doi.org/10.1098/rsta.2013.0302

Jedermann, R., Ruiz-Garcia, L., & Lang, W. (2009). Spatial temperature profiling by semi-passive RFID loggers for perishable food transportation. *Computers and Electronics in Agriculture*, *65*(2), 145–154.

Kreyenschmidt, J., Hübner, A., Beierle, E., Chonsch, L., Scherer, A., & Petersen, B. (2010). Determination of the shelf life of sliced cooked ham based on the growth of lactic acid bacteria in different steps of the chain. *Journal of Applied Microbiology*, *108*(2), 510–520.

Lafaye De Micheaux, T., Ducoulombier, M., Moureh, J., Sartre, V., & Bonjour, J. (2015). Experimental and numerical investigation of the infiltration heat load during the opening of a refrigerated truck body. *International Journal of Refrigeration*. https://doi.org/10.1016/j.ijrefrig.2015.02.009

Mercier, S., Villeneuve, S., Mondor, M., & Uysal, I. (2017). Time–Temperature Management Along the Food Cold Chain: A Review of Recent Developments. *Comprehensive Reviews in Food Science and Food Safety*. https://doi.org/10.1111/1541-4337.12269

Mirzaei, S., & Seifi, A. (2015). Considering lost sale in inventory routing problems for perishable goods. *Computers and Industrial Engineering*. https://doi.org/10.1016/j.cie.2015.05.010

Moureh, J., Menia, N., & Flick, D. (2002). Numerical and experimental study of airflow in a typical refrigerated truck configuration loaded with pallets. *Computers and Electronics in Agriculture*. https://doi.org/10.1016/S0168-1699(01)00178-8

Nakandala, D., Lau, H., & Zhang, J. (2016). Cost-optimization modelling for fresh food quality and transportation. *Industrial Management and Data Systems*. https://doi.org/10.1108/IMDS-04-2015-0151

Novaes, A. G. N., Lima Jr, O. F., Carvalho, C. C. de, & Bez, E. T. (2015). Thermal performance of refrigerated vehicles in the distribution of perishable food. *Pesquisa Operacional*, *35*, 251–284. Retrieved from http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0101-74382015000200251&nrm=iso

Nychas, G.-J. E., Marshall, D. L., & Sofos, J. N. (2007). Meat, Poultry, and Seafood. In *Food Microbiology: Fundamentals and Frontiers, Third Edition* (pp. 105–140). American Society of Microbiology. https://doi.org/10.1128/9781555815912.ch6

Nychas, G.-J. E., Skandamis, P. N., Tassou, C. C., & Koutsoumanis, K. P. (2008). Meat spoilage during distribution. *Meat Science*, *78*(1–2), 77–89.

Osvald, A., & Stirn, L. Z. (2008). A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. *Journal of Food Engineering*. https://doi.org/10.1016/j.jfoodeng.2007.07.008

Rahbari, A., Nasiri, M. M., Werner, F., Musavi, M. M., & Jolai, F. (2019). The vehicle routing and scheduling problem with cross-docking for perishable products under uncertainty: Two robust bi-objective models. *Applied Mathematical Modelling*. https://doi.org/10.1016/j.apm.2019.01.047

Rai, A., Sun, J., & Tassou, S. A. (2019). Numerical investigation of the protective mechanisms of air curtain in a refrigerated truck during door openings. *Energy Procedia*, *161*, 216–223. https://doi.org/10.1016/J.EGYPRO.2019.02.084

Rong, A., Akkerman, R., & Grunow, M. (2011). An optimization approach for managing fresh food quality throughout the supply chain. *International Journal of Production Economics*, *131*(1), 421–429.

Rong, A., & Grunow, M. (2010). A methodology for controlling dispersion in food production and distribution. *OR Spectrum*. https://doi.org/10.1007/s00291-010-0210-7

Spence, S. W. T., Doran, W. J., & Artt, D. W. (2004). Design, construction and testing of an air-cycle refrigeration system for road transport. *International Journal of Refrigeration*. https://doi.org/10.1016/j.ijrefrig.2004.02.003

Taoukis, P. S. (2010). Modelling the use of time-temperature indicators in distribution and stock rotation. In *Food Process Modelling*. https://doi.org/10.1533/9781855736375.5.402

Tarantilis, C. D., & Kiranoudis, C. T. (2002). Distribution of fresh meat. *Journal of Food Engineering*.

https://doi.org/10.1016/S0260-8774(01)00040-1
Tekin, P., & Erol, R. (2017). A New Dynamic Pricing Model for the Effective Sustainability of Perishable Product Life Cycle. *Sustainability*, *9*(8), 1330.
Tsironi, T., Dermesonlouoglou, E., Giannoglou, M., Gogou, E., Katsaros, G., & Taoukis, P. (2017). Shelf-life prediction models for ready-to-eat fresh cut salads: Testing in real cold chain. *International Journal of Food Microbiology*. https://doi.org/10.1016/j.ijfoodmicro.2016.09.032
Tso, C. P., Yu, S. C. M., Poh, H. J., & Jolly, P. G. (2002). Experimental study on the heat and mass transfer characteristics in a refrigerated truck. *International Journal of Refrigeration*. https://doi.org/10.1016/S0140-7007(01)00015-9
U.S. EPA. (2017). *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2015*. Retrieved from https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2015
Van Impe, J. F., Nicolai, B. M., Martens, T., De Baerdemaeker, J., & Vandewalle, J. (1992). Dynamic mathematical model to predict microbial growth and inactivation during food processing. *Applied and Environmental Microbiology*.
Wang, S., Tao, F., & Shi, Y. (2018). Optimization of Location-Routing Problem for Cold Chain Logistics Considering Carbon Footprint. *International Journal of Environmental Research and Public Health*, *15*(1), 86.
Wang, X., Wang, M., Ruan, J., & Zhan, H. (2016). The Multi-objective Optimization for Perishable Food Distribution Route Considering Temporal-spatial Distance. In *Procedia Computer Science*. https://doi.org/10.1016/j.procs.2016.08.165
Weiss, D., Stangierski, J., Baranowska, H. M., & Rezler, R. (2018). Kinetic models of quality parameters of spreadable processed Gouda cheese during storage. *Food Science and Biotechnology*. https://doi.org/10.1007/s10068-018-0377-2
Yan, C., Banerjee, A., & Yang, L. (2011). An integrated production distribution model for a deteriorating inventory item. In *International Journal of Production Economics* (Vol. 133, pp. 228–232). https://doi.org/10.1016/j.ijpe.2010.04.025
Yu, M., & Nagurney, A. (2013). Competitive food supply chain networks with application to fresh produce. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2012.07.033
Zanoni, S., & Zavanella, L. (2012). Chilled or frozen? Decision strategies for sustainable food supply chains. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2011.04.028
Zhou, G. H., Xu, X. L., & Liu, Y. (2010). Preservation technologies for fresh meat - A review. *Meat Science*. https://doi.org/10.1016/j.meatsci.2010.04.033

Appendix

Fictitious data to create used in creating the results in Table 3-1

	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
Ex. 1	3	1	14	65	15	51	90	52	16	4	27	286
			22		39	65				7	31	281
			11		198	11				6	29	284
Ex. 2	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	4	2	13	42	88	49	100	50	15	4	22	290
			22	39	44	76			16	5	26	283
			14		128	93				3	29	286
			21		180	17				5	26	287
Ex. 3	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	5	2	24	53	114	28	84	49	15	4	28	280
			18	58	30	92			16	3	34	294
			13		123	57				6	22	290
			23		49	78				3	28	286
			11		128	31				5	33	282
Ex. 4	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	7	3	17	89	130	3	111	57	15	5	32	291
			23	55	194	30			16	6	32	280
			13	63	73	68			16	4	30	286
			19		136	11				5	31	283
			22		181	55				6	32	294
			24		120	52				3	30	283
			19		129	1				4	30	290
Ex. 5	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	8	3	12	72	129	1	119	46	15	7	33	280

			15	44	9	53			16	5	39	288
			11	38	116	17			15	6	26	282
			11		54	31				7	24	287
			13		158	60				6	24	282
			23		144	82				7	25	280
			14		86	58				4	29	285
			16		152	7				5	36	290
Ex. 6	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	12	4	13	49	138	12	97	43	15	8	40	286
			24	86	180	93			16	6	43	292
			11	48	107	51			15	7	32	291
			23	64	148	60			15	8	39	284
			12		171	40				6	34	288
			13		148	41				7	44	293
			15		193	17				6	27	285
			10		154	78				6	41	283
			10		197	58				7	40	288
			21		77	12				6	39	283
			11		99	17				8	32	292
			17		43	30				8	28	289
Ex. 7	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	13	5	11	95	57	46	82	41	15	4	31	286
			21	89	48	52			15	4	35	290
			13	78	137	82			15	5	28	289
			19	86	143	39			16	3	28	286
			17	86	194	88			16	6	37	293
			24		154	54				5	28	286
			21		153	49				6	37	294
			22		35	42				6	38	289
			19		113	17				4	36	292
			19		181	23				6	29	289
			12		8	26				6	35	293
			21		187	74				5	36	293
			23		29	27				3	29	283
Ex. 8	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	15	5	24	68	95	45	93	40	15	5	38	284
			20	92	29	77			15	6	37	280
			18	89	121	13			15	8	43	294
			23	93	151	20			15	5	37	281
			16	94	158	87			15	6	27	280
			13		51	57				4	35	288
			20		130	22				6	32	284
			14		136	95				7	39	285
			16		130	56				4	40	288
			22		124	1				8	39	290
			20		177	2				5	39	281
			21		187	50				6	43	283
			18		103	12				6	28	289
			14		51	14				8	35	282
			16		3	10				5	38	287
Ex. 9	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	17	5	18	73	14	36	88	44	16	6	36	280
			10	64	137	84			16	9	44	284
			11	92	176	88			15	8	31	281
			12	74	42	42			16	5	34	283
			18	59	42	11			15	6	44	294
			14		75	96				7	43	280
			12		26	70				6	35	293
			11		105	90				5	41	290
			12		79	94				7	32	294
			22		181	20				8	42	281
			11		179	2				8	47	286
			17		60	79				5	34	292
			18		176	12				9	44	281
			12		16	88				6	46	282
			19		72	49				6	45	287
			16							5	42	282
			23		16	77				7	43	293
Ex. 10	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	19	6	23	85	127	3	114	51	16	6	46	285
			19	87	81	86			16	6	32	289
			11	56	134	67			15	7	31	280
			10	75	133	50			16	4	31	288
			17	71	70	90			15	5	44	287
			18	92	164	1			16	8	47	282
			20		7	97				6	32	293
			18		93	86				4	43	280
			23		170	81				7	39	280
			18		115	74				7	28	286
			12		34	43				4	43	280
			16		119	99				8	43	294

			17		116	84				8	38	290
			22		54	55				6	33	284
			19		122	12				4	35	292
			15		197	60				4	47	285
			18		179	32				6	47	283
			15		108	15				6	29	291
			21		48	31				6	42	284
	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	20	6	10	65	174	35	94	50	15	8	49	287
			13	86	181	68			16	5	30	289
			17	73	68	54			16	7	35	291
			20	112	161	17			16	9	43	288
			11	96	39	34			15	5	47	282
			21	75	34	57			16	9	38	290
			22		77	74				9	33	287
			20		175	40				5	37	283
			23		191	42				8	33	287
Ex. 11			10		183	66				8	43	286
			23		152	64				6	41	283
			24		152	15				6	45	280
			14		44	90				7	37	285
			16		71	36				5	42	293
			18		194	22				6	36	283
			20		197	31				7	49	283
			16		12	40				6	49	286
			23		10	26				6	47	285
			23		20	11				7	33	285
			10		9	47				8	33	281
	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	30	5	22	204	68	83	89	43	16	10	80	284
			15	155	180	66			15	9	60	280
			15	109	165	13			15	17	80	290
			12	172	146	26			15	11	77	288
			23	126	140	80			15	15	62	281
			18		82	16				12	70	287
			12		23	36				14	82	282
			10		186	51				15	66	290
			16		12	63				13	71	286
			22		136	60				11	56	284
			17		175	82				13	88	280
			18		128	19				9	62	280
			16		3	21				14	72	289
Ex. 12			14		98	58				12	84	287
			21		26	61				17	89	284
			21		152	38				10	69	290
			19		85	85				13	80	291
			13		187	36				9	86	291
			15		58	35				17	65	289
			18		130	57				16	55	285
			10		100	13				12	81	288
			24		130	69				14	86	288
			16		124	87				10	73	282
			23		195	5				14	83	285
			22		132	63				16	75	294
			20		40	40				14	84	283
			12		58	9				11	88	282
			22		107	0				11	67	283
			19		80	20				12	83	283
			20		96	58				13	61	283
	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
	35	7	14	166	173	17	114	49	16	7	48	294
			22	133	190	81			15	13	58	294
			23	160	28	28			16	11	50	287
			12	108	65	82			15	12	45	281
			12	102	16	68			16	12	60	287
			18	170	65	27			15	10	48	291
			10	133	155	52			15	11	68	288
			22		176	98				12	46	280
			13		120	66				14	45	283
Ex. 13			18		163	67				10	71	280
			20		89	22				12	67	286
			24		41	57				9	59	285
			23		68	29				13	59	282
			15		93	87				10	64	288
			20		72	67				8	46	287
			19		70	95				11	65	290
			23		93	60				14	58	290
			16		50	60				7	54	281
			18		170	9				8	55	290
			16		149	44				11	51	289
			19		25	67				7	61	282
			17		89	14				13	53	285

			21		51	45				7	67	287
			11		85	89				9	57	283
			22		51	78				11	51	280
			21		24	82				12	67	294
			11		136	93				9	55	283
			11		170	10				12	67	286
			20		30	71				11	53	292
			21		47	24				9	50	287
			22		14	98				12	58	285
			16		102	80				7	54	288
			24		169	17				9	46	283
			17		58	68				10	68	289
			17		26	94				7	64	292

	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
Ex. 14	40	6	15	121	70	73	84	41	16	12	70	283
			11	168	118	83			16	10	70	294
			23	130	20	53			15	12	91	284
			12	212	130	26			15	16	82	289
			23	150	158	68			15	14	73	290
			13	177	13	82			15	17	91	286
			17		44	46				19	69	292
			24		182	20				15	84	281
			15		122	76				16	73	291
			16		14	78				18	77	283
			12		8	30				10	71	290
			21		132	69				17	64	291
			24		138	59				18	78	285
			15		108	14				18	63	284
			21		149	6				11	70	293
			21		167	54				15	88	281
			20		36	27				11	63	280
			13		71	17				19	81	290
			20		153	78				12	78	293
			13		171	20				11	70	287
			15		165	68				15	64	283
			16		133	92				11	65	284
			12		19	33				11	78	281
			10		44	37				10	67	288
			20		78	80				16	95	292
			23		122	48				19	94	290
			18		161	13				15	70	293
			17		0	32				14	70	292
			15		79	24				13	62	280
			23		171	71				19	97	289
			17		37	49				16	81	282
			19		101	31				12	97	294
			16		3	67				10	68	280
			13		191	76				11	70	292
			21		10	99				17	95	294
			24		113	87				10	99	286
			16		188	25				14	78	291
			24		12	64				16	65	287
			13		61	11				15	76	294
			18		14	35				14	82	294

	No. of Cust.	No. of Vehicles	Customers demand	Cap. of Vehicles	X Coord. of Cust.	Y Coord of Cust.	X Coord of depot	Y Coord of depot	Speed of vehicles	Earliest time	Latest time	Ambient Temp.
Ex. 15	50	7	14	127	145	9	111	57	16	16	89	287
			13	117	51	3			16	10	79	280
			17	209	147	0			16	13	71	292
			10	198	124	68			16	16	67	293
			19	121	43	7			16	19	65	285
			10	183	88	92			15	19	78	287
			16	123	129	15			15	19	65	284
			10		155	65				20	72	287
			10		103	82				12	104	286
			20		72	13				18	64	285
			21		21	14				17	102	294
			16		89	42				12	84	292
			14		92	51				20	73	288
			16		63	77				15	70	290
			16		187	91				19	66	290
			19		141	19				17	98	291
			20		59	20				15	78	285
			16		132	12				13	89	293
			23		124	89				20	76	284
			20		195	44				14	85	286
			10		106	4				13	83	289
			21		172	21				12	101	283
			11		39	57				20	80	285
			14		84	20				13	95	293
			11		56	27				15	66	285
			22		16	37				17	64	283
			15		173	56				14	76	287

			17		17	85				17	73	280
			13		50	73				13	91	291
			17		187	94				12	76	286
			15		63	87				11	83	286
			23		29	97				12	83	284
			24		19	56				15	84	281
			16		137	95				11	98	292
			11		52	98				10	68	285
			15		71	53				15	100	282
			17		20	52				18	91	290
			21		11	0				10	92	292
			23		38	5				16	88	282
			14		105	84				13	103	282
			23		180	20				20	79	292
			10		198	61				10	95	292
			14		109	11				13	105	282
			16		196	23				18	82	292
			12		79	27				18	71	289
			21		72	33				13	101	289
			19		82	86				18	98	285
			11		162	76				20	82	281
			15		112	53				19	96	280
			12		95	3				17	97	281

Chapter 4 A Multi-Objective Model for Sustainable Perishable Food Distribution Considering the Impact of Temperature on Vehicle Emissions and Product Shelf Life

Amin Gharehyakheh, Caroline Krejci, Jaime Cantu, Jamie Rogers

The University of Texas at Arlington

Arlington, TX, 76019, USA

Abstract

The food distribution process is responsible for a huge loss in the quality of perishable products. However, preserving the quality is costly and it consumes lots of energy. A novel multi-objective model is proposed to tackle these sustainability challenges by setting transportation costs and CO_2 emission minimization and freshness maximization objectives. The accuracy of measuring the sustainability goals is enhanced by integrating the multi-objective sustainable vehicle routing problem with temperature, shelf life, and energy consumption prediction models. Non-dominated sorting genetic algorithm II is adapted to solve the proposed model for the set of Solomon test data. The conflicting nature of these objectives and the sensitivity of the model to shelf life and temperature setting in the container are analyzed in this study.

Keywords: Sustainable distribution; Food perishability; Multi-objective optimization; Temperature prediction; Shelf life; Food waste; NSGA-II

1. Introduction

Sustainability in food distribution operations can guarantee the flow of essential nutrients among human society. 14^{th} annual Food Health and Safety Survey reveals that consumers recognized the necessity of sustainability in food operations and the sustainable production and distribution of food is important for 54% of the consumers (Meyer, 2019). In response to this demand, food distributors and producers are seeking new approaches to improve their sustainability goals. Achieving sustainability in any distribution network involves tradeoffs between multiple conflicting objectives, including minimizing transportation costs (e.g., fuel and vehicle maintenance costs, driver salaries), fulfilling customer requirements (e.g., on-time deliveries, short lead times), and limiting environmental impact (e.g., vehicle emissions). However, optimizing sustainability in perishable food distribution is particularly challenging, primarily because of temperature control requirements.

Temperature is a major determinant of the shelf life of a perishable product (James, James, & Evans, 2006; Tarantilis & Kiranoudis, 2002). Even small and/or infrequent deviations from recommended temperature settings can significantly reduce product shelf life (Bruckner, Albrecht, Petersen, & Kreyenschmidt, 2013; Gharehyakheh, Krejci, Cantu, & Rogers, 2019; Göransson, Jevinger, & Nilsson, 2018) because increased temperature accelerates the growth rate of the microorganisms that are responsible for quality degradation in perishable foods (Bruckner et al., 2013; Kreyenschmidt et al., 2010). This loss in quality increases the likelihood that the food is wasted (Mercier, Villeneuve, Mondor, & Uysal, 2017). According to the United States Department of Agriculture, 30-40% of food in the U.S. is wasted ("Food Waste and Loss," 2015), with 40% of these losses occur post-harvest (FAO- Food and Agriculture Organization of the United Nations, 2011). As a result, much of the resources consumed by the production and distribution of perishable food, as well as their associated environmental impacts, are in vain (FAO- Food and Agriculture Organization of the United Nations, 2011). It is estimated that food waste costs the U.S. economy $218 billion each year (Young, 2012). Moreover, as described by Mercier et al. (2017), quality loss due to inadequate temperature control increases food safety risk. In the U.S., the annual societal costs of foodborne illness are estimated to be $50 billion (Scharff, 2012), with more than 120,000 hospitalizations and 3,000 fatalities annually (CDC, 2011).

Therefore, it is crucial to maintain the predefined temperature range for perishable food products during distribution to ensure their quality and safety (Adekomaya, Jamiru, Sadiku, & Huan, 2016; Ketzenberg, Bloemhof, & Gaukler, 2015; Stellingwerf, Kanellopoulos, van der Vorst, & Bloemhof, 2018). Although refrigerated vehicles' cargo is well-isolated, it can experience frequent exposure to increased temperature when the vehicle stops to make deliveries to other customers (James et al., 2006; Novaes, Lima Jr, Carvalho, & Bez, 2015). As a result, an estimated 8-23% loss in perishable food quality occurs during the distribution process (Osvald & Stirn, 2008). A distribution plan that emphasizes short transit times and few stops can preserve product quality and reduce waste. Food waste is not the only environmental impact of perishable food distribution networks. The energy required to transport and refrigerate perishable products during distribution is supplied by burning fossil fuels, which releases greenhouse gases into the environment (Stellingwerf et al., 2018). In fact, food refrigeration during transportation accounts for 15% of global fossil fuel consumption and 40% of global greenhouse effect (Adekomaya et al., 2016), with up to

40% of refrigerated vehicles' emissions generated by a conventional diesel engine vapor compression refrigeration system (Tassou, De-Lille, & Ge, 2009). Therefore, improving the efficiency of perishable food distribution systems can have a significant impact on energy consumption and vehicle emissions.

However, attempts to simultaneously minimize food waste, vehicle emissions, and transportation costs in a perishable food distribution network involve tradeoffs. For example, delivering multiple orders using a single full truck is more efficient than delivering each individual order on its own dedicated route, in terms of cost and energy. However, a full truckload increases orders' transit times, as well as the frequency of temperature abuses during unloading, thereby reducing product quality and increasing food waste. These tradeoffs indicate the necessity of incorporating multiple objectives when studying the problem of perishable food distribution. For example, some studies consider both product perishability and distribution costs (e.g., X. Wang et al. (2016) and Rahbari et al. (2019)). The tradeoff between emissions and distribution costs has also been analyzed (see e.g. Xiao et al. (2012)). However, few studies integrate distribution costs, freshness, and CO_2 emissions simultaneously, and the precision of existing studies has been limited by simplifying assumptions (e.g. Musavi & Bozorgi-Amiri (2017)).

The research presented in this paper introduces a novel extension of the multi-objective vehicle routing problem for the sustainable distribution of perishable food products. In this multi-objective sustainable vehicle routing problem (MO-SVRP), products are dispatched from a depot and are delivered to a set of customers having deterministic demand. Temperature is the primary controllable element in preserving the quality of perishable food products. To capture this, the MO-VRP model is extended by integrating a method for predicting heat exchange and temperature inside the shipping container, thereby allowing product freshness and vehicle energy consumption to be accurately estimated. This integrated model considers three objectives: maximization of average product freshness, minimization of total CO_2 emissions, and minimization of total distribution costs. The MO-SVRP is solved using a non-dominated sorting genetic algorithm (NSGA-II), which provides schedules and routes for the efficient distribution of perishable products using refrigerated vehicles.

The paper is organized as follows: Section 2 presents a review of the related literature. Section 3 provides the problem statement and model formulation. Section 4 shows the solution procedure. In Section

5, computational results and a discussion of the findings are presented. Finally, the conclusion of this research and recommendations for future research are provided in Section 6.

2. Literature Review

There is a rich literature related to the distribution of perishable food. The review presented in this paper focuses on literature that uses mathematical modeling to optimize food distribution systems.

As previously mentioned, transit time and temperature are the two most influential factors on the quality of delivered perishable food products. Integrating product transit time is straightforward for mathematical models that are already tracking delivery times for other purposes, such as time window constraints. Therefore, many studies that take perishability into account consider the reduction of transit time directly or indirectly in their models (Ahumada & Villalobos, 2011; Albrecht & Steinrücke, 2018; Chen, Hsueh, & Chang, 2009; Farahani, Grunow, & Günther, 2012; Ghezavati, Hooshyar, & Tavakkoli-Moghaddam, 2017; Hsu, Hung, & Li, 2007; Osvald & Stirn, 2008). These models assume that the rate of product deterioration is constant over time, such that minimizing product time in transit is linearly equivalent to an increase in the quality of the delivered products (Bortolini, Faccio, Ferrari, Gamberi, & Pilati, 2016). Hence, transit time is used as a proxy for product quality loss, either as part of cost minimization or revenue maximization objective.

However, the inherent tradeoffs between delivering high-quality products and minimizing distribution costs have inspired researchers to consider them as separate objectives. Bortolini et al. (2016) minimized delivery time as a different objective to represent the freshness of the delivered foods in their multi-objective study. Similarly, (Amorim & Almada-Lobo, 2014; Musavi & Bozorgi-Amiri, 2017; Rahbari et al., 2019) used a multi-objective approach to study product freshness maximization, where freshness is linearly estimated. (Amorim, Günther, & Almada-Lobo, 2012; Hsu, Chen, & Wu, 2013) integrated the effect of temperature into the rate of quality degradation such that the rate of quality degradation increases as the storage temperature goes up. Since the growth rate of microorganisms that spoil food is exponential, the impact of temperature variations on product shelf life can be estimated using exponential functions, which can then be maximized (Gallo, Accorsi, Baruffaldi, & Manzini, 2017; Hsiao, Chen, & Chin, 2017; S. Wang, Tao, & Shi, 2018; X. Wang et al., 2016).

Most models in the literature seek to maximize product quality throughout the distribution process. By contrast, (Devapriya, Ferrell, & Geismar, 2017; Khalili-Damghani, Abtahi, & Ghasemi, 2015; Nakandala, Lau, & Zhang, 2016) added a set of constraints to their model to ensure that the quality of the delivered products meets customers' expectations. (Hsu et al., 2007) calculated the volume of spoiled products based on the duration and ambient temperature of each delivery stop. (Novaes et al., 2015) used commercial software to predict the temperature inside the shipping container, and they used time-temperature data to evaluate the quality of products at each delivery location via a statistical indicator in a traveling salesman problem.

Temperature-controlled transportation is energy-intensive and consequently releases a large volume of CO_2 emissions into the environment. The energy required to carry a load between two locations is evaluated in (Bektaş & Laporte, 2011) with respect to traveled distance, vehicle acceleration speed, the slope of the road, the weight of the load, the density of air, and the frontal surface of the vehicle. (Stellingwerf et al., 2018) adapted this methodology to evaluate CO_2 emissions for both transportation and refrigeration, based on the assumption of constant energy losses during unloading and through the walls of the vehicle. S. Wang et al. (2018) transformed CO_2 emissions and the energy required for transportation and refrigeration into costs, which were minimized. Accorsi, Gallo, & Manzini (2017) calculated the energy consumption of distribution activities, which are then minimized in the objective function. Hsu et al. (2007) integrated the effects of energy required for refrigeration of perishable products as a part of a cost minimization objective. In this study, the cost of energy is a function of the constant and predetermined temperature inside the container, ambient temperature, volume of the container, duration of each stop, and frequency of opening the container. (Hsu et al., 2013) optimized the delivery of perishable products with different temperature requirements, accounting for refrigeration costs as a part of distribution costs. Some studies include CO_2 emissions in a separate objective of a multi-objective model (see e.g. (Bortolini et al., 2016; Govindan, Jafarian, Khodaverdi, & Devika, 2014; Molina, Eguia, Racero, & Guerrero, 2014; Musavi & Bozorgi-Amiri, 2017; F. Wang, Lai, & Shi, 2011)), allowing decision-makers to assess the impact of reducing CO_2 emissions on other food distribution system objectives, as well as the marginal cost of reducing environmental effects.

A diverse set of solution strategies have been used to solve the perishable food distribution problem. (Ghezavati et al., 2017) adapted a Benders decomposition model to solve a mixed-integer linear program. (Chen et al., 2009; Farahani et al., 2012) adapted a heuristic algorithm to solve the distribution planning problem as part of their production and distribution model. Metaheuristic approaches have also been widely used to find good-quality solutions in a reasonable amount of time. These approaches are also useful for finding a Pareto optimal frontier in multi-objective problems. Musavi & Bozorgi-Amiri (2017) applied NSGA-II on a multi-objective hub location scheduling problem, in which total transportation costs and carbon emissions were minimized and food freshness was maximized. Amorim & Almada-Lobo (2014) applied ε-constraint method to a small-scale problem and NSGA-II to a large-scale multi-objective problem that aimed to minimize total routing costs and maximize average freshness in a food distribution problem. Khalili-Damghani et al. (2015) solved a bi-objective location-routing problem for the distribution of perishable products using ε-constraint and NSGA-II algorithm. Their result showed that NSGA-II provided solutions as good as ε-constraint, but the metaheuristic algorithm outperformed the exact method in solving time, especially for larger-scale problems. Govindan et al. (2014) used a hybrid approach that integrated an adapted multi-objective particle swarm optimization (MOPSO) and an adapted multi-objective variable neighborhood search (AMOVNS) to solve a bi-objective location routing problem for perishable products with economic and environmental minimization objectives.

A summary of the important features of the related literature is shown in Table 1. Most of these studies either focus on food product perishability or the environmental impacts of temperature-controlled distribution. Only two studies cover cost, freshness, and emissions, and only (Novaes et al., 2015) and (Novaes et al., 2015) have considered the effect of temperature on product quality and carbon emissions.

To the best of our knowledge, the multi-objective VRP model presented in this paper is the first to use an integrated temperature prediction method to estimate product quality and refrigeration energy consumption while accounting for cost, freshness, and emissions in a perishable food distribution system. Specifically, this paper extends the MO-SVRP by adding a heat exchange model to accurately estimate the temperature inside the refrigerated container. This allows for a more accurate prediction of product freshness (i.e., shelf life) upon delivery, as well as improving the estimation of total emissions generated by refrigerated trucks. This paper also utilizes a novel adaptation of the NSGA-II metaheuristics algorithm to solve the MO-SVRP model.

Table 4-1. Comparing the important features of the related literature

Literature	Quality degradation changes				Method of addressing perishability	Temperature effect on quality	Emissions		Temperature effect on emissions	Temperature prediction	Objectives			Solution method		
	Linear over time	Linear over temperature	Nonlinear over time	Nonlinear over temperature			Transportation	Refrigeration			Economic	Perishability	Emissions	Exact	Heuristic	Metaheuristic
(Hsu et al., 2007)	x				The predicted amount of spoiled products are added to the shipment to ensure the right amount of delivery	x		x	x		x				x	
(Osvald & Stirn, 2008)	x				Minimize delivery time						x				x	
(Chen et al., 2009)	x				Minimize product deterioration, assuming a constant rate						x				x	
(F. Wang et al., 2011)							x				x		x	x		
(Ahumada & Villalobos, 2011)	x				Minimize product decay						x			x		
(Farahani et al., 2012)	x				Minimize time between production and delivery						x				x	
(Amorim et al., 2012)	x	x			Maximize fractional remaining shelf life						x	x		x		
(Hsu et al., 2013)								x			x					x
(Govindan et al., 2014)							x				x		x			x
(Molina et al., 2014)							x				x		x		x	
(Amorim & Almada-Lobo, 2014)	x				Maximize average freshness						x	x		x		x
(Khalili-Damghani et al., 2015)	x				Constrained delivery of products before they expire						x			x		x
(Novaes et al., 2015)			x	x	Temperature as a proxy for product quality	x				x	x					x
(Nakandala et al., 2016)			x	x	Minimize devalue costs, and restrict the quality of delivered products to an acceptable level						x					x
(Bortolini et al., 2016)	x				Minimize delivery time		x				x	x	x	x		
(X. Wang et al., 2016)			x	x	Maximize freshness						x	x			x	
(Ghezavati et al., 2017)	x				Minimize quality degradation and disposal costs						x			x		
(Devapriya et al., 2017)	x				Constrained delivery of products before they expire						x				x	
(Hsiao et al., 2017)			x	x	Minimize loss in shelf life as product-related costs						x					x
(Gallo et al., 2017)			x	x	Minimizes the energy consumed to cool down the products spoiled in transportation		x	x					x	x		
(Musavi & Bozorgi-Amiri, 2017)	x				Maximize purchase probability		x				x	x	x			x
(Albrecht & Steinrücke, 2018)	x				Maximize revenue from the grade of quality						x			x		
(S. Wang et al., 2018)			x		Product damage costs in the objective function		x	x			x					x
(Stellingwerf et al., 2018)							x	x			x		x	x		
(Rahbari et al., 2019)	x				Maximize freshness						x	x		x		
This research			x	x	Maximize average freshness	x	x	x	x	x	x	x	x			x

3. Problem Statement and Model Formulation

Distribution problems typically seek to consolidate the flow of goods from a depot to their demand destinations into fewer routes. The vehicle routing problem (VRP) is often utilized to formulate this problem, such that an optimal (i.e., minimum distance) route is determined, subject to constraints such as route connectivity, vehicle capacity limits, and the number of available vehicles. The model described in this paper integrates accurate methods into a VRP to accurately measure sustainability goals in a perishable food distribution problem. These methods include temperature prediction, CO_2 emission estimation, and freshness prediction methods.

In the proposed approach, the temperature inside the refrigerated containers of delivery vehicles is predicted. The predicted temperature then serves as an input to food quality prediction and vehicle CO_2 emission estimation methods, which are components of the objective function of the MO-SVRP, along with the distribution cost. Figure 1 presents the integrated structure of the MO-SVRP model. In the remainder of this section, each of these methods and their mathematical relations are presented, and then the MO-SVRP assumptions, notations, and model are illustrated.

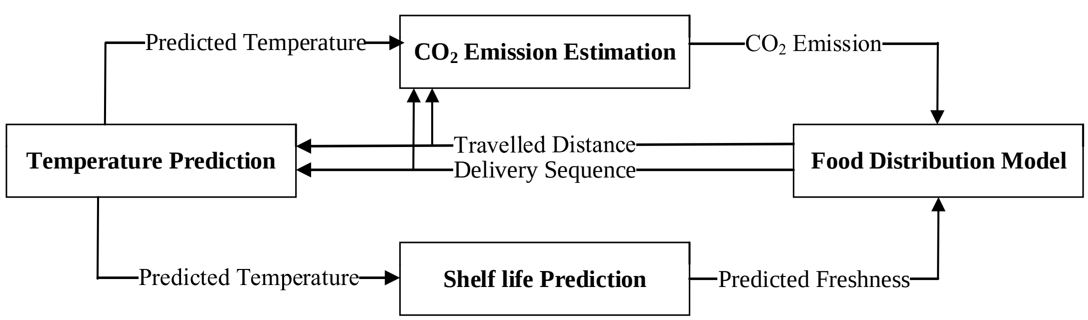

Figure 4-1. Integrated Structure of MO-SVRP model

3.1. Temperature Prediction Based on Heat Transfer

The cooling unit in a refrigerated vehicle is constantly trying to preserve the temperature inside the container by blowing cold air. However, each time the vehicle makes a delivery stop and opens the container door for unloading, the heat exchange between the hot ambient air and cold container air raises the temperature inside the container. The capacity of the cooling equipment and the amount of heat exchange are the main factors that determine the temperature inside the container. In the MO-SVRP model, energy balance equations are applied to predict the temperature inside the container.

Since heat exchange when the vehicle is in transit differs from unloading, the container temperature in each of these stages is predicted using different methods. When the vehicle is moving, the cooling system is on until the temperature inside the container reaches the desired level (T_d), when a thermostat turns the cooling system off. In most cases, the vehicle's cooling system and engine are turned off during unloading to protect the engine and to avoid polluting the air around the delivery dock. Therefore, it is assumed that the cooling system is not running during unloading, and therefore the temperature inside the container can only increase.

3.1.1. Temperature Prediction in Unloading

According to the energy balance equation, the overall heat that enters the container is equal to the accumulated heat inside the container (Equations 1-2; Holdsworth et al., 2008). The heat entering and accumulating inside the container at customer location j are denoted by AE_j and AH_j, respectively.

$$AE_j = m_a . r_o . s_a . (T_j - T_0) . t \tag{1}$$

m_a: air mass (kg)
r_a: air transfer ratio
s_a: specific heat of the air (J kg^{-1} K^{-1})
T_j: the ambient temperature at location j (K)
T_0: current temperature inside the container (K)
t: Portion of unloading time ($t \leq u_j$)

$$AH_j = \left(m_j s_c + m_a s_a\right) \frac{dT}{dt} \tag{2}$$

m_j: cargo mass at location j (kg)
m_a: air mass (kg)
s_c: specific heat of cargo (J kg^{-1} K^{-1})
s_a: specific heat of the air (J kg^{-1} K^{-1})
$\frac{dT}{dt}$: rate of change in temperature (K)

Following the energy balance equation, the temperature at customer j, given an unloading time t, can be estimated by theorem 1, Equation 3.

$$T_j = T_a - (T_a - T_0).\, e^{-\frac{m_a.r_O.s_a}{\left(m_j s_c + m_a s_a\right)}.t} \tag{3}$$

m_j: cargo mass at location j (kg)
m_a: air mass (kg)
s_c: specific heat of cargo (J kg^{-1} K^{-1})
s_a: specific heat of the air (J kg^{-1} K^{-1})
$\frac{dT}{dt}$: rate of change in temperature (K)

3.1.2. Temperature Prediction in Transportation

When the engine is running, the cooling equipment begins to remove the heat absorbed during the unloading process until the container temperature reaches T_d. The rate of heat removal is denoted by Q_c:

$$Q_C = (m_{ij}s_c + m_a s_a)\frac{dT}{dt} \tag{4}$$

m_{ij}: cargo mass between location i and j (kg)
m_a: air mass (kg)
s_c: specific heat of cargo (J kg^{-1} K^{-1})
s_a: specific heat of the air (J kg^{-1} K^{-1})
$\frac{dT}{dt}$: rate of change in temperature (K H^{-1})

Applying the energy balance enables the prediction of container temperature during transportation between locations i and j (T_{ij}):

$$T_{ij} = \frac{Q_C}{\left(m_{ij}s_c + m_a s_a\right)}.\, t + T_0 \tag{5}$$

Q_c: the capacity of cooling equipment (J H^{-1})
m_{ij}: cargo mass between location i and j (kg)
m_a: air mass (kg)
s_c: specific heat of cargo (J kg^{-1} K^{-1})
s_a: specific heat of the air (J kg^{-1} K^{-1})
t: time duration (h)
T_0: current temperature inside the container (K)

Equation 5 shows that the cooling equipment reduces the temperature at a rate of $\frac{Q_c}{\left(m_{ij}s_c + m_a s_a\right)}$. However, since the cooling equipment stops blowing cold air when the temperature reaches T_d, the actual temperature is as follows:

$$T_{ij}^{*} = Max\{T_{ij}, T_d\} \tag{6}$$

3.2. CO_2 Emissions

The main source of CO_2 emissions in a perishable food distribution system is the fuel that is burned to provide energy for transport and refrigeration. The energy required for transportation, which is not specific to perishable products, depends primarily on the distance traveled, the weight of the vehicle and its cargo, the vehicle speed, and road/vehicle specifications. Bektaş & Laporte (2011) developed a widely used method that integrates all of these factors to predict road transportation energy consumption:

$$p_{ij} \approx \alpha_{ij}(w + f_{ij})d_{ij} + \beta v_{ij}^2 d_{ij} \tag{7}$$

w: vehicle weight
f_{ij}: weight of the load between node i to j
v_{ij}: vehicle velocity
d_{ij}: distance between nodes i and j
α_{ij}: arc constant (i.e., road specification)
β: vehicle constant
(Bektaş & Laporte, 2011) calculated α_{ij} and β as follows:

$$\alpha_{ij} = a + g sin\theta_{ij} + gC_r cos\theta_{ij} \tag{8}$$

a: vehicle acceleration
g: gravitational constant
C_r: rolling resistance
θ_{ij}: slope of the road between locations i and j

$$\beta = 0.5C_d A\rho \tag{9}$$

C_d: drag coefficient
A: vehicle frontal surface area
ρ: air density

Stellingwerf et al. (2018) added a method to calculate the energy consumed by refrigeration in temperature-controlled distribution. They illustrated that heat exchange between the air in the container and the ambient air during distribution is equal to the energy that the cooling system requires to remove the heat to reduce the temperature inside the container. The MO-SVRP model presented in this paper extends their work by considering the air transfer ratio, air mass, unloading time, ambient air temperature, and predicted temperature inside the container (Section 3.1) to accurately estimate the heat exchange during unloading at location j using Equation (1). It is assumed that the heat exchange during transportation is negligible since refrigerated containers are well-isolated. Considering both transportation and refrigeration energy consumption, the total energy consumption for a refrigerated vehicle *v* that is assigned to the visit a set of locations L_v is:

$$TE_v = \sum_{i,j \in L_v} p_{ij} x_{ij} + \sum_{j \in L_v} AE_j \quad (10)$$

x_{ij}: equals 1 if location j is visited immediately after location i; 0 otherwise

Using the approach of Stellingwerf et al. (2018), a refrigerated vehicle's total energy consumption can be converted to CO_2 emissions as follows:

$$E_v = \frac{TE_v}{\mu F} . glb. e \quad (11)$$

E_v: total CO2 emissions of vehicle v (lb)
TE_v: total energy consumption of vehicle v (kWh)
μ: the efficiency of converting the chemical energy of the fuel to vehicle energy consumption (dimensionless)
F: energy content of a gallon of fuel (kWh g-1)
glb: conversion factor for fuel: gallons to pounds (lb g^{-1})
e: conversion factor: fuel to emissions (dimensionless)

3.3. Food Product Freshness Based on Shelf Life Prediction

Increased temperature can increase the growth rate of specific spoilage organisms (SSOs) in perishable food products (Mercier et al., 2017). Therefore, most shelf life prediction models require the temperature of the product over time, as well as product characteristics, to predict the remaining shelf life. Using the temperature prediction method explained in Section 3.1., an accurate estimate of product temperature from the time of vehicle departure from the depot until delivery is possible.

While most studies assume that the remaining shelf life of a product declines at a constant rate over time, the shelf life prediction model provided by (Bruckner et al., 2013) predicts a nonlinear increase in the number of SSOs in non-isothermal conditions. A product reaches the end of its shelf life when the number of SSOs reaches its maximum acceptable level. The product is not safe for consumption beyond this point and is considered spoiled. The remaining shelf life of food products can be estimated at any point in time, given the initial count of SSOs and characteristics of the food at presumed future storage temperature. Figure 2 shows the number of SSOs over time for a unit of product volume for constant temperature.

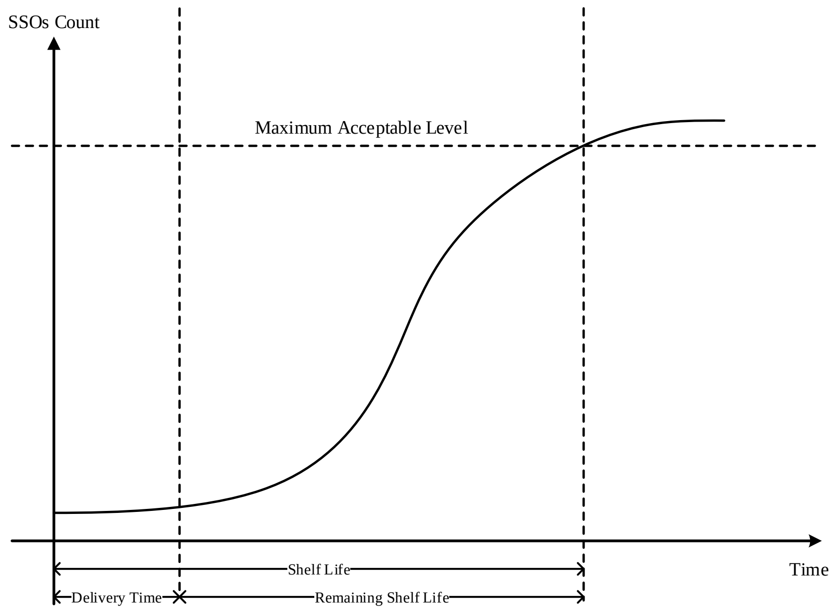

Figure 4-2. The growth rate of SSOs over time at a constant temperature.

The Gompertz model (Gibson, Bratchell, & Roberts, 1987) predicts the number of SSOs over time:

$$N(t) = A + C * e^{-e^{-B(t-M)}} \qquad (12)$$

N(t): SSO count ($\log_{10}$ cfu g^{-1}) at time *t*,
A: initial SSO count of the food product at the time it is loaded into a refrigerated vehicle (log10 cfu g^{-1})
C: the difference between the maximum SSO population level (a constant defined for each type of food product) and the initial SSO count *A* ($\log_{10}$ cfu/g)
M: time at which the maximum growth rate is obtained (h)
B: relative growth rate at time *M* (h^{-1})

The relative growth rate (B) is a function of temperature and is predicted by the Arrhenius equation (Arrhenius, 1889):

$$ln(B) = \ln(F) - \frac{E_a}{R}.(\frac{1}{T}) \qquad (13)$$

F: pre-exponential factor describing the number of times two molecules collide
E_a: activation energy for growth of SSOs (J/mol)
R: gas constant (8.314 J/mol K)
T: absolute temperature (K)

The freshness of the delivered products at location j (fr_j) can be measured in Eq. 14 by the percentage of the remaining shelf life over the maximum predicted shelf life of a product before distribution to location j with estimated time and temperature condition. The remaining shelf life is the time that the number of SSOs will take to climb from their current point to the maximum acceptable level.

$$fr_j = \frac{Remaining\ shelf\ life_j}{shelf\ life_j} \times 100 = (1 - \frac{delivery\ time_j}{shelf\ life_j}) \times 100 \quad (14)$$

3.4. Mathematical Model

The freshness prediction and CO_2 emission modules are integrated with a VRP model to create the MO-SVRP model. The perishable food distribution problem is defined as a directed graph in which a fleet of homogenous vehicles (V), each with a capacity of Q, deliver perishable food from a depot (node 0) to a set of customers (C) using a set of transportation paths (A) which connect the nodes. The order that fulfills the demand of customer i (d_i) must be delivered in the customer's required time window ($[a_i, b_i]$). For ease of reference, all notations are given in Table 2.

Table 4-2. Notations used in the MO-SVRP model.

Sets:
$C = \{1, \ldots, n\}$: set of customers $V = \{1, \ldots, v\}$: set of vehicles $N = \{0\} \cup C$: set of depot and customers $A = \{(i, j): i, j \in N, \text{ and } i \neq j\}$: set of paths from node i to node j
Parameters:
c_{ij}: cost of traveling from node i to node j t_{ij}: travel time from node i to node j F: fixed dispatching cost Q: vehicle capacity d_i: customer I demand $[a_i, b_i]$: required time window for delivery to customer i ut: average unloading time for one unit of product u_i: unloading time at customer i, where $u_i = \frac{d_i}{ut}$ and $u_i \leq b_i - a_i$

Decision variables:

y_{ik}: time that vehicle k arrives at node i

x_{ijk}: equals 1 if vehicle k travels from node i to node j, 0 otherwise

l_{ijk}: units of product carried by vehicle k between nodes i and j

The MO-SVRP model is formulated as multi-objective mixed-integer programming, and the mathematical formulation is as follows:

$$Minimize\ Z_1 = \sum_{k\epsilon V}\sum_{i\epsilon N}\sum_{j\epsilon N} c_{ij}\, x_{ijk} + \sum_{j\in C}\sum_{k\in V} F x_{0jk} \quad (15)$$

$$Maximize\ Z_2 = \sum_{i\epsilon C} fr_i \frac{d_i}{\sum_{j\epsilon C} d_j} \quad (16)$$

$$Minimize\ Z_3 = \sum_{k\epsilon V} E_k \quad (17)$$

Subject to

$$\sum_{k\epsilon V}\sum_{j\epsilon N} x_{ijk} = 1 \qquad \forall i \epsilon C, i \neq j \quad (18)$$

$$\sum_{i\epsilon C} d_i \sum_{j\epsilon N} x_{ijk} \leq Q \qquad \forall k \epsilon V, i \neq j \quad (19)$$

$$\sum_{j\in C} x_{0jk} \leq 1 \qquad \forall k \epsilon V \quad (20)$$

$$\sum_{i\epsilon N} x_{ihk} - \sum_{j\epsilon N} x_{hjk} = 0 \qquad \forall h \epsilon N, k \epsilon V \quad (21)$$

$$\sum_{j\epsilon N}\sum_{k\epsilon V} l_{jik} - \sum_{j\in N}\sum_{k\epsilon V} l_{ijk} = d_i \qquad \forall i \epsilon C \quad (22)$$

$$y_{ik} + u_i + t_{ij} - M(1 - x_{ijk}) \leq y_{jk} \qquad \forall i \epsilon C, j \epsilon N, k \epsilon V \quad (23)$$

$$t_{0j} \leq y_{jk} + M(1 - x_{0jk}) \qquad \forall j \epsilon C, k \epsilon V \quad (24)$$

$$a_i \leq y_{ik} \leq b_i \qquad \forall i \epsilon C \quad (25)$$

$$l_{ijk} \leq (Q - d_i)x_{ijk} \qquad \forall i \epsilon N, j \epsilon N, k \epsilon V \quad (26)$$

$$d_j x_{ijk} \leq l_{ijk} \qquad \forall i \epsilon N, j \epsilon C, k \epsilon V \quad (27)$$

$$y_{ik} \geq 0 \qquad \forall i \epsilon C, k \epsilon V \quad (28)$$

$$l_{ijk} \geq 0 \qquad \forall i \epsilon N, j \epsilon C, k \epsilon V \quad (29)$$

$$x_{ijk} \epsilon \{0,1\} \qquad \forall i \epsilon C, k \epsilon V \quad (30)$$

The first objective (Eq. 15) minimizes transportation costs, including the cost of traveling between customer locations as the first term and dispatching costs associated with the fixed costs of using a vehicle in the distribution plan as the second term. The second objective (Eq. 16) maximizes the total freshness of the delivered products at each customer location. The third objective (Eq. 17) minimizes total CO_2 emissions generated by refrigerated vehicles during transit and unloading. Constraint (18) ensures that each customer location can be visited only by one vehicle. Constraint (19) prevents the load carried between two locations from being greater than the capacity of the vehicles. A vehicle can only leave the depot once (Eq. 20), and if a vehicle arrives at a location, it must also leave that location (Eq. 21). The amount of cargo unloaded at a customer location must equal that customer's demand (Eq. 22). Constraint 23 ensures that a customer cannot be visited prior to the time that the previous customer is visited plus the unloading travel times between these two customers. Similarly, constraint 24 prevents the first customer from being visited earlier than the time required to travel from the depot to that customer's location. Deliveries must occur within customers' required time windows (Eq. 25). A vehicle's load after leaving a customer location must be less than the capacity of the vehicle minus the demand of the visited customer (Eq. 26), and constraint 27 ensures that the load carried between two customer locations is at least equal to the demand of the next customer. Constraints 28 and 29 prevent the arrival time and the load carried by a vehicle from taking negative values, and constraint 30 defines a vehicle's path as a binary variable.

4. Solution Procedure

The MO-SVRP model presented in the previous section is difficult to solve. Even a VRP problem with a single objective and fewer parameters and variables is categorized as an NP-hard problem (Savelsbergh, 1985; Xiao et al., 2012). Consequently, a meta-heuristic approach was applied to solve the problem in a reasonable time. NSGA-II is an efficient and widely applied meta-heuristic approach introduced by Deb et al. (2002) as a search technique for finding optimal solutions to multi-objective problems. This algorithm works based on iterative improvements in the pool of solutions' quality. On each iteration, genetic algorithm, operators create new offsprings from the existing solutions pool of solutions with size p, and they create a new pool of solutions. The solutions in this new pool are sorted based on the non-dominated sorting algorithm and crowding distance index, and then, the pool of top solutions with size p is selected for the next iteration. This approach has been applied to solve the MO-SVRP and the details will be described in this section.

4.1. Chromosome Encoding

In the NSGA-II algorithm, a “chromosome” represents a solution that assigns a list of customers to each vehicle in a particular delivery sequence. Each chromosome is an array consisting of $n+v-1$ elements, in which n represents the number of customers and v represents the number of vehicles. An example is given in Figure 3. There are v-1 special characters in the array (“*” in Figure 3), which divide the array into v sections (i.e., one section for each vehicle). The n remaining elements of the array are integer values from 1 to n, each of which is assigned to a customer. Thus the sections between two special characters are lists of customers assigned to each vehicle, and the order of these numbers represents the delivery sequence.

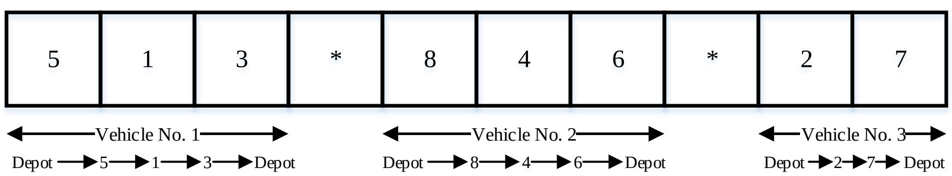

Figure 4-3. NSGA-II chromosome encoded as a MO-SVRP solution

Initially, n customers and v-1 special characters are randomly assigned to p (size of the pool of solutions) chromosomes. Then, crossover and mutation operators are used to generate new solutions as the algorithm iterates.

4.2. Crossover Operator

The single point crossover operator is used to generate P_c (size of the crossovered pool of solution) chromosomes from the previous pool of solutions. Figure 4 provides an example, in which the first three elements the parent chromosomes are swapped to create two new offsprings.

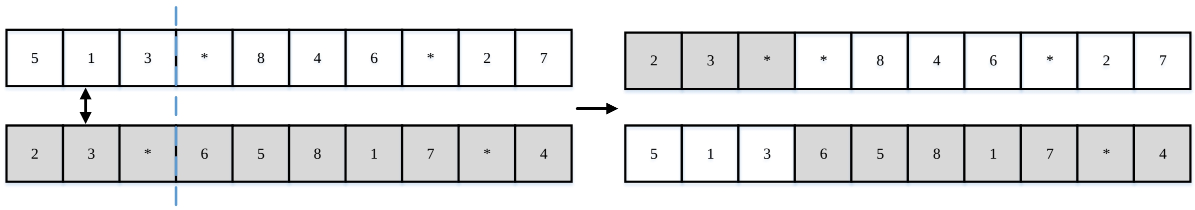

Figure 4-4. Crossover operation

The crossover procedure is followed by a repair procedure (Musavi & Bozorgi-Amiri, 2017), which is applied to fix chromosomes that have duplicated or missing customers or special characters. An example is shown in Figure 5.

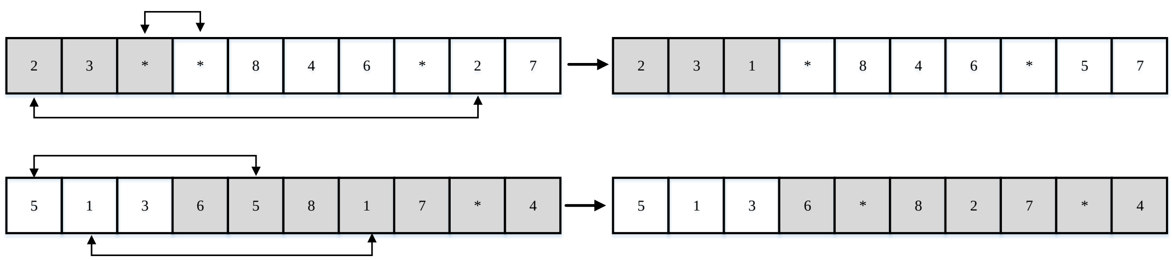

Figure 4-5. Repair procedure for crossover operation

4.3. Mutation Operator

P_m (size of the mutated pool of solutions) is randomly selected from the previous pool of solutions. The locations of two randomly selected elements from each chromosome are then swapped. An example is shown in Figure 6.

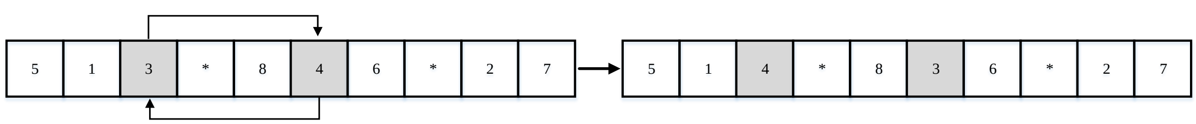

Figure 4-6. Mutation operator

4.4. Non-Dominated Sorting

In the pool of solutions, the solutions are categorized based on the number of solutions that are dominated by. Front i (F_i, *i ϵ K, K is the number of categories*) includes the solutions with rank *i* dominated by *i-1* other solutions. Solutions that cannot be dominated by any other solutions from their pool are called Pareto frontier. Figure 7 shows how the pool of solutions in domains D_1 and D_2 is categorized in three fronts.

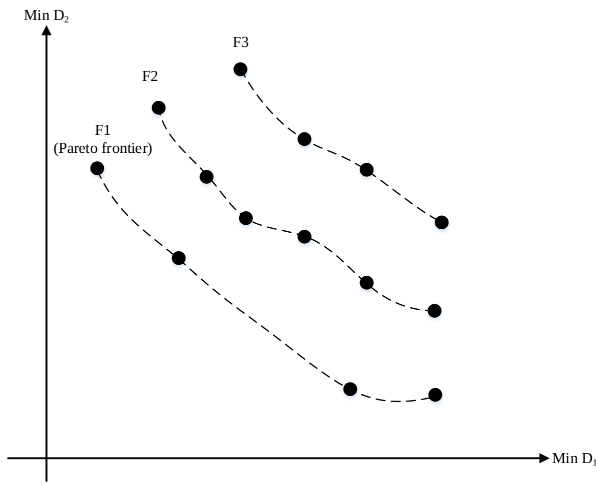

Figure 4-7. Rank of chromosomes in one iteration (F1 is Pareto frontier)

4.5. Crowding Distance

Crowding distance is an estimate of the density of solutions around a particular solution in a front. The value of crowding distance for a particular solution is the summation of distances of the solutions with the neighboring solutions of the same front. Equations 31-32 show the mathematical equations by which crowding distance is calculated.

$$d_i^j = \left|f_j^{i+1} - f_j^{i-1}\right| \tag{31}$$

d_i^j: distance of solution *i* with its neighbors in domain *j*
f_j^i: value of function *f* for solution *i* in domain *j*

$$d_i = \sum_{j \in D} d_i^j \tag{32}$$

d_i: crowding distance of solution *i*
D: set of the problem domains

In each iteration, binary tournament selection is applied to sort the solutions first based on their ranks, and then, based on their crowding distance.

4.6. NSGA-II Main Loop

The NSGA-II main loop consists of offspring generation and ranking and sorting modules. Algorithm 1 presents a pseudocode that illustrates an iteration of the NSGA-II algorithm. At the end of each iteration, solutions with rank 1 are stored as Pareto-frontier.

Algorithm 1. NSGA-II main loop pseudocode

```
p = population of randomly generated chromosomes with size pops
for i = 1 to Max number of iterations do
        for j =1 to (pc ÷ 2) do
                c1 = 1st randomly chosen parent chromosome
                c2 = 2nd randomly selected parent chromosome
                popc = append crossover (c1, c2)
        for k = 1 to pm do
                m = a randomly chosen parent chromosome
                popm = append mutate (m)
        pop = merge (p, popc, popm)
        function (non-dominated sorting (input: pop))
                return: Rank of chromosomes
        function (crowding distance (input: pop, rank))
                return: crowding distance value for each chromosome
        function (sort population (input: pop, rank, crowding distance)
                return: sorted pop based on 1) rank, 2) crowding distance
        pop = store only the top pop and truncate the others
        function (non-dominated sorting (input: pop))
                return: Rank of chromosomes
        function (crowding distance (input: pop, rank))
                return: crowding distance value for each chromosome
        function (sort population (input: pop, rank, crowding distance)
                return: sorted pop based on 1) rank, 2) crowding distance
        Pareto_frontier = chromosomes with rank 1
        Go to the next iteration if the stopping criteria are not met
```

5. Computational Results and Discussion

5.1. Performance of the solution method

First, the performance of the NGSA-II solution algorithm in solving the MO-SVRP was tested on Solomon's datasets which are widely applied to measure the quality solutions for a VRP (Solomon, 1983). The geographical distribution of the visiting location has a substantial impact on the performance of the VRP solution algorithm. So, these instances were provided in three categories: *R*, *C*, and *RC*, representing randomly generated, clustered, and mixed generated geographical data, respectively. Within these three categories, the MO-SVRP was solved for small instances (25 customers) and large instances (100 customers). However, the solutions should be compared with a competitor algorithm to verify the efficiency and accuracy of them.

Weighted simulated annealing (*w-SA*) was used to solve the single objective weighted problem. According to the L_1 metric method, the inverse of the optimum solution for each objective can be used as the weight of the objectives in a single weighted objective function (Rahbari et al., 2019).

The NSGA-II and w-SA algorithms were coded in Python and run on a computer with 3.10 GHz Intel Core i9 CPU, 64 GB of RAM, and Windows 10 operating system. The parameter values that were used are given in Table 3. NSGA-II and w-SA algorithms stop when respectively solutions in Pareto front or optimum solution after an iteration do not have improved after a certain number of iterations based on the size of the problem.

Table 4-3. Test problem and solution algorithm parameters

w-SA parameters	*value*	*NSGA-II parameters*	*value*	*test problem parameters*	*value*
Initial temperature	20	Population size	20	Vehicle speed (km h^{-1})	15
Damping rate	0.99	Crossover rate	0.7	Product shelf life (h)	2880
		Mutation rate	0.4	Fixed cost per vehicle (\$ km^{-1})	1000
				Transportation cost (\$)	1.5
				Service time (minute)	10^{*} 90^{**}
				Vehicle capacity (kg)	200

* for *R* and *RC* test problems ** for *C* test problems

In Table 4, the column “w-SA” provides the values of each of the three objective functions for the best solution to each test problem instance. The values of the objective functions in the “NSGA-II” column correspond to the best solution that was found among the Pareto front solutions for each objective. The gap shows the difference between the objective values divided by the best value in these algorithms.

The results in Table 4 show that, on average, NSGA-II provides solutions that are 9.2%, 4.2%, and 8.0% better than w-SA in terms of cost, freshness, and emission objectives, respectively. The advantage of NSGA-II over w-SA is more pronounced for the cost objective when the size of the problem increases, or when the customers are more geographically clustered (i.e., the gap is largest for the *C* instances).

Table 4-4. Summary of the results of comparing the performance of w-SA and NSGA-II

Test problem	*w-SA*			*NSGA-II*			*Gap*		
	Costs ($)	*Freshness (%)*	*CO_2 (lbs×10^3)*	*Costs ($)*	*Freshness (%)*	*CO_2 (lbs×10^3)*	*Costs ($)*	*Freshness (%)*	*CO_2 (lbs×10^3)*
R101 (25)	5,233	89%	4,164	4,886	95%	3,848	6.6%	4.8%	17.5%
R101 (100)	13,450	90%	48,042	12,356	94%	45,026	8.1%	2.3%	6.3%
C101 (25)	3,065	90%	2,452	2,761	96%	2,305	9.9%	6.7%	6.0%
C101 (100)	10,655	92%	39,787	9,452	94%	38,564	11.3%	2.2%	3.1%
RC101 (25)	3,318	90%	3,075	3,027	92%	2,684	8.8%	4.6%	12.7%
RC101 (100)	11,569	91%	47,666	10,335	93%	42,597	10.7%	4.5%	2.4%

5.2. Optimality Analysis

Balancing cost, freshness, and emission objectives are necessary to achieve sustainability in perishable food distribution networks.

The results in Table 5 demonstrate the conflicting nature of the three objectives: if the MO-SVRP problem is solved for a single objective, the values of the other two objective functions deviate significantly from optimality. Because the traveled distance is the primary driver of transportation cost and emissions, it is unsurprising that the emissions objective in the cost-optimal solution has only a 4% gap with the emission-optimal solution, and cost objective in the emission-optimal solution is only 14% higher than in the cost-optimal solution. However, keeping perishable products fresh requires faster delivery and fewer stops, which means that capacity of trucks is not necessarily fully filled. This increases the traveled distance, and consequently, transportation cost and energy consumption, such that a solution that preserves 95% of the product's freshness results in 95% and 94% optimality gaps for cost and emissions objectives, respectively. In contrast, when a solution is a cost- or emissions-optimal, freshness is 42% and 41% less than optimal, respectively.

Table 4-5. Impact of choosing a non-dominated solution on the optimality of the transportation costs, freshness, and emission for R101(25) instance

Optimality	*No. of Vehicles*	*Costs ($)*	*Freshness (%)*	*CO_2 (lbs×10^3)*
Cost	7	4886 (*)	55% (42% gap)	3997 (4% gap)
Freshness	8	112123 (95% gap)	95% (*)	66413 (94% gap)
Emission	7	5723 (14% gap)	56% (41% gap)	3848 (*)
Final solution	7	10213 (52% gap)	75% (21% gap)	8892 (57% gap)

* optimum

Most likely, there is more than one non-dominated solution in the Pareto frontier. So, a final solution that properly reflects the impact of all the objectives is chosen from the non-dominated set of solutions in the Pareto frontier. To choose a final solution, the approach developed by Bortolini et al. (2016) was adapted.

$$Min\ \theta_l \tag{33}$$

$$\theta_l = \frac{\alpha_l}{\alpha_l^*} \cdot \frac{\beta_1^*}{\beta_1} \cdot \frac{\gamma_l}{\gamma_l^*} \tag{34}$$

θ_l: represents a single calculated value for a solution *l* in Pareto frontier
α_l: value of the first objective function for solution *l*
α_l^*: optimum value of the first objective function for solution *l*
β_l: value of the second objective function for solution *l*
β_l^*: optimum value of the second objective function for solution *l*
γ_l: value of the third objective function for solution *l*
γ_l^*: optimum value of the third objective function for solution *l*

As shown in Table 5, the optimality gaps for each objective in the final solution are 52%, 57%, and 21% for cost, emissions, freshness, respectively. When the objective of the problem only is the maximization of the freshness, it means that the refrigerated vehicles potentially carry loads far less than their capacity, and the order of the customers are not combined into a single vehicle as much as possible to ensure fast delivery and the least stops. In this scenario, the traveled distances of the vehicles are very high, and consequently, distribution costs and CO_2 emission are at their highest level. Combining the orders in one single vehicle and utilizing more capacity of the vehicles provides a substantial improvement in the cost and emission objectives, and the gaps of these objectives associated with the final solution reflect this potential improvement opportunity.

5.3. Sensitivity to Shelf Life

For the results presented in the previous sections, it was assumed that the products have similar characteristics and the same shelf life (i.e., 2,880 hours), but in reality, perishable products' shelf life can range from 168 hours for highly perishable products, such as tomatoes, to 1,440 hours for moderately perishable products, such as oranges, and 2,880 hours for products with low perishabilities, such as apples. Therefore, the sensitivity of the MO-SVRP model to long, medium and short shelf life scenarios was analyzed. The final solutions for three objectives in these shelf life scenarios are shown in Table 6. The results illustrate that distributing more perishable items are more costly and energy-consuming, and the freshness of the delivered products decreases for the lower shelf life products. The results provide an insight into food distributors to invest more money and time on improving isolation of container and efficiency of the diesel engine to reduce energy consumption and preserve the quality of products when they are distributing products with lower shelf life.

Table 4-6. Final solutions for transportation costs, freshness, and CO_2 emissions in case of different shelf life for R101(25) instance

Shelf life (h)	*Costs ($)*	*Freshness (%)*	*CO_2 (lbs×10^3)*
168	13522	62%	12916
1440	11390	71%	10662
2880	10213	75%	8892

5.4. Sensitivity to Temperature Setting

Although there are recommended temperature ranges for perishable product storage, determining the specific temperature setting for a refrigerated shipping container can be challenging. Lower temperature settings preserve product quality, but this requires more energy. Therefore, the sensitivity of the MO-SVRP model to various temperature settings was assessed by solving the R101(25) instance at temperature settings between 263-269 degrees Kelvin (14º-25º F) in two-degree increments.

Table 7 shows that the final solutions for the three sustainability objectives for different temperature settings inside the container. Increasing the temperature setting from 263 ºK to 269 ºK causes 15% reductions in product freshness, from 75% to 60%. Because the MO-SVRP recommends faster delivery to compensate for the loss in quality that results from an increase in temperature, transportation distance, and cost increase at higher temperature settings. The effect of increased temperature setting on emissions is complex. On one hand, transportation consumes more energy due to the increase in traveled distance. On the other hand, energy consumption for refrigeration decreases. This leads to a decrease in overall energy consumption in the distribution network. Storage temperature range recommended by regulation and authorities does not clearly help to choose the temperature settings inside the container, and analyzing the tradeoff between the energy consumption and freshness of the products under different ambient temperature conditions is necessary.

Table 4-7. Final solutions for transportation costs, freshness, and CO_2 emissions in case of different temperature settings for R101(25) instance

Temperature (ºK)	*Costs ($)*	*Freshness (%)*	*CO_2 (lbs×10^3)*
263	10213	75%	8892
265	10**52**6	72%	8556
267	1**10**13	68%	8436
269	1**15**96	60%	8301

6. Conclusions and Future Research

In this paper, VRP is extended to consider the perishability of the food products and refrigerated vehicles' CO_2 emissions in a multi-objective framework. The model combines sustainability concerns of perishable food distribution problem in a mathematical model with transportation costs and CO_2 emission minimization and freshness maximization objectives. Applying the temperature estimation model provided an accurate prediction for the refrigeration related emission and quality loss during the distribution.

This research aimed to investigate the relation of the sustainability objectives and the behavior of these objectives under distribution scenarios. Therefore, the presented MO-SVRP model was solved by an adapted NSGA-II algorithm, and the performance of the solution algorithm is tested and verified against the w-SA algorithm over the Solomon (1983) data sets. The results of the analysis revealed that the sustainability goals are conflicting, and optimality in one of the objectives can worsen the other two objectives; i.e. the freshness objective recommends using the available vehicles as much as possible to minimize delivery time and the effect of temperature abuses at the delivery locations. Therefore, the optimality gap in distribution costs and CO_2 emission objectives are high when only the freshness objective is optimized. Furthermore, the MO-SVRP model recommends faster delivery with lesser unloading stops for the vehicles for high perishable products comparing to the low perishable foods which means the energy consumption and distribution costs associated with the increase in the total traveled distance goes higher. The sensitivity analysis over the temperature settings inside the container shows even small increments in the temperature settings can have a huge impact on CO_2 emissions and freshness objectives. This sensitivity analysis can be a helpful tool to determine the best temperature setting to achieve sustainability goals. The outcomes of this research highlight the necessity of integration and accurate estimation of the influential factors in the sustainability of the perishable food distribution network which lead to finding cost-effective solutions, reduce food waste, and decrease the emission caused by refrigerated vehicles.

Future studies can focus on expanding this model for multi-products in which their desired temperature range and perishability properties are different. In addition, The framework of this research to incorporate projected temperature variation and estimation of product freshness in other supply chain disciplines.

References

Accorsi, R., Gallo, A., & Manzini, R. (2017). A climate driven decision-support model for the distribution of perishable products. *Journal of Cleaner Production*, *165*, 917–929. https://doi.org/10.1016/j.jclepro.2017.07.170

Adekomaya, O., Jamiru, T., Sadiku, R., & Huan, Z. (2016). Sustaining the shelf life of fresh food in cold chain–A burden on the environment. *Alexandria Engineering Journal*, *55*(2), 1359–1365.

Ahumada, O., & Villalobos, J. (2011). A tactical model for planning the production and distribution of fresh produce. *Annals of Operations Research*, *190*(1), 339–358. https://doi.org/10.1007/s10479-009-0614-4

Albrecht, W., & Steinrücke, M. (2018). Coordinating continuous-time distribution and sales planning of perishable goods with quality grades. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2017.1384584

Amorim, P., & Almada-Lobo, B. (2014). The impact of food perishability issues in the vehicle routing problem. *Computers and Industrial Engineering*. https://doi.org/10.1016/j.cie.2013.11.006

Amorim, P., Günther, H. O., & Almada-Lobo, B. (2012). Multi-objective integrated production and distribution planning of perishable products. *International Journal of Production Economics*, *138*(1), 89–101. https://doi.org/10.1016/j.ijpe.2012.03.005

Arrhenius, S. (1889). Über die Reaktionsgeschwindigkeit bei der Inversion von Rohrzucker durch Säuren. *Zeitschrift Für Physikalische Chemie*, *4*(1), 226–248.

Bektaş, T., & Laporte, G. (2011). The pollution-routing problem. *Transportation Research Part B: Methodological*, *45*(8), 1232–1250.

Bortolini, M., Faccio, M., Ferrari, E., Gamberi, M., & Pilati, F. (2016). Fresh food sustainable distribution: Cost, delivery time and carbon footprint three-objective optimization. *Journal of Food Engineering*. https://doi.org/10.1016/j.jfoodeng.2015.11.014

Bruckner, S., Albrecht, A., Petersen, B., & Kreyenschmidt, J. (2013). A predictive shelf life model as a tool for the improvement of quality management in pork and poultry chains. *Food Control*, *29*(2), 451–460.

CDC. (2011). Burden of Foodborne Illness: Findings. Retrieved April 10, 2020, from https://www.cdc.gov/foodborneburden/2011-foodborne-estimates.html

Chen, H. K., Hsueh, C. F., & Chang, M. S. (2009). Production scheduling and vehicle routing with time windows for perishable food products. *Computers and Operations Research*. https://doi.org/10.1016/j.cor.2008.09.010

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*. https://doi.org/10.1109/4235.996017

Devapriya, P., Ferrell, W., & Geismar, N. (2017). Integrated production and distribution scheduling with a perishable product. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2016.09.019

FAO- Food and Agriculture Organization of the United Nations. (2011). Global food losses and food waste: extent, causes and prevention. In *Save Food! Global Food Losses and Food Waste*. https://doi.org/10.1098/rstb.2010.0126

Farahani, P., Grunow, M., & Günther, H. O. (2012). Integrated production and distribution planning for perishable food products. *Flexible Services and Manufacturing Journal*. https://doi.org/10.1007/s10696-011-9125-0

Food Waste and Loss. (2015). Retrieved February 9, 2020, from https://www.fda.gov/food/consumers/food-waste-and-loss

Gallo, A., Accorsi, R., Baruffaldi, G., & Manzini, R. (2017). Designing sustainable cold chains for long-range food distribution: Energy-effective corridors on the Silk Road Belt. *Sustainability (Switzerland)*. https://doi.org/10.3390/su9112044

Gharehyakheh, A., Krejci, C., Cantu, J., & Rogers, J. (2019). Dynamic Shelf-Life Prediction System to Improve Sustainability in Food Banks. In *IISE Annual Conference and Expo*.

Ghezavati, V. R., Hooshyar, S., & Tavakkoli-Moghaddam, R. (2017). A Benders' decomposition algorithm for optimizing distribution of perishable products considering postharvest biological behavior in agri-food supply chain: a case study of tomato. *Central European Journal of Operations Research*, *25*(1), 29–54. https://doi.org/10.1007/s10100-015-0418-3

Gibson, A. M., Bratchell, N., & Roberts, T. A. (1987). The effect of sodium chloride and temperature on the rate and extent of growth of Clostridium botulinum type A in pasteurized pork slurry. *Journal of Applied Bacteriology*, *62*(6), 479–490.

Göransson, M., Jevinger, & Nilsson, J. (2018). Shelf-life variations in pallet unit loads during perishable food supply chain distribution. *Food Control*. https://doi.org/10.1016/j.foodcont.2017.08.027

Govindan, K., Jafarian, A., Khodaverdi, R., & Devika, K. (2014). Two-echelon multiple-vehicle location-routing problem with time windows for optimization of sustainable supply chain network of perishable food. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2013.12.028

Holdsworth, S. D., Simpson, R., & Barbosa-Cánovas, G. V. (2008). *Thermal processing of packaged foods* (Vol. 284). Springer.

Hsiao, Y.-H., Chen, M.-C., & Chin, C.-L. (2017). Distribution planning for perishable foods in cold chains with quality concerns: Formulation and solution procedure. *Trends in Food Science & Technology*, *61*, 80–93.

Hsu, C. I., Chen, W. T., & Wu, W. J. (2013). Optimal delivery cycles for joint distribution of multi-temperature food. *Food Control*. https://doi.org/10.1016/j.foodcont.2013.04.003

Hsu, C. I., Hung, S. F., & Li, H. C. (2007). Vehicle routing problem with time-windows for perishable food delivery. *Journal of Food Engineering*. https://doi.org/10.1016/j.jfoodeng.2006.05.029

James, S. J., James, C., & Evans, J. A. (2006). Modelling of food transportation systems - a review. *International Journal of Refrigeration*. https://doi.org/10.1016/j.ijrefrig.2006.03.017

Ketzenberg, M., Bloemhof, J., & Gaukler, G. (2015). Managing perishables with time and temperature history. *Production and Operations Management*. https://doi.org/10.1111/poms.12209

Khalili-Damghani, K., Abtahi, A. R., & Ghasemi, A. (2015). A New Bi-objective Location-routing Problem for Distribution of Perishable Products: Evolutionary Computation Approach. *Journal of Mathematical Modelling and Algorithms in Operations Research*. https://doi.org/10.1007/s10852-015-9274-3

Kreyenschmidt, J., Hübner, A., Beierle, E., Chonsch, L., Scherer, A., & Petersen, B. (2010). Determination of the shelf life of sliced cooked ham based on the growth of lactic acid bacteria in different steps of the chain. *Journal of Applied Microbiology*, *108*(2), 510–520.

Mercier, S., Villeneuve, S., Mondor, M., & Uysal, I. (2017). Time–Temperature Management Along the Food Cold Chain: A Review of Recent Developments. *Comprehensive Reviews in Food Science and Food Safety*. https://doi.org/10.1111/1541-4337.12269

Meyer, M. (2019). Interest in Sustainability , Plant-Based Diets Among Trends in IFIC Foundation ' s 2019 Food & Health Survey, 1–4. Retrieved from https://foodinsight.org/interest-in-sustainability-plant-based-diets-among-trends-in-ific-foundation-2019-food-and-health-survey/

Molina, J. C., Eguia, I., Racero, J., & Guerrero, F. (2014). Multi-objective Vehicle Routing Problem with Cost and Emission Functions. *Procedia - Social and Behavioral Sciences*. https://doi.org/10.1016/j.sbspro.2014.12.137

Musavi, M. M., & Bozorgi-Amiri, A. (2017). A multi-objective sustainable hub location-scheduling problem for perishable food supply chain. *Computers and Industrial Engineering*. https://doi.org/10.1016/j.cie.2017.07.039

Nakandala, D., Lau, H., & Zhang, J. (2016). Cost-optimization modelling for fresh food quality and transportation. *Industrial Management and Data Systems*. https://doi.org/10.1108/IMDS-04-2015-0151

Novaes, A. G. N., Lima Jr, O. F., Carvalho, C. C. de, & Bez, E. T. (2015). Thermal performance of refrigerated vehicles in the distribution of perishable food. *Pesquisa Operacional*, *35*, 251–284. Retrieved from http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0101-74382015000200251&nrm=iso

Osvald, A., & Stirn, L. Z. (2008). A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. *Journal of Food Engineering*. https://doi.org/10.1016/j.jfoodeng.2007.07.008

Rahbari, A., Nasiri, M. M., Werner, F., Musavi, M. M., & Jolai, F. (2019). The vehicle routing and scheduling problem with cross-docking for perishable products under uncertainty: Two robust bi-objective models. *Applied Mathematical Modelling*. https://doi.org/10.1016/j.apm.2019.01.047

Savelsbergh, M. W. P. (1985). Local search in routing problems with time windows. *Annals of Operations Research*, *4*(1). https://doi.org/10.1007/BF02022044

Scharff, R. L. (2012). Economic burden from health losses due to foodborne illness in the united states. *Journal of Food Protection*, *75*(1), 123–131. https://doi.org/10.4315/0362-028X.JFP-11-058

Solomon, M. M. (1983). *Vehicle routing and scheduling with time windows constraints: Models and algorithms*. University of Pennsylvania, USA. https://doi.org/10.1007/bfb0121107

Stellingwerf, H. M., Kanellopoulos, A., van der Vorst, J. G. A. J., & Bloemhof, J. M. (2018). Reducing CO 2 emissions in temperature-controlled road transportation using the LDVRP model. *Transportation Research Part D: Transport and Environment*, *58*, 80–93.

Tarantilis, C. D., & Kiranoudis, C. T. (2002). Distribution of fresh meat. *Journal of Food Engineering*. https://doi.org/10.1016/S0260-8774(01)00040-1

Tassou, S. A., De-Lille, G., & Ge, Y. T. (2009). Food transport refrigeration–Approaches to reduce energy consumption and environmental impacts of road transport. *Applied Thermal Engineering*, *29*(8–9), 1467–1477.

Wang, F., Lai, X., & Shi, N. (2011). A multi-objective optimization for green supply chain network design. *Decision Support Systems*. https://doi.org/10.1016/j.dss.2010.11.020

Wang, S., Tao, F., & Shi, Y. (2018). Optimization of Location-Routing Problem for Cold Chain Logistics Considering Carbon Footprint. *International Journal of Environmental Research and Public Health*, *15*(1), 86.

Wang, X., Wang, M., Ruan, J., & Zhan, H. (2016). The Multi-objective Optimization for Perishable Food Distribution Route Considering Temporal-spatial Distance. In

Procedia Computer Science. https://doi.org/10.1016/j.procs.2016.08.165
Xiao, Y., Zhao, Q., Kaku, I., & Xu, Y. (2012). Development of a fuel consumption optimization model for the capacitated vehicle routing problem. *Computers and Operations Research*, *39*(7), 1419–1431. https://doi.org/10.1016/j.cor.2011.08.013
Young, L. (2012). Our biggest problem? We’re wasting food. Retrieved April 6, 2020, from http://www.canadiangrocer.com/top-stories/what-a-waste-19736

Appendix

Theorem 1. shows how to use the energy balance equation to predict the temperature when the container door is open to unload the products.

$$m_a.r_o.s_a.\Delta T_j.t = \left(m_{c_j}s_c + m_a s_a\right)\frac{dT}{dt}$$

$$\int_0^t \frac{m_a.r_o.s_a}{\left(m_{c_j}s_c+m_a s_a\right)}dt = \int_{T_0}^{T_j}\frac{dT}{(T_{out}-T)}$$

$$\frac{m_a.r_o.s_a}{\left(m_{c_j}s_c+m_a s_a\right)}(t-0) = -(\ln\left(T_{out}-T_j\right) - ln(T_{out}-T_0))\ )$$

$$-\frac{m_a.r_o.s_a}{\left(m_{c_j}s_c+m_a s_a\right)}.t = \ln\frac{\left(T_{out}-T_j\right)}{(T_{out}-T_0)}$$

$$T_j = T_a - (T_a - T_0).e^{-\frac{m_a.r_o.s_a}{\left(m_j s_c+m_a s_a\right)}.t}$$

Theorem 2. shows implementing the energy balance equation to predict the temperature when the container door is closed during transportation.

$$Q_C = AE$$

$$Q_C = (m_c s_c + m_a s_a)\frac{dT}{dt}$$

$$\int_0^t \frac{Q_c}{(m_c s_c+m_a s_a)}dt = \int_{T_0}^{T_p} dT$$

$$\frac{Q_c}{(m_c s_c+m_a s_a)}(t-0) = (T_p - T_0)$$

$$T_p = \frac{Q_c}{(m_c s_c+m_a s_a)}.t + T_0$$

Chapter 5 Conclusion

This dissertation discusses a new integrated approach to modeling food supply chain activities with a focus on sustainability. The overarching contribution of this research is the integration of accurate temperature and shelf-life prediction models with perishable food distribution models to assist stakeholders in making decisions that support the economic, environmental, and social sustainability of food supply chains. These integrated models were designed to provide improved inventory management policies for food banks, reduce transportation and quality costs associated with refrigerated vehicle routing, and optimize transportation cost, product freshness, and CO_2 emissions for perishable food distribution systems. Developing and solving such models are very challenging because of the tradeoffs involved in achieving multiple conflicting sustainability goals.

The answers to the research questions posed in this dissertation are summarized below:

1) How can we accurately measure the shelf life of perishable food products in the food supply chain operations?

   The Gompertz and Arrhenius models can be applied to perishable food time-temperature data that has been collected from food supply chain operations to provide an accurate estimate of perishable food product shelf life.

2) Which inventory management policy is suitable for managing the perishable food inventory in food banks, and how should it be implemented?

   The least shelf life first-out inventory management policy is suitable for managing perishable food inventory in food banks, and shelf life prediction models based on time-temperature data are cost-effective and reliable tools for implementing this policy.

3) How can we predict the temperature fluctuations inside the container of a refrigerated vehicle in the food distribution process?

   Applying energy balance equations in transportation and unloading phases of food distribution provides an accurate estimation of the temperature inside the container of the refrigerated vehicles.

4) How can a food shelf life prediction model be integrated with a perishable food distribution model?

   The food shelf life prediction model yields estimates of lost revenue and disposal costs associated with quality loss, which can be added to the other distribution costs in a single objective function of a perishable food distribution model. Alternatively, the predicted shelf life can serve as a proxy for food product freshness, which can then be integrated as a separate objective in a multi-objective perishable food distribution model.

5) How can we integrate multiple sustainability elements, including the freshness of food, distribution costs, and CO2 emissions, in a perishable food distribution model?

   Multiple sustainability elements can be integrated as separate objectives of a multi-objective perishable food distribution model.

Chapter 2 describes a reliable shelf life prediction model based on time-temperature data, which can serve as a cost-effective tool to help food banks implement the last shelf life first out inventory management policy. Improved inventory management will help to reduce food waste, and therefore, provide more food to people in need. The computational analysis performed in this study also demonstrates that improved warehouse labor management and proper food storage temperature settings can have a significant impact on reducing food quality loss.

The effect of temperature on the perishability of foods is analyzed in the food distribution problem by integrating shelf life and temperature prediction models with VRP with time window (VRPTW) in Chapter 3. The tradeoff between costly not fully loaded truck delivery with the least possible stops in a route and the economic fully loaded truck delivery with frequent stops are analyzed to integrate quality cost in distribution cost. An adapted simulated annealing algorithm was used to provide optimum solutions to the NP-hard problem. The result of comparing the integrated quality dependent VRPTW (QD-VRPTW) model with the original VRPTW for a series of randomly generated test problems shows that even though solutions to the QD-VRPTW have higher transportation costs, the overall quality and transportation costs are lower in the proposed approach. Moreover, sensitivity analysis illustrates that solutions generated by the QD-VRPTW model are highly dependent on the type of food product being shipped and its quality characteristics.

In Chapter 4, CO_2 emissions, food freshness, and transportation costs are recognized as the main elements of sustainability in perishable food distribution networks. Therefore, these sustainability goals are set as the objectives of a multi-objective mixed-integer linear problem to provide solutions that balance the major sustainability goals in a perishable food distribution network. The proposed multi-objective sustainable VRP (MO-SVRP) is solved using an adapted version of the nondominated sorting genetic algorithm (NGSA-II). An adapted version of an optimization algorithm is then used to find a final solution from a set of Pareto-optimal solutions. The sensitivity of the proposed MO-SVRP to the perishability of food products shows that the final solution for distributing the products with lower shelf life has higher cost and emission, and lower freshness comparing with the distribution of higher shelf life products. The results of sensitivity analysis over different temperature settings in the container of a refrigerated vehicle illustrates that setting the cooling equipment to a higher temperature causes a tremendous reduction on the quality of the delivered products, but although transportation cost slightly increases for higher temperature settings, total CO_2 emissions in the food distribution network decline.

While the consideration of sustainability goals in a single food supply chain stage shows promising results, it would be interesting to see the impact of these goals in the integrated food supply chain problems which encompasses more than one stages in the model; i.e. inventory routing problem, and integrated production and distribution problem. The third and fourth chapter of this dissertation is dedicated to investigating how to address sustainability concerns in a single product perishable food distribution network which is not a common case in reality. It is highly recommended to expand this problem by considering multi-product perishable foods in the distribution model.

The implementation of this study can help to enhance the health and safety of our community by distributing foods with higher quality and preserving the quality of food through the supply chain operations which can reduce food waste economical and environmental effects. Moreover, the results of this study can help food distributors to measure and achieve their sustainability goals.