Controlled Perishable Goods Logistics:

Real-Time Coordination for Fresher Products

X. Lin

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Real-Time Coordination for Fresher Products

Proefschrift

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“Knowledge puffs up, but love builds up.”

Preface

It feels amazing, and somehow strange, to try to recall what I have experienced in the last four years. This part of my short life, that has ticked away in time, has left projections blinking in the ocean of my memory. I feel so much appreciation towards so many that I need to figure out where to start, like a jeweler carefully checking and tenderly dusting his shining collections, which he holds the most dear.

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Finally, there is no way I can repay my parents for their unconditional love. Each of my steps relies on the fuel of their warm understanding and firm support.

Xiao (Graham) Lin,
Delft, December 2018

Contents

Chapter 1

Introduction

1.1 Perishable goods logistics and wastage

Global perishable goods logistics has accomplished a great deal of achievements, resulting in profound changes of people's lifestyles. With each sip of coffee or banana smoothie, each bite of chocolate, and each splash of roses, consumers all over the world enjoy the convenience brought by these global supply chains.

To meet the demand of the ever growing global market, perishable goods are produced and transported in enormous amounts. For instance, the estimated amount of bananas imported globally in 2016 is 17 million tonnes [49]. Thanks to technologies such as refrigerated vessels and containers, the freshness of these perishable products can often be preserved along supply chains.

Unfortunately, one third of the total agricultural products intended for human consumption still fails to complete their journey, according to the Food and Agriculture Organization [48]. Especially, 45% of fruit and vegetables are spoiled. This also leads to significant waste of natural and industrial resources for production and transportation [76]. If half of the waste food is saved, more than a million people can be fed [48].

Wastage can happen at any stage in a perishable goods supply chain, including production, postharvest, processing, distribution, and consumption as shown in Table 1.1. Although wastage that happens in households might appear to be only related to consumer behavior, mishandling in earlier stages of supply chains can also be responsible for the wastage that occurs later. Many factors can contribute to spoilage in perishable goods supply chains. For instance, inefficiencies in supply chains, such as congestions at a sea port terminal, can lead to delayed delivery time; environmental conditions like malfunctioning of cooling infrastructures can cause more rapid deterioration. Better decision making in logistic activities and coordination in supply chains urgently requires the consideration of these factors, in order to reduce the loss of perishable goods.

Table 1.1: Weight percentages of food loss and waste of two types of perishable goods in Europe (in percentage of what enters each step). Adapted from [48].

	Roots and tubers	Fruits and vegetables
Production	20%	20%
Postharvest	9%	5%
Processing	15%	2%
Distribution	7%	10%
Consumption	17%	19%

1.2 Opportunities for perishable goods supply chains

In general, an international supply chain for perishable goods consists of several stakeholders, namely growers, exporters, importers, wholesalers, retailers, and consumers. Logistic service providers are hired for transport and storage. In this section, factors related to freshness of products are discussed. Potential opportunities in waste reduction for the stakeholders and logistics providers are pointed out subsequently.

1.2.1 Perishable goods and shelf-life

When fresh products perish, their quality becomes unsuitable for consumption. The change of quality is a direct result from the deterioration process, which are in fact very complex chemical or biochemical reactions [139]. It is not efficient nor necessary to consider all these complex reactions when making decisions regarding logistic activities. Therefore, the term "shelf-life" can be used when quantifying quality in supply chains. It can be defined as "the period that the decreasing quality of perishables remains acceptable for the end users" [132].

Figure 1.1 describes how shelf-life can be affected, determined, and reflected by different factors and indicators. The length of shelf-life is determined by the rate of reactions that happen within the products, e.g., degradation of vitamins, formation of sugar, or growth of mold. These processes can be affected by environmental factors such as temperature or humidity, resulting in less or more rapid reactions. During the process, the changes of chemical substances can be estimated by observing the appearance of the products. Quality of fresh products is reflected by indicators like color, aroma, or firmness. A perishable goods supply chain can be better controlled and coordinated if the shelf-life of the goods are made known.

1.2.2 Towards real-time quality controlled logistic systems

The first step of building a controlled logistic system for perishable goods is to gain real-time quality-awareness during supply chains. By monitoring certain indicators, the quality of products can then be assessed. Moreover, if the future environmental factors can be predictable, the shelf-life of perishable goods can also be estimated even in a dynamic environment.

With the development of modern technology, the freshness and location of perishable goods can be made known in real-time. For instance, time-temperature indicators (TTIs)

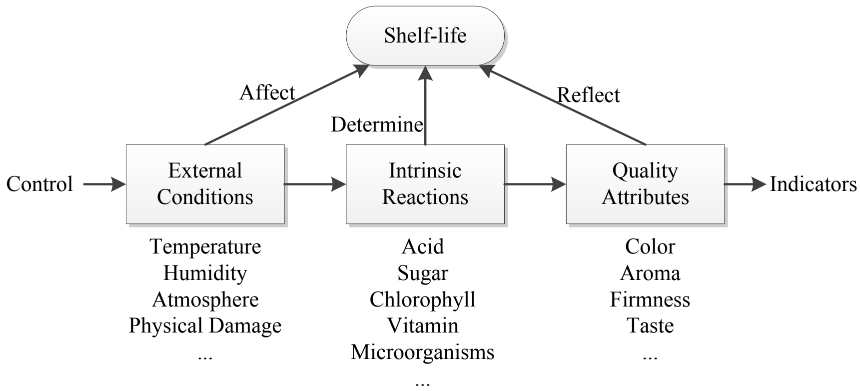


Figure 1.1: Factors and indicators of shelf-life of perishable goods, adapted from [90]

can record the temperature history inside a box, providing reference for shelf-life estimation [131]. Radio frequency identification (RFID) technology can transmit the quality information to electronic terminals without opening the box [1]. Through wireless communication technologies, quality and location information of all perishable goods can be gathered and summarized for decision makers [153].

This information brings new insights to logistic dynamics and can assist planners with trading, sourcing, routing, and processing, when delivering fresh products with well-allocated resources. Based on the insights of real-time condition of perishable goods, decisions can be pro-actively made and adjusted in real-time. Thus perishable goods supply chains can be controlled with quality consideration, providing the potential capacity of better scheduling and coordination like never before.

In order to make available the information that could be beneficial in the aforementioned ways, sensors and communication technologies need to be deployed according to the types of supply chains [118]. Nevertheless, most logistics decision makers today do not explicitly consider real-time freshness information when scheduling logistic activities, since such information is rarely available in traditional supply chains. One reason is because stakeholders are uncertain about the benefit of investing in technology, especially in sectors with fierce competition and low profit margin. The applicability of real-time freshness information is only discussed in academia, which is addressed in Chapter 2.

1.3 Research questions

The main research question of this thesis is:

Given real-time information of perishable goods logistics, in what ways can perishable goods supply chain players better control and coordinate logistic processes to reduce loss of perishable products?

The key questions are listed as follows:

1. How does perishability of products affect logistic processes in perishable goods sup-

ply chains?

2. In what way can mathematical models be built to represent both quality and logistic features of perishable goods when planning logistic processes?
3. Given the information on incoming disturbances on both quality and logistic side of a perishable goods supply chain, what strategy can be used by decision makers to control the logistic processes?
4. How to optimize the logistic process of a supply chain using a mathematical model that considers perishability?
5. How to design real-time control strategies for perishable goods logistics where supply chain players share the same interest?
6. How to design real-time control strategies in a perishable goods supply chain where supply chain players do not share the same interest?

In order to address these questions, a comprehensive literature review is conducted with the objective of understanding the causes of loss in perishable goods supply chains, and the state-of-the-art technologies that can be used to further tackle the problem. Then a methodological part is presented, in which a general framework of modeling and controlling perishable goods supply chains is proposed. The modeling and control method are subsequently proposed for application in three different case studies, with the general framework implemented in different ways as perishable goods and supply chains vary in their dynamics.

1.4 Thesis outline

The outline of this thesis is shown in Figure 1.2. A literature review is conducted in Chapter 2 on how perishability can be estimated and what impacts it has on logistic processes. The chapter also identifies the main research gaps. Chapters 3 and 4 propose a general framework to deal with logistic operations considering goods' changing quality. The general framework consists of two parts: quality-aware modeling method, which is developed in Chapter 3; and model predictive control strategy, which is discussed in Chapter 4. Both chapters use numerical examples to illustrate the effectiveness of the proposed approach. Chapters 5, 6, and 7 address the application side, in which logistic activities in three different supply chains are studied. Chapter 5 uses the quality-aware modeling method developed in Chapter 3 on a banana distribution network. Chapter 6 combines the quality-aware modeling method and model predictive control strategy in the general framework, and implements the theories in a starch potato postharvest scheduling problem. Chapter 7 focuses on cut rose logistics, where goods move fast through several stakeholders. Chapter 8 concludes the thesis and provides directions for future research.

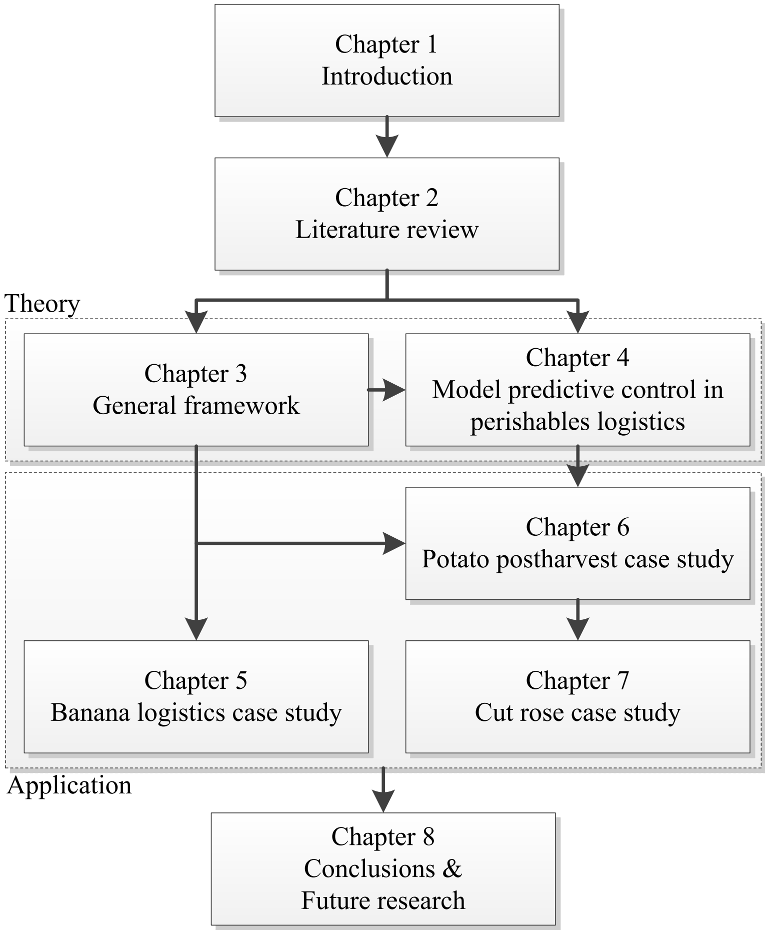


Figure 1.2: The outline of this thesis.

Chapter 2

Perishable goods logistics: physiology, technology, and methodology

Chapter 1 has emphasized that as technologies develop, the quality of fresh produce can be made visible along supply chains. With this information, new opportunities emerge for better scheduling and coordination of perishable goods logistics. In this chapter, a literature review is conducted to identify potentials emerging technologies have in the processes of perishable goods logistics. Three main aspects are addressed , namely physiology, technology, and methodology.

This chapter is organized as follows: Section 2.1 briefly introduces the concept of a quality-aware and controlled supply chain. Section 2.2 reviews the physiological aspects of perishable goods. It includes perishing features of fresh agricultural products and models describing such nature. Section 2.3 investigates technological aspects of supply chains, including approaches used to preserve freshness and existing mathematical models that estimate and predict remaining shelf-life of fresh products. Section 2.4 evaluates the recently developed methodologies for supply chain players to improve scheduling of logistic activities considering quality information. Section 2.5 concludes the chapter and provides motivations for the following chapters.

Parts of this chapter have been published in [90].

2.1 Perishable goods logistic system: present and future

To identify the gap between present and future, this section firstly focuses on today's perishable goods supply chains. Then, the vision for a quality controlled logistic system in the near future is presented.

2.1.1 Typical perishable goods supply chains

To illustrate the typical features of perishable goods logistics, two types of perishable goods are looked into: berries and bananas.

Berries have a relatively short shelf-life, and are highly sensitive to temperature: the quality of blueberries, for instance, when stored at 2°C up to 11 days, was acceptable in experiments in [78]; while the decay significantly increased after holding the blueberries at 2°C for 3 days and then 21°C for 4 days. A typical blueberry supply chain is discussed in [40]. In this supply chain, Canadian grown blueberries are transported to the US, going through harvest and postharvest processes with growers. They are then sent to the warehouse of a US brand owner, and then to a retailer distribution center. Afterwards, they are transported to retailer stores for sale. The total time of the whole logistic process can take 5 to 15 days depending on their final destinations.

Another example from literature is a banana supply chain from Costa Rica to Germany [69]. Bananas are climacteric fruit. They are green when ready for harvest and have to go through a ripening process in sealed chambers, so that they will become shiny yellow when displayed on shelves in supermarkets. Bananas are very sensitive to temperature and ethylene, which may trigger their ripening process before reaching the ripening facilities, resulting in uncontrolled quality and shelf-life. It takes less than a day to harvest bananas and transport them from farms to port terminals in Central America by growers and exporters. After two weeks of sea transport, it takes three to twelve days to reach ripening facilities and go through a ripening process for six days. Then the bananas go to wholesalers or supermarket chains.

Several common characteristics can be recognized from the instances discussed above. Firstly, because fresh products have various natures, their perishing features appear in different patterns. Every supply chain of each product has developed its unique way to organize logistic activities, so that the perishing feature of the product is taken care of. Secondly, a perishable supply chain can involve multiple players, namely growers, exporters, importers, wholesalers, and retailers. Therefore, a perishable supply chain is complex in the sense that it consists of dynamics of interactions amongst players, which can be competitive, cooperative, or both.

Among these supply chains, despite the various ways they are organized, the challenges they face remain the same. As can be seen from the aforementioned examples, travel times of products can differ greatly because of logistic reasons such as differences in destinations, limited capacity of infrastructures, and demand-supply relations between supply chain players. Another challenge is the perishing nature, as products may decay over time or start to ripen, especially in unwanted temperature or atmosphere conditions. A delay in logistics or malfunction of infrastructure may cause such incidents, leading to quality loss of perishable goods, and ultimately financial loss for supply chain stakeholders.

2.1.2 Controlled perishable goods logistic system

To tackle the challenges mentioned above, this thesis proposes a controlled perishable goods logistic system as illustrated in Figure 2.1 [90]. Normally, perishable goods start from production/harvest and end up at consumers, following the material flow of a supply chain. Freshness of the products is monitored and together with the location of the products, this

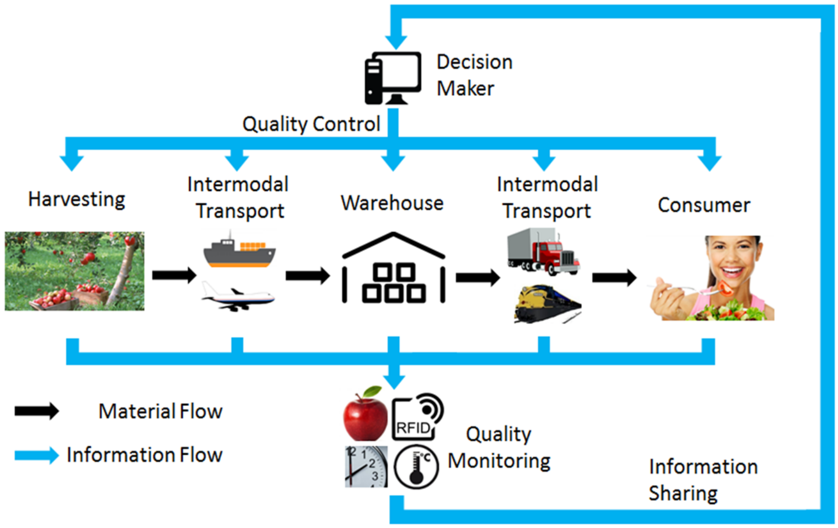


Figure 2.1: Quality controlled perishable goods logistic system for perishable goods, adapted from [90].

information is shared in real-time with supply chain planners. The sharing of information increases the transparency and flexibility of supply chains and their operations. Stakeholders can cooperate with the awareness of the freshness of the products and can make decisions accordingly regarding movements as well as quality control.

In order to evaluate the feasibility of the proposed logistic system and identify gaps between the current situations and this vision for the future, these three aspects are considered in this chapter. Firstly, an understanding of the nature of perishable products and how to model the loss of value over time is considered. Subsequently, availability of technology to estimate and preserve freshness of products is discussed. Finally, literature on planning models for perishable goods logistics is reviewed.

2.2 Physiology: Quality features of perishable agricultural products

It is the mission of the supply chain to maintain the quality of perishable products at a required level. Because the quality of fresh agricultural products has a strong relation with customer satisfaction [105] and thus the value of products. An increased awareness of the quality features and the real-time quality information can help supply chain planners better fulfill the mission by planning logistic activities accordingly. This section discusses how the quality of perishable products changes and in what ways the quality can be modeled mathematically.

2.2.1 Quality indicators, internal properties, and factors affecting quality

The word "quality" is a general term that can describe the overall acceptance of perishable products. However, the exact meaning may differ depending on its context. For instance, to government regulators, "quality" is related to public health and risk, in terms of entomological and microbiological issues, or the presence of chemical residues and microbial contaminants [146]. From a consumer's point of view, it can refer to the color, aroma, firmness, or taste of products. These human sense-associated features help consumers decide whether to accept or reject the product. For stakeholders in a supply chain, "quality" can mean shelf-life, which refers to the time left for the product to stay acceptable for consumers. Therefore, "shelf-life" is a more objective and measurable term that can be considered from a technical point of view. In the following, the relation between shelf-life and perishing features of fresh products is considered from three aspects: shelf-life indicators, internal properties, and factors that can affect shelf-life.

In the literature, it is observed that three types of indicators are often used in estimating shelf-life of perishable products, namely weight loss, color, and firmness. Weight loss over time is used as an indicator for quality estimation in apples [61], mushrooms [18], and broccoli [130]. Color examining is used for tomatoes [62], bananas [69], and cucumbers [123]. Firmness is used for shelf-life estimation for nectarines [159]. Indicators can reflect the progress of physical changes or chemical/biochemical reactions inside fresh products. By examining these indicators, customers can have an idea of the products' quality.

Behind the changes of these indicators are products' internal properties. These include physical, chemical, and biochemical changes. For instance, color changes of products can be triggered by the degradation of chlorophyll [38, 69] or the change of carotene [134]. Some of these internal properties cannot be directly picked up by human senses, but can be measured by using certain instruments or methods. Although agricultural products are incredibly complex [139], it is worthwhile to investigate these key internal properties that are closely related to the quality of the products. For instance, the shelf-life of frozen spinach can be modeled by measuring chlorophyll [38]; Vitamin C can be examined to model the quality of fresh melons [5]. Bacteria, yeasts, and mold may also affect the quality and safety of fresh products [58]. Understanding how and why the changes take place may open up possibilities in better preserving freshness by influencing the rate these properties change.

Some environmental factors can affect internal changes of fresh products, slowing down or speeding up some processes as products decay over time. Therefore, for some products it is critical to keep them in favorable environments during supply chains so that they are still of good quality when delivered to customers. For instance, physical impact and vibration can affect the quality of apples [142]; humidity in atmosphere can affect the rate of water loss in mature tomatoes [13].

For most physical and chemical changes, ambient temperature and atmosphere are key environmental factors. Literature addresses temperature [12, 45, 47, 69, 99, 147] and atmosphere [11, 42, 70, 84, 102, 149] as influencing factors or indicators of the quality of products. Most agricultural products are sensitive to temperature and ambient atmosphere, as they affect rates of reactions taking place in products. Some products in turn, generate heat or produce certain gas due to respiration. A good example is banana [69], of which the ripening process is influenced by temperature and ethylene in the air. When bananas are being shipped over sea, they need to be kept in reefer containers with ventilation, for once some bananas start to ripen, they generate more heat and ethylene, which can trigger other bananas to ripen in the same container.

Understanding how perishable goods lose their freshness gives insight to supply chain planners, so that they can organize the delivery of goods in more effective way. By controlling these influencing factors in supply chains, perishable goods can be better preserved and have a longer shelf-life, so that goods remain acceptable for consumers in terms of quality. Nevertheless, physiological processes inside perishable goods can be highly complex. Therefore, the criterion to indicate quality should be chosen with careful consideration [38] to properly reflect the decaying process. In this way, mathematical models can be developed to describe the relation between quality and the chosen criterion.

2.2.2 Models describing and predicting quality

The ideal situation of a quality monitoring system for perishable goods logistics is that each product is under watch at anytime. However, this requires a large amount of sensors and processing capacity, which can be too expensive for perishable goods logistics. One cost-efficient alternative is keeping records of external conditions that affect the quality change and using mathematical models of shelf-life as references to estimate the quality. These approaches could largely reduce the cost and time for installing devices for sensing, communicating, and processing.

Palh and Voß [112] observe that the relation between value of perishable items and time takes three patterns in general: step-wise perishability, discrete deterioration, and continuous deterioration. Some products have even more complex patterns in the quality evolution such as bananas [69] and tomatoes [62], due to their ripening processes. Choosing a proper criterion to indicate quality in a model is the first step to integrate the information of quality of goods in logistic planning. Once a quality indicator has been determined for a fresh product, models can be build through experiments to describe and predict quality changing and loss of value over time. This section lists the models that are commonly used in scientific articles.

Markovian models

Ledauphin *et al.* [82] use a Markovian model to describe the decaying stages of salmon according to scores given by expert assessors. The stages include “fresh”, “decayed” and “very decayed”. The transition matrix between different stages is determined using the scores given by human experts. The result shows that fresh salmon has a probability of 39% of turning decayed after one week of storage and 2% of turning very decayed. Decayed salmon has a probability of 6% of turning very decayed. In [83], the model has been extended to a hidden Markov model using the same dataset and bringing the possibility of relating the prediction to external conditions. The paper points out the limitation that the performance of the model strongly depends on the data, which is related to the scores determined according to the sensory attributes, which makes the evaluation subjective.

Artificial Neural Networks

Lin and Block [89] use a 2-stage artificial neural network to predict the remaining shelf-life of lettuce under storage in fluctuating temperature and relative humidity. The temperature is selected as the input of the neural network model. The 2-stage neural network is trained using heuristics based on the data from experiments. The study indicates that the 2-stage neural network has a higher accuracy than a 1-stage neural network and regression models, indicating its potential for shelf-life prediction of lettuce. Another study develops a three-stage artificial neural network to predict the shelf-life of milk [138]. Experiments are conducted for milk of different quality. Volatiles of the milk are detected and used as the input for the neural network. The study also uses a principle component regression model for comparison. The results show that the neural network approach has a higher prediction performance than the principle component regression model.

Kinetic models and Arrhenius Law

Chemical kinetics is widely applied in modeling food quality and shelf-life estimation [139]. The models are based on internal, time-dependent features of products. The established kinetic models need to be validated by experiments before they come to actual use. A kinetic model can generally be described as follows:

$$r(t) = -\frac{dQ(t)}{dt} = kQ(t)^n, \tag{2.1}$$

in which $r(t)$ is the reaction rate of a chosen criterion, which can be represented as the decreasing rate of quality overtime $-\frac{dQ(t)}{dt}$. The rate is proportional to the quality $Q(t)$ to the power of n. Variable k is determined by the reaction type and external conditions like temperature. When using kinetics for shelf-life estimation, shelf-life t_{SL} can be calculated from the kinetic model, with a degrading quality indicator at a static external condition:

$$t_{SL} = \frac{f(Q(t), Q_1)}{k}, \tag{2.2}$$

where the quality function $f(Q(t), Q_1)$ represents the actual physiological mechanism, considering the initial quality Q and the lowest acceptable quality Q_1 [63]. The quality function depends on how the concentration of chemical substance affects the reaction rate. Variable k can be affected by one or more attributes. In kinetic models for quality estimation, temperature is one of the attributes that generates the most uncertainty affecting shelf-life of perishable goods [131]. Therefore, Arrhenius law [8] is applied for determining variable k. To identify the type of $f(Q(t), Q_1)$, experiments are needed for each type of product. Labuza [77] categorizes deterioration in two different orders of kinetic models with different values of k: zero-order and first-order, which are the most common categorizes. In addition, Chen [25] points out that second-order kinetic models are also suitable for some reactions. Table 2.1 shows the reaction rate and calculated shelf-life of different types of kinetic models.

From the literature on modeling perishable goods (especially foods) it can be seen that chemical kinetics are used for various substances in different orders. Zero-order kinetic

Table 2.1: Types of kinetic models, adapted from [90].

Reaction type	Reaction rate	Remaining shelf-life
Zero-order	$-\dfrac{dQ}{dt} = k$	$t_{SL} = \dfrac{Q - Q_l}{k}$
First-order	$-\dfrac{dQ}{dt} = kQ$	$t_{SL} = \dfrac{\ln \frac{Q}{Q_l}}{k}$
Second-order	$-\dfrac{dQ}{dt} = kQ^2$	$t_{SL} = \dfrac{\frac{1}{Q_l} - \frac{1}{Q}}{k}$
Logistic	$-\dfrac{dQ}{dt} = kQ\left(1 - \dfrac{Q}{Q_{\text{inf}}}\right)$	$t_{SL} = \dfrac{\ln \dfrac{Q_{\text{inf}} - Q_l}{Q_l C_{\text{ba}}}}{k}$
Michaelis-Menten	$-\dfrac{dQ}{dt} = \dfrac{V_{\max} Q}{K_{\text{m}} + Q}$	–

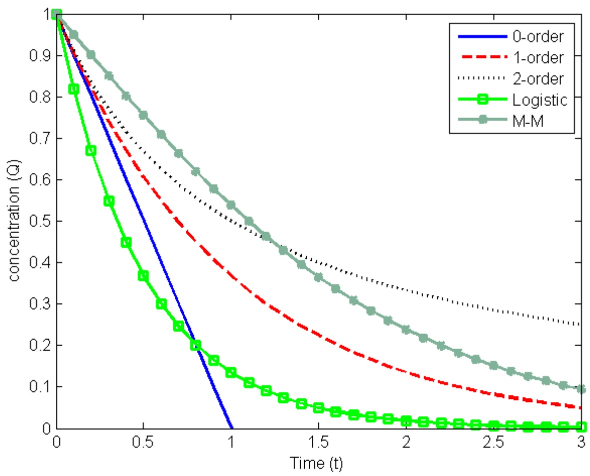


Figure 2.2: Reactions having the same initial concentration and rate constant but a varying order n, adapted from [139].

models are frequently used in describing reactions that are not affected by the amount of substance. They are also used for modeling dehydration process in potatoes and onions [72, 104]. Experiments show that the degradation of Vitamin C in frozen spinach fits a first-order kinetic model [38]. First-order kinetic models are also proved to be useful in describing peach color change in [10]. Oxidation of extractable color pigments in chili pepper is modeled using a second-order kinetic model in [25].

Other types of kinetic models like logistic models [97] as well as Michaelis-Menten models are reported [135]. In Table 2.1, Q_{inf} is the possible quality maximally possible, while C_{ba} is a constant representing information regarding the biological age of the product [134], and $C_{\text{ba}} = \frac{Q_{\text{inf}-Q_0}}{Q_0}$, in which Q_0 is the initial quality.

In Michaelis-Menten kinetic models, parameter $V_{\max}$ is the maximum reaction rate. Parameter K_{m} is the Michaelis constant representing the substance concentration when the reaction rate reaches half of the maximum rate. The relationship between the concentration of O_2, and the respiration rate of stored apples is modeled using a Michaelis-Menten kinetic model [7]. Table 2.1 does not list the remaining shelf-life calculated by Michaelis-Menten kinetics, because the solution of t_{SL} is not explicit.

As shown in (2.2), chemical kinetics can be applied in modeling and estimating quality of perishable products. In all kinetic models mentioned above, the variable k is usually determined by Arrhenius law, which in effect describes how the temperature affects reaction rate [115]. According to Arrhenius law, the rate constant k of a reaction can be obtained as follows:

$$k = Ae^{-\frac{E_a}{RT}}, \tag{2.3}$$

in which E_a is the activation energy, while A represents the rate k at which all molecules have sufficient energy to react. R and T are the gas constant and the temperature in Kelvin, respectively [139].

Figure 2.2 illustrates the relationships between time and concentration of substances in different reaction mechanisms. It can be seen that except for zero-order reaction, the reaction rate drops while the concentration is reducing at a different rate. In the zero-order model, the concentration has no influence on the reaction rate, while for other types of models the concentration does have an impact on the reaction rate.

Other models

Other models are reported in shelf-life or quality evaluation. Chatterjee *et al.* [22] use fuzzy logic analysis to evaluate shelf-life of fried potato wedges. Sensory properties of sausages are evaluated also using fuzzy logic in [64]. A decision tree model is applied in meat quality evaluation in [127]. Although these models may be successful in describing the quality decreasing process of some products, they are generally not explanatory and rely heavily on the dataset used for training as mentioned in [41, 83].

2.2.3 Discussion

For quality to be taken care of during each stage of perishable goods supply chains, it is important to understand how perishable products lose their freshness. The reviewed literature covers three aspects related to quality and shelf-life of perishable products, namely indicators, internal properties, and factors. These three aspects explain how to estimate quality of products, why perishable goods lose their freshness, and what influence the rate of loss of freshness. This knowledge is useful when developing models for shelf-life estimation and providing shelf-life prediction under forecasted environmental conditions. From the examples listed above, it can also be concluded that a one-for-all model describing the quality of perishable products does not exist. The variability of types of perishable goods makes their supply chains different from each other: from how they are organized, to what equipment needs to be involved. Therefore, to improve logistic systems for perishable products, each commodity and their supply chains need to be studied specifically.

2.3 Technology: Shelf-life preservation and awareness

This section reviews the technologies that are developed and used to preserve and estimate products' quality in supply chains, based on the quality information provided by Section 2.2.

2.3.1 Quality preservation

In Section 2.2, it is explained that the temperature and the atmosphere are the most relevant quality influencing factors. In this part, approaches of controlling temperature and adjusting atmosphere are discussed.

Temperature control in logistics

Cooling equipment has been widely used in warehouses, distribution centers, retailers, and households. In international sea transportation, products that need cooling started to be transported by refrigerated ships around 1880 [106]. A refrigerated ship can have one or more cooling chambers for storage of perishable goods. Later, perishable goods supply chains have benefited greatly from the containerization of sea transportation by means of refrigerated containers, also called reefers. Today, reefers have become the major part of sea transport [58] for refrigerated cargo. Mostly powered by electricity, reefers allow transporters to have various types of perishable goods stored on the same ship without having to worry about different temperature requirements as well as influences on each other. Reefers have enabled more flexible perishables transportation using different modalities and as such have enhanced the quality of perishable goods logistics [37].

Atmosphere control in logistics

Packaging techniques are widely used for keeping the shelf-life of perishable goods. Modified atmosphere packaging (MAP) creates the initial package atmosphere according to the types of products to slow down the process of deterioration [54]. Controlled atmosphere storage (CAS) allows the atmosphere in the storage to stay static. Experiments in [102] test tomatoes in three different storage conditions. Results show that tomatoes in CAS and MAP storages remain their high quality for longer time than those stored in cold storage with normal atmosphere. Yam *et al.* [154] propose a conceptual framework for intelligent packaging, defined as "a packaging system that is capable of carrying out intelligent functions to facilitate decision-making, to extend shelf-life, enhance safety, improve quality, provide information and warn about possible problems". The realization of this concept relies on sensor and information technologies [59].

Supply chain players invest for the equipment, the infrastructure, and electricity that provide and carry out the aforementioned technologies, which have greatly contributed to the modern perishable goods logistic systems today. If used more efficiently, the equipment and infrastructure can be more helpful in preventing loss of quality in perishable goods. Using sensors and information communication technologies is one of the approaches to make the usage more organized.

2.3.2 Sensor technologies

Sensors used for measuring the quality of perishable goods are generally of two types: destructive and non-destructive. This section reviews how these two types of sensors can be used for perishable goods logistics.

Destructive sensors

Destructive sensors directly measure chemical contents in products. For instance, penetrometers are effective ways to examine the quality change in perishable products such as fruits. In literature, firmness of apples, kiwifruits, and lemons is measured using penetrometers in [14, 57]. Impact analysis and acoustic impulse response are methods for measuring fruit and vegetable quality by striking the surface and detecting the response in either the time or the frequency domain [34, 122]. Such direct measurements are highly accurate. However, the downside of these measurements is that they can damage the products, and can be difficult to implement in an unmanned, automated environment. Therefore, these approaches are not suitable for consecutive quality monitoring during perishables supply chains.

Non-destructive sensors

Other approaches are called non-destructive methods in which products are examined without being damaged. For instance, the sensing of color can be done using cameras and computer vision technology. This approach is used for color detection for the classification of bananas [103] and tomato ripening [96].

As discussed in Section 2.2, the change of temperature and atmosphere (e.g., concentration of CO_2, O_2, and ethylene) are indicators as well as triggers of quality changing. These reactions, which bring changes to the atmosphere, can in turn affect the rate of the reactions. Therefore, for certain products, quality information can be obtained by monitoring temperature or atmosphere during transportation. This can be done by sensors and data logs.

Time-temperature indicators (TTIs, or in some literature, time temperature-integrators) are applied in perishable goods logistics [73]. TTIs are cheap, active labels that show a time-temperature dependent change that reflects the full or partial temperature history of a product to which it is attached. Based on shelf-life of products and kinetic response of TTIs, quality of perishables can be monitored throughout the supply chain. Tsironi *et al.* [137] illustrate how a specific TTI works: Photosensitive compounds are exposed to low wavelength light, making them dark blue. This color state reverses to the initial colorless at a temperature depended rate. In this way, a time-temperature history can be effectively estimated, which provides quality information to examiners in supply chains.

2.3.3 Information sharing

Once the information of product quality has been obtained by sensors, it needs to be transmitted to examiners to assist decision making in logistics. This section then discusses technologies that enhance quality awareness of perishable goods in their supply chains.

RFID technology

The development of Radio Frequency Identification (RFID) technology has received significant attention in literature. It has promising potential to enable fresh goods supply chains with better traceability and integration [1, 29]. The technology does not require any direct contact to exchange information. This greatly enhances efficiency of information exchange between goods/carriers and infrastructures when handling large amount of pallets or boxes. Chen *et al.* [26] propose a food trace system within a smart cold chain system by 2G-RFID-system. Jedermann *et al.* [67] use semi-passive RFID temperature data loggers and models in perishable goods supply chains. Semi-passive RFID chips not only transmits identification information, but also other information such as the temperature. This provides transporters insights of the quality of the goods and can support transport scheduling based on the estimated shelf-life.

The use of RFID faces opportunities as well as great challenges [118]. The cost of RFID chips can still be too expensive for wide application in logistic systems. Yan *et al.* [155] compare fresh supply chains with and without RFID tags and calculate the total profit. The results show that fresh supply chains with RFID and a reduced cargo loss rate have a higher total profit even when costs of devices are taken into account. This shows that the utilization of RFID technology is beneficial in practice.

Information communication technology

Information communication technology (ICT) can be widely used in different steps of perishable goods supply chains [29], from harvesting [19, 46] to warehouse [88], transport [157], etc. With the support of ICT, actions of infrastructures in perishables supply chains can be better planned according to real-time information (e.g., demand and remaining shelf-life). Ketzenberg *et al.* [74] measure the importance of information and value of centralized control of a supply chain between one supplier and one retailer. The study shows in this case, the total supply chain profit can increase by an average of 5.6% with shared information on the shelf-life based inventory status and a centralized control strategy. According to [119], information sharing helps improve traceability, efficiency, information accuracy, and can reduce inventory loss. Haass *et al.* [56] use simulation to show how intelligent containers can reduce the loss of bananas with information sharing and environment controlling. The result indicates that with a proper control 22% of banana spoilage can be reduced. Li *et al.* [85] study a case of perishables supply chain optimization considering the quality loss due to commodity deterioration. In their simulation scenario it is found that a thorough value loss tracking can help reduce costs by 7% in comparison with scenarios with no assessment of value loss. Lang *et al.* [80] introduce a cognitive sensor network for reefer container transport management. The network gathers information on temperature and atmosphere, then evaluates the remaining shelf-life of the perishable goods inside containers, which can contribute to better decision making to reduce loss and carbon emission.

The above examples show that planners can benefit from the awareness of supply chain information by means of ICT. Nevertheless, ICT is not limited to information sharing. By realizing the concept of Internet of Things [9], ICT can be fully integrated in a supply chain. Enabled by technologies discussed in this section, sensors and actuators can all be connected with supply chain decision makers. This can assist decision makers in supply chains in improving and carrying out their operations with real-time awareness as well as controllability.

2.3.4 Potential benefits of adopting new technologies

For the emerging technologies to be adopted in the perishable goods logistic industry, it is suggested that companies should conduct their analysis to estimate whether the application is worthy of the investment. For instance, Musa and Dabo [107] conduct a review on the adoption of RFID technology in supply chains. They conclude that in spite of the potential benefit, high investment cost could be one of the concerns that deters enterprises, especially for small- and medium-sized ones. Companies in sectors where the competitions are fierce and the profit margin is small (e.g., banana sector [43]) may also be more prudent in investing in new technologies.

Quantitative studies on the cost-benefit analyses can be found in several papers. Reported in [71], the Sainsbury's, a chain of supermarkets in UK, conducted an experiment of applying RFID for short shelf-life retailers. The estimated total benefit of full-scale implementation without supplier participation are £8.5 million a year. Increased asset visibility, increased inventory accuracy, and better control of stock rotation can contribute to the increased retail store replenishment productivity and the reduction of stockloss. The estimated payback period is between two and three years. Mai *et al.* [101] conducted cost-benefit analyses for seafood processing and trading companies on the implementation of RFID and radio frequency-time temperature indicators. They conclude that their research provides empirical support of benefits from applying RFID-based traceability solutions.

Despite the amount of attention being given to RFID, this technology only provides awareness of location and information like temperature if used together with sensors (semi-passive RFID [67]). To pro-actively control logistic operations, other technologies such as sensors and ICT are also needed. Nevertheless, apart from RFID, limited research is conducted to quantify the economic value of adopting new technologies and solutions such as Internet of Things [145].

2.3.5 Discussion

The rapid development of sensor and communication technologies has allowed supply chains to be more transparent than ever before. With physiological knowledge of perishable goods, modern technologies can bring to logistic planners real-time awareness of perishable goods' status in supply chains. The development of cheaper and more effective devices has been enabling large scale applications in logistics with feasibility and profitability. This opens up new opportunities as well as challenges for supply chain players to schedule logistic operations like never before. One of the challenges is how to utilize quality information once it is available and can be communicated in real-time. The other challenge is to quantify the potential benefit of investing in supporting technologies. The next section reviews quantitative methods such as planning models which schedules logistic activities with consideration of real-time information.

2.4 Methodology: Scheduling perishable goods logistics

This section focuses on literature that makes use of the information of quality features of perishable goods. As discussed in the last sections, this information can be acquired by supply chain players using quality models and sensor/communication technologies. This chapter reviews the application of such information in scenarios of internal and external logistics.

Academia has long been trying to incorporate deteriorating features of perishable goods in logistic planning models. Several papers are devoted to literature review of logistic systems for perishable goods [3, 4, 6, 112]. This section does not replicate the discussions in the reviewed literature, but works with these review papers to identify the methodological challenges and opportunities in relation to the real-time awareness of product quality provided by physiological knowledge and recent technological development.

The review paper [112] identifies several patterns of depreciation of perishable goods, and then mainly focuses on business planning with decision making in inventory management. They point out that the number of models integrated lifetime constraints of products is limited. Ahumada and Villalobos [3] review agricultural supply chain planning models, especially models that have been successfully implemented. They observe a trend in supply chain coordination. They also report a lack of models including more realistic features such as uncertain information and logistic integration, possibly due to the added complexity to solving the developed models. Akkerman *et al.* [4] focus on quantitative operations management approaches to food distribution management from three main aspects, namely food quality, food safety, and sustainability. The paper points out that most papers reviewed do not relate quality to environmental conditions. The review paper [6] classifies perishability as three dimensions, namely physical product deterioration, authority limits, and customer value. It then discusses models in production and distribution planning dealing with perishability. An identified challenge is a lack of models considering dynamic elements such as perishability, travel time, and demand.

This chapter does not seek to exhaust all literature, but to identify the state-of-the-art approaches and what are needed to reach the objective of this thesis. Therefore, the following sections discuss most commonly and successfully used methods in internal and external logistics.

2.4.1 Scheduling for internal logistics

Internal logistic considers scenarios with only one party or actor of supply chains such as warehouse management and inventory control. One particular field considered is postharvest planning of agricultural products.

In warehouse management, the “first-in-first-out” (FIFO) and “last-in-first-out” (LIFO) strategies are commonly used for perishable goods logistics ([16, 113, 158]). These strategies assume that all products have the same pattern of decreasing shelf-life, and set higher priority in moving out a product according to its time of arrival regardless of products’ actual quality. With the increasing awareness of products’ actual quality information, strategies such as the “first-expire-first-out” (FEFO) are becoming available for supply chain players to adjust the decisions with the objective of reducing the quality loss and improving customer satisfaction [63]. In [33], a simulation model is designed for a distribution center handling perishable goods. Different issuing policies are adopted and compared considering perishability of products. The model integrates quality features of the products using a normal distribution, and deterioration by a fixed amount per day.

Another area considered as internal logistics is postharvest operations for agricultural products. Literature has investigated optimization taking into account information on product quality. López-Milán and Plà-Aragonés [98] develop a decision support system (DSS) for sugarcane harvesting operations. Freshness of sugarcanes is only inexplicitly considered in their model. Ferrer *et al.* [46] investigate a grape harvesting problem. A mixed-integer linear programing model is proposed to support decision making on harvest scheduling, labor allocation, and routing, with the aim of minimizing the handling cost and loss of quality due to delays in harvesting. Similarly, Gonzalez *et al.* [52] develop an optimization model for apple orchards with the goal of minimizing handling costs and loss of quality. The method considers different categories of apples, which should be harvested in different time windows of the year to achieve the overall maximum quality. Caixeta-Filho [19] investigates an orange harvest scheduling problem. A model is built to maximize the total soluble solids produced from oranges by selecting when and which grove to be harvested. None of the above methods consider decision making based on real-time quality information.

2.4.2 Scheduling for external logistics

External logistic operations are multi-echelon, involving more than one stakeholders in a distribution network. In such context, demand-supply interaction and quality requirements from different players should be considered.

Network flow models have been proved to be very useful in conventional logistic systems (e.g., [23, 86]). In perishable goods supply chains, researchers have made attempts to incorporate freshness as quantitative variable in network flow models. Yu and Nagurney [156] develop a network-based model for food supply chains. The model considers the food deterioration by introducing arc multipliers: when flowing through an arc, the products in this flow deteriorate by a certain degree decided by the attribute of that arc. De Keizer *et al.* [35] apply a network flow model to represent the amount of flowers being transported from auctions to wholesalers and finally to retailers. Quality aspects are considered in a way where time-temperature sums are attached to nodes (locations) and arcs (transportations) in the network model. Another network flow model developed by Rong *et al.* [116] incorporates deterioration in a different way: the model duplicates each location in order to represent different temperature and quality of products. De Keizer *et al.* [36] use fractions of a flow to represent goods with different quality categories in the same flow.

The listed examples of using network flow models show a disadvantage in capturing

Table 2.2: Approaches in logistic scheduling for perishable goods.

Approaches	References	Quality features	Drawbacks
FEFO	[33]	Normal distribution	Do not distinguish by products, do not consider environmental disturbances
Optimization in postharvest	[19, 46, 52, 98]	Fixed or empirical quality	Do not consider real-time quality information
Network flow models 1	[35, 156]	Dynamic quality	Do not distinguish quality differences between products
Network flow models 2	[36, 116]	Dynamic quality	Quality differences are distinguished by expanding networks
Flow shop	[31]	Dynamic quality, the quality feature does not depend on the logistic feature	Route choice is not allowed

perishing natures of agricultural products in logistic networks: quality features have to be attached to network features. However, deterioration of products can be influenced by uncertainties of environments and products' variabilities [139]. In other words, deterioration from the quality aspect and movements from the logistic aspect of perishable goods are separate aspects of logistic activities. Although these two aspects can influence each other, they *do not depend* on each other.

From a different perspective, Dabbene *et al.* [31] develop a flow shop approach. The approach considers both logistic planning and product quality measuring in optimization. In the accompanying paper [32], the developed method is applied in a beef supply chain. The logistic costs can be reduced using an optimization algorithm on this model. Although the approach separates perishing features from logistic features, it does not consider route choice as part of the model.

2.4.3 Discussion

The reviewed papers apply different approaches in various areas to make use of quality information in perishable goods supply chains. These approaches are listed in Table 2.2 for a clearer comparison and a discussion on their contributions, such as how quality is integrated, what the advantages of such integration are, and what the limits are. Again the literature review in this chapter is conducted not to repeatedly discuss state-of-the-art approaches in general, but to identify the gap between current research and the objective of this thesis. Therefore, this chapter does not seek to exhaust all research papers but focuses only on the relevant approaches that are relevant to and could be potentially used in this thesis.

Considering real-time quality features of goods in a logistics system can be challenging in conventional approaches. An FEFO approach is used in inventory management [33]. The paper uses a normal distribution to represent the quality variety of the products in the same batch. However, this approach does not specify the quality of a certain product, nor consider disturbances of quality change caused by environmental factors or products' internal features. In postharvest optimizations [19, 46, 52, 98], quality is considered in different ways, either static, or empirical. But quality in real-time is not considered. In some papers [156], network flow models are used to represent external logistic systems. De Keizer *et al.* [35], a simulation approach is combined with a network flow model, but products are not explicitly distinguished in terms of quality. Network flow models in [36, 116] use duplications of the network (by multiple nodes or arcs) to represent differences of products' quality. The drawback of these methods is that they represent quality features of perishable products using logistic terms. None of the aforementioned models are capable of capturing real-time quality feature and use it in decision making processes.

Dabbene *et al.* [31] is the only paper that considers the dynamics of quality without depending on the logistic features. This allows the model to keep track on the two separate series of events: quality change and location change, and can capture their effect on each other. For instance, quality features may affect logistic events in the form of quality requirement, as a retailer may reject products with too low quality. On the other hand, logistic events can in turn affect quality events (e.g., transporting under poor cooling condition, or prolonged duration due to a congestion). Nevertheless, the formulation in the paper [31] focuses too much on the quality aspect and lacks flexibility on the logistic aspect.

From the literature reviewed above, a concluding point can be drawn that recently developed approaches lack the capability of making real-time schedules facilitated by the real-time quality awareness. This observation is in line with [3, 4, 6, 112]. All the literature is pointing to the lack of approaches with the inclusion of shelf-life constraints, uncertain information, supply chain coordination, relationship between quality and environmental factors, and stochastic elements from quality and logistic aspects. In order to fully benefit from the advantage brought by the physiological knowledge about agricultural products and the technological developments on sensors and communication, the urgent need for developing new methodological approaches is evident.

2.5 Conclusions

This chapter reviews three aspects of perishable goods logistics, namely physiology, technology, and methodology. It addresses the Research Question 1: the impact of perishability on perishable goods logistics from these three aspects. Section 2.2 shows that each type of agricultural products has unique physiological features, resulting in different forms of supply chains and logistic procedure in handling and transporting. Perishable goods supply chains are therefore not only transporting goods from one place to the other, but also taking care of the goods according to their perishing natures. Section 2.3 demonstrates that products' perishability is an important reason for supply chains to adopt technologies. In addition, the development of modern technologies have enabled previously unseen options for supply chains of perishable products. Nevertheless, the purpose of each supply chain, despite the product, remains the same: to bring fresh products to consumers in a cost-efficient way. Section 2.4 shows that although the physiological knowledge and technologies have made such quality-aware logistics possible, there is still a lack of approaches to make use of the provided real-time information. It can be concluded that the impact of perishability on perishable goods logistics has been profound, and yet it can still further benefit the decision making in perishable goods supply chains. The remainder of the thesis focuses on developing one of such approaches, which is able to simultaneously consider the quality and the logistic features.

Chapter 3

The general framework Part I: Quality-aware modeling approach

As Chapter 2 concludes, to better schedule perishable goods logistics, real-time information of goods' freshness should be taken into account. This thesis proposes a general framework in Chapters 3 and 4 as the principle to describe and control logistic processes for perishable goods supply chains. In this chapter, a quality-aware modeling approach is developed, with consideration of both logistic and quality features of the goods, allowing supply chain players to better plan logistic activities.

Section 3.1 introduces the general framework from a system and control perspective. Section 3.2 focuses on the quality-aware modeling approach. Section 3.3 demonstrates how the quality-aware model could work by means of an example. Section 3.4 concludes this chapter.

Parts of this chapter have been published in [92].

3.1 The system and control perspective

Each perishable goods supply chain is unique, due to the differences in the quality features of the product and the logistic features of the supply chain. Nevertheless, all supply chains have the same goal, as illustrated in Chapter 2, to bring fresh products to customers in a cost-efficient way. This thesis presents a general framework on modeling and managing logistic activities while considering perishability of goods in supply chain planning. A system and control perspective is adopted in this thesis as a starting point, for structuring the relation between logistic processes (system), and decision making (control).

Fig. 3.1 illustrates the conceptual general framework. Quality features and logistic features of the goods in the supply chain are captured in this framework as the *system*. A decision maker of the supply chain is referred to as a *controller*. The controller observes the system by measuring some of its variables (e.g., freshness and location of each product), and makes decisions (e.g., relocating products) that direct the system to achieve an objective (e.g., having a certain amount of products delivered while minimum amount of quality is lost). A controller can be a person or a computer aided agent.

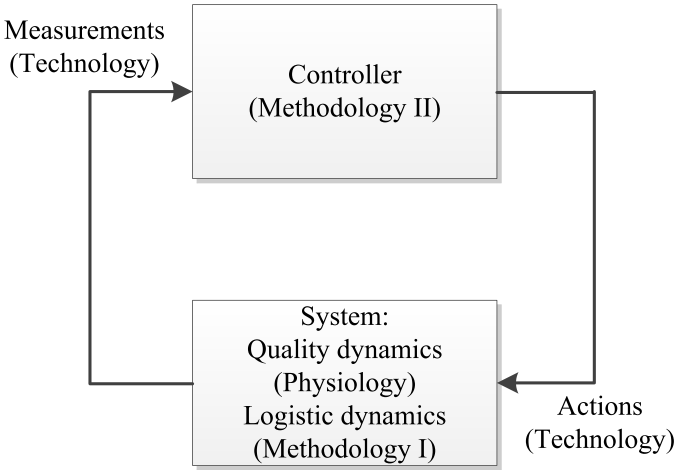


Figure 3.1: System and control perspective.

Table 3.1: A comparison of literature reviewed in Chapter 2 and elements in the proposed general framework.

General framework	Logistic elements
Measurements and actions	Technology
System	Physiology (Quality dynamics) Methodology (Logistic dynamics)
Controller	Methodology

Table 3.1 compares the elements in this general framework to the logistic elements presented in literature review in Chapter 2. The technological developments enable measurements and actions taken by controllers. The physiological features of perishable goods provide insight for the system on the quality side. The methodological part of literature review however, as concluded in Chapter 2, shows a lack of adequate planning strategies that can effectively describe dynamics in perishable goods supply chains. The controller in the general framework represents decision makers in logistics. This comparison helps to visualize the focus of this thesis: the combination of logistic and quality dynamics as the system and the control strategies. This chapter addresses the system part. Control strategies are discussed in Chapter 4.

Here a general, mathematical representation of system dynamics on discrete time steps is presented:

$$\mathbf{x}(k+1) = f\left(\mathbf{x}(k), \mathbf{u}(k), \mathbf{d}(k)\right), \tag{3.1}$$

$$\mathbf{y}(k) = g\left(\mathbf{x}(k), \mathbf{u}(k), \mathbf{d}(k)\right), \tag{3.2}$$

$$f_1\left(\mathbf{x}(k), \mathbf{y}(k), \mathbf{u}(k), \mathbf{d}(k)\right) \geq 0, \tag{3.3}$$

$$f_2\left(\mathbf{x}(k), \mathbf{y}(k), \mathbf{u}(k), \mathbf{d}(k)\right) = 0, \tag{3.4}$$

in which $\mathbf{x}(k)$, $\mathbf{u}(k)$, $\mathbf{d}(k)$, and $\mathbf{y}(k)$ represent the system state, the decisions made on the system, the disturbances, and the output of the system at time step k ($k \in \{1,2,\dots\}$), respectively. Eq. (3.1) indicates that the state of the system of the next time step is determined by the state of the system, decisions made, and disturbances at the current time step. Eq. (3.2) represents that the output of the system depends on the system state, decisions, and disturbances of the current time step. A general form of the system constraints are represented by (3.3) and (3.4).

The adoption of the system and control perspective can shed some light on modeling perishable goods logistics. It looks at this issue from a different angle: rather than focusing on facilities and vehicles like other model do, the general framework can focus on perishable goods themselves. The decisions being made change the status (e.g., quality and location) of those perishable goods. The next section explains such a modeling approach in a general formulation.

3.2 Quality-aware modeling

This section proposes an effective method to describe a perishable goods logistic system using a state-space representation, in which quality features can be considered simultaneously with the logistic features.

3.2.1 System dynamics: Logistics

Inspired by [31], this chapter proposes a quality-aware modeling method for perishable goods logistics. The products being handled in a supply chain are considered as *units*. A unit is a controllable and undividable entity, and has its own quality features (i.e., the shelf-life of the products within the unit) and logistic features (the location of the unit). Depending on the types of supply chains, one unit can refer to a pallet of flowers, a container of bananas, or a truckload of potatoes. A system of the general framework (shown in Fig. 3.1) includes all the units $m \in \mathcal{M}$ considered in the considered part of the supply chain. System state $\mathbf{x}$ therefore represents the states of all units in $\mathcal{M}$.

Each unit m goes through a series of logistic stages (e.g., being at the importer, at a warehouse, or at a terminal) before reaching its final destination. The decisions are then at what time the units should move from one stage to the next one, to fulfill the quantity and quality requirements of the destination. The dynamics of *each* unit m are represented by a directed graph $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$, with $\mathcal{N}$ the nodes representing possible stages of unit m, and $\mathcal{E}$ the directed arcs representing possible transitions between stages. The stage of unit m at time step k is represented by a series of binary variables $l_{mi}(k), i \in \mathcal{N}$, denoted as:

$$l_{mi}(k) = \begin{cases} 1, & \text{if unit } m \text{ is at stage } i \text{ at time step } k, \\ 0, & \text{otherwise.} \end{cases} \tag{3.5}$$

For example, $l_{56}(7) = 1$ represents that unit 5 is at stage 6 at time step 7. It is logical to have the constraint that at each time step, each unit must, and can only be at one of the stages:

$$\sum_{i \in \mathcal{N}} l_{mi}(k) = 1, \forall m \in \mathcal{M}, k \in \{1,2,\dots\}. \tag{3.6}$$

The action of moving unit m from stage i to stage j at time step k is denoted by a series of binary variables $u_{mij}(k)$, $(i,j) \in \mathcal{E}$. This action is made at time step k, and will result in the new system state at time step $k+1$. For $\forall m \in \mathcal{M}, i, j \in \mathcal{N}, k \in \{1,2,\dots\}$, the following equations describe these dynamics:

$$u_{mij}(k) = \begin{cases} 1, & \text{if unit } m \text{ is moved from stage } i \text{ to stage } j \text{ at time step } k, \\ 0, & \text{otherwise.} \end{cases} \tag{3.7}$$

$$l_{mj}(k+1) = \begin{cases} 1, & \text{if } u_{mij}(k) = 1, \text{ and } (i,j) \in \mathcal{E}, \\ 0, & \text{Otherwise.} \end{cases} \tag{3.8}$$

Note that $(i,i) \in \mathcal{E}$, meaning it is allowed to have a unit waiting at a certain stage until the operation of the stage is finished or the next stage has room to take in the unit. In this case, $u_{mii}(k) = 1$.

Let $\mathcal{S}(i)$ be the collection of all j that satisfy $(i,j) \in \mathcal{E}$ $(j \neq i)$, and call any $j \in \mathcal{S}(i)$ a successor of i. Let $\mathcal{P}(j)$ be the collection of all i that satisfy $(i,j) \in \mathcal{E}$ $(i \neq j)$, and call any $i \in \mathcal{P}(j)$ a predecessor of j. To ensure the movements of units follow the directed arcs of the network, the following constraints must be satisfied:

$$\sum_{i \in \mathcal{P}(j) \cup \{j\}} u_{mij}(k) = l_{mj}(k+1), \qquad \forall m \in \mathcal{M}, \forall j \in \mathcal{N}, \forall k \in \{1,2,\dots\}, \tag{3.9}$$

$$\sum_{j \in \mathcal{S}(i) \cup \{i\}} u_{mij}(k) = l_{mi}(k), \qquad \forall m \in \mathcal{M}, \forall i \in \mathcal{N}, \forall k \in \{1,2,\dots\}. \tag{3.10}$$

Eq. (3.9) represents that unit m can move from any predecessors of stage j (including j itself) at time step k and end up at stage j at time step $k+1$. Eq. (3.10) represents that if unit m is at stage i at time step k, it can move to any successors (including i itself) of stage i.

Next, two of the most common constraints, *capacity* and *lead time*, are discussed.

Capacity Units in the logistic system may not be moving freely in the network. They can be held back because of capacity limits. This can refer to e.g., space in a warehouse, or availability of infrastructures. In general, there can be two types of capacity constraints:

$$\sum_{m \in \mathcal{M}} l_{mi}(k) \leq C_i^{\text{node}}, \qquad \forall i \in \mathcal{N}, \tag{3.11}$$

$$\sum_{m \in \mathcal{M}} u_{mij}(k) \leq C_{ij}^{\text{arc}}, \qquad \forall (i,j) \in \mathcal{E}. \tag{3.12}$$

Eq. (3.11) represents a "node" capacity imposed by a stage, limiting the maximum number (C_i^{node}) of units staying at that stage simultaneously. Eq. (3.12) represents an "arc" capacity imposed by an arc, limiting the maximum number (C_{ij}^{arc}) of units moving through this particular arc.

Lead time In some stages it may take more than one time step to finish the handling of a unit. Examples can be ripening bananas in a ripening facility [69]. A constraint of lead time ensures when a unit enters a stage, it does not move to the next stage until the process of this stage is finished. For this, let $\lambda_{mi}^{\text{t}}(k)$ be the actual number of time steps of unit m staying at

i up to time step k, let Q be a sufficiently large number, and let λ_i^{c} be the lead time at stage i. Lead time constraint is then presented as follows:

$$\lambda_{mi}^{\mathrm{t}}(k) = \sum_{\tau=1}^{k} \sum_{p \in \mathcal{P}(i) \cup \{i\}} u_{mpi}(\tau), \qquad \forall m \in \mathcal{M}, \forall i \in \mathcal{N}, \forall k \in \{1,2,\dots\}, \tag{3.13}$$

$$\sum_{p \in \mathcal{P}(i) \cup \{i\}} \lambda_i^{\mathrm{c}} u_{mpi}(k) - \lambda_{mi}^{\mathrm{t}}(k) - Q u_{mii}(k+1) \leq 0, \quad \forall m \in \mathcal{M}, \forall i \in \mathcal{N}, \forall k \in \{1,2,\dots\}, \tag{3.14}$$

in which (3.13) counts the number of time steps for which unit m stays at stage i; (3.14) ensures that the unit does not move to a next stage before lead time is reached.

3.2.2 System dynamics: Quality

During the transport time, the quality of products can decrease by different rates depending on environmental conditions, which can be time-variant and related to locations of units. In turn, quality of products can affect their logistic processes. For instance, if the quality of a unit gets too low, it can be rejected by a downstream player. Let $q_m(k)$ be the quality index of unit m at time step k. Consider the following equations:

$$q_m(k+1) = q_m(k) - \sum_{i \in \mathcal{N}} \Delta q_i(k) l_{mi}(k), \qquad \forall m \in \mathcal{M}, k \in \{1,2,\dots\}, \tag{3.15}$$

$$Q(1 - u_{mij}(k)) \geq q_j^{\mathrm{low}} - q_m(k), \qquad \forall m \in \mathcal{M}, (i,j) \in \mathcal{E}, k \in \{1,2,\dots\}, \tag{3.16}$$

where (3.15) describes that time and stage can affect a unit's quality. Variable $\Delta q_i(k)$ denotes the change in the quality, which can be time and/or stage dependent. Note that the dynamics of q have a linear relation with time in this instance. Other non-linear relations may apply for different products. (3.16) enforces that unit m cannot take the route (i, j) if quality is lower than q_j^{low}, which is imposed by stage j.

3.2.3 Implementation steps for quality-aware modeling

This section lists the general steps that needs to be followed to implement the quality-aware modeling approach for describing logistic processes of a supply chain.

1. Determine a suitable length of discrete time steps, according to the frequency of decision making and the deteriorating rate of perishable goods.

2. Determine the size of a basic unit, which is an aggregated object in which the average product quality is assumed to decrease, following a certain pattern.

3. Identify the possible logistic states (e.g., locations) of the units.

4. Identify the influence of logistic states on the deterioration rate, linking the logistic features to the quality features.

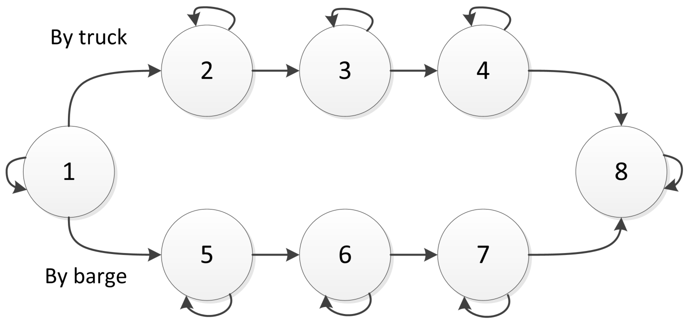


Figure 3.2: Transport process with 8 stages.

5. Identify the dynamics **x** of the quality features and the logistic features, including the input **u**, the output **y**, and the disturbance **d** of the system.

6. Identify other constraints of the system, e.g., capacity and lead time.

3.2.4 Discussion

The majority of the existing modeling methods (e.g., network flow models, see Chapter 2) consider infrastructure as logistic systems, in which goods are handled as tasks to be finished. In the quality-aware modeling method proposed in this chapter, goods being transported are considered as the system, and the infrastructure is seen as resources to fulfill demand from end stages (e.g., downstream customers). The state of the system consists of goods' quality and stage. The proposed approach focuses on the goods being handled in logistic activities, and thus allows more details of goods to be taken into account. As a result, quality-aware models have the capability of considering quality and logistic features of perishable goods at the same time.

3.3 Example of quality-aware modeling

After introducing the quality-aware modeling method, this chapter uses an initial example in which containers are being transported through a multimodal network from a sea terminal to a destination in the hinterland.

To begin with this example, 10 reefer containers arrive at the stacking area (stage 1) at place A, and need to be moved to a warehouse (stage 8) at place B. The transport between these two locations can be realized by two modalities, truck or barge. The sequence "$1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 8$" represents the route by truck, in which stage 2 is a transition stage, where containers wait to be handled by a stacking crane from the storage area to a truck; stage 3 represents the stage in which a container is being transported by truck from A to B; and stage 4 represents the stage in which a container being put into the warehouse. The sequence "$1 \rightarrow 5 \rightarrow 6 \rightarrow 7 \rightarrow 8$" represents the transport route by barge: Stage 5 represents the transition stage in which a container waits being moved from the stacking area to a waiting barge; stage 6 represents the stage in which a container is being carried by barge from A to B; stage 7 represents the stage in which a container is put into the warehouse. The objective can be defined as maximizing the overall quality of all goods in the 10 containers. Therefore the decisions can be determined by solving an optimization problem of the following form:

$$\max J = \sum_{m\in\mathcal{M}} \sum_{k=1}^{N_\mathrm{p}} \sum_{i\in\mathcal{P}(j)} q_m(k)u_{mi8}(k), \tag{3.17}$$

subject to (3.6), (3.9), (3.10), (3.11), (3.13), (3.14), (3.15). In (3.17), $(i,8)\in\mathcal{E}$ is the arrival at the destination. The considered number of time steps of the experiment N_p can be set to 20, since already before time step 20 all containers should have already been moved to the destination stage. Loading or unloading the truck takes 1 time step, while loading/unloading for barge takes 2 time steps ($\lambda_2^\mathrm{c} = \lambda_4^\mathrm{c} = 1$, $\lambda_5^\mathrm{c} = \lambda_7^\mathrm{c} = 2$). For truck transport it takes 3 time steps from A to B; as for barge it takes 5 time steps ($\lambda_3^\mathrm{c} = 3, \lambda_6^\mathrm{c} = 5$). The capacity of a truck and a barge are set to 2 and 3, respectively, while equipments involved in each loading/unloading stage has a capacity of 1 ($C_3^\mathrm{node} = 2, C_6^\mathrm{node} = 3$, $C_2^\mathrm{node} = C_4^\mathrm{node} = C_5^\mathrm{node} = C_7^\mathrm{node} = 1$). While being transported, perishable goods start to deteriorate. The rate in stage 1, 2, and 3 is 2 per time step, and 1 per time step for stage 4, 5, 6, and 7 ($\Delta q_1 = 2, q_2 = 2, q_3 = 2, q_4 = 1, q_5 = 1, q_6 = 1, q_7 = 1$). The quality change after arriving at stage 8 is not considered and thus is 0. At initial state when $k = 1$, all containers start from stage 1 with a quality of 100 ($l_{m1}(0) = 1, \forall m \in \mathcal{M}$, and $q_m(0) = 100, \forall m \in \mathcal{M}$).

Problem (3.17) is in the form of a mix-integer linear programming (MILP). It is solved in Matlab 2015b by a Cplex (v12.5.1) MILP solver. Fig. 3.3 shows the quality of each container over time. In the figure, the lines stop at the time step when the container is delivered to the warehouse (stage 8). The total quality loss is 137 units. The movements of each container are shown in Fig. 3.4. The figure illustrates that 4 containers are transported by barge and the other 6 containers by truck. It takes 16 time steps to transport all 10 containers to the destination. With this initial example, the idea of quality-aware modeling method is illustrated. The simulation experiment illustrate that the method can describe both quality features and logistic features of the perishable goods, as well as consider the two aspects together in a decision making process. In this case, the quality feature is represented with a linear model; the logistic features include lead times and node capacities. Although this example does not demonstrate the full potential of quality-aware models, more complex quality and logistic features are investigated in the remainder of the thesis.

3.4 Conclusions

This chapter proposes to tackle planning issues in perishable goods logistics using a general framework from a system and control perspective. To address Research Question 2, in this framework, a quality-aware modeling approach is proposed to describe a logistic system. Mathematical models built in this way are capable of considering simultaneously quality features and logistic features of perishable goods in a supply chain. The numerical example shows that the quality-aware modeling has potential in planning of perishable goods logistics. The next chapter will introduce controller design, as the other component of the general framework.

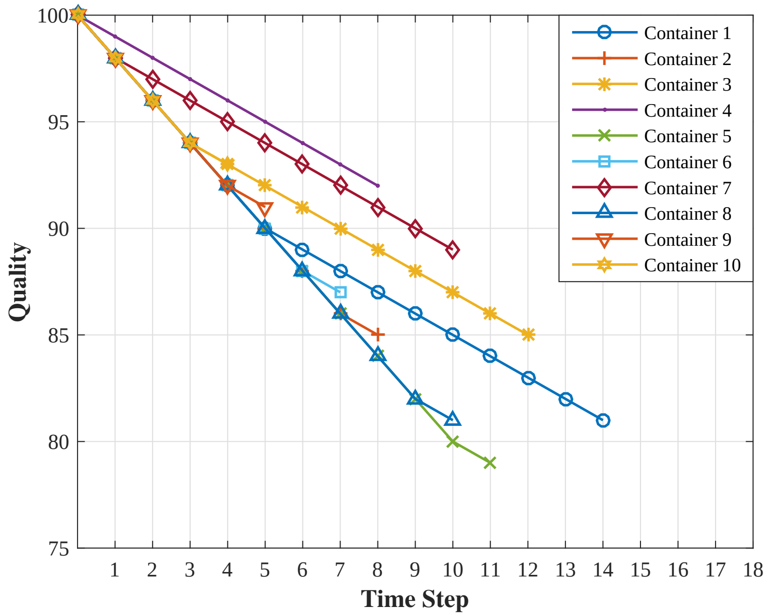


Figure 3.3: Quality loss of perishable goods in each container.

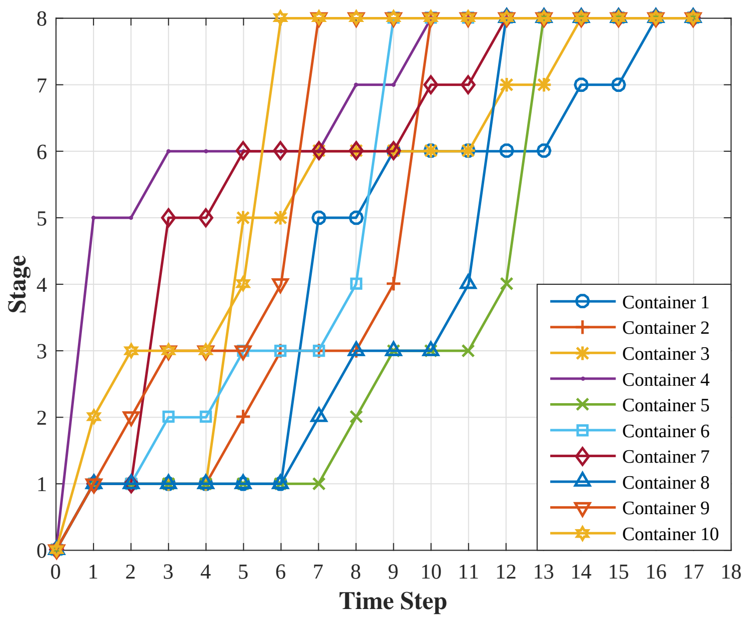


Figure 3.4: Movements of each container.

Chapter 4

The general framework Part II: Model predictive control

To develop methods for planning perishable goods logistics, Chapter 3 proposes a general framework from a system and control perspective and then focuses on the system part of the general framework, in which a quality-aware model can be used to represent a perishables logistic system. This chapter discusses the other part of the general framework, controller design. A model predictive control strategy is proposed to determine control actions, taking into account of information on the system dynamics and disturbances in the near future. This strategy allows supply chain players make decisions based on up-to-date quality and logistic information.

Section 4.1 compares the several control strategies mostly used for supply chain planning. Section 4.2 introduces the model predictive control strategy, which can effectively tackle disturbances happening in supply chains. Section 4.3 uses a brief instance to illustrate the capabilities of MPC. Section 4.4 briefly introduces distributed control architectures. Section 4.5 lists the general steps for implementing MPC in a perishable goods supply chain. Section 4.6 concludes this chapter.

Parts of this chapter have been published in [91].

4.1 Real-time control strategies

This section reviews control strategies used in supply chain management and logistics reported in literature. They can be categorized mainly in three groups: optimal control, model predictive control (MPC), and robust control.

An optimal control strategy is always formulated with an objective function and often with constraints [51]. Solutions generated by an optimal control strategy are optimal or near optimal depending on the solving technique. Ivanov *et al.* [65] analyzed the potential for optimal control being applied in supply chain decision making. They report that centralized optimal control strategies may generate better solutions rather than decentralized control. Cheng and Duran [27] use optimal control policy to aid decision making in an international crude supply chain. Interestingly in the article they mention that a rolling horizon control scheme could provide future direction for large scale industrial problems. Due to its open-loop nature, the solutions generated by an optimal control strategy is only valid under dynamic environments.

Model predictive control, also known as receding horizon control, has wide applications in transportation and logistics. The advantage of MPC is that it can easily incorporate constraints and can formulate computationally tractable optimization problems compared with optimal control strategy [120]. Li *et al.* [87] investigate synchromodal freight transport planning in multiple interconnected service networks. Xin *et al.* [152] and Zheng *et al.* [160] focus on the scheduling of autonomous guided vehicles on land and water using model predictive control. Chen *et al.* [24] investigate vessel train formation problems using MPC. Nabais *et al.* [108] use MPC to determine flow assignments in transportation networks. Seferlis and Giannelos [124] developed a two-layer MPC for multi-echelon supply chain networks. Subramanian *et al.* [129] develop a cooperative MPC strategy and apply it on a single-product, two-echelon supply chain. They demonstrate that any system that can be stabilized by a centralized MPC can be also stabilized by a cooperative MPC.

In an environment with unknown-but-bounded uncertainties, a robust control strategy can be used to tackle the stochastic features. Boukas *et al.* [15] deal with a inventory-production control problem with perishable goods. They formulated the problem as a jump linear quadratic control problem. Laumanns and Lefeber [81] consider information flows and material flows in supply networks represented by directed graphs. Demands are represented by unknown-but-bounded disturbances.

As concluded in Chapter 2, this thesis mainly investigate how real-time quality information can benefit perishable goods logistics in dynamic environments with deterministic disturbances. Therefore, the thesis chooses to focus on MPC as the control strategy. The potential of MPC for planning perishable goods logistics is evident. With prediction of products' quality and logistic conditions, MPC is able to consider what will likely happen in near future and make decisions accordingly. This allows MPC to consider any upcoming disturbances, since quality of goods and environmental factors (such as temperature) can change rapidly. Decisions obtained from the MPC approach in response to these changes could increase the efficiency of logistic activities and reduce loss of perishable goods.

4.2 Model predictive control strategy

Inaccuracy of quality measurements and disturbances in logistic events may cause loss in perishable goods supply chains. Most of the logistic planning approaches reviewed in Chapter 2 are open-loop – after decisions are made, no further adjustments to the decisions will be carried out, which may lead to certain deviations from the expected performances. A close-loop control strategy that considers the latest and future system states and disturbances can reduce such loss. According to [110], MPC is an optimization-based control technique that includes:

1. a mathematical model to represent and predict the system's behavior over a given horizon,
2. an objective function of what system behavior is desirable,
3. a mathematical formalization of operational constraints that needs to be satisfied,

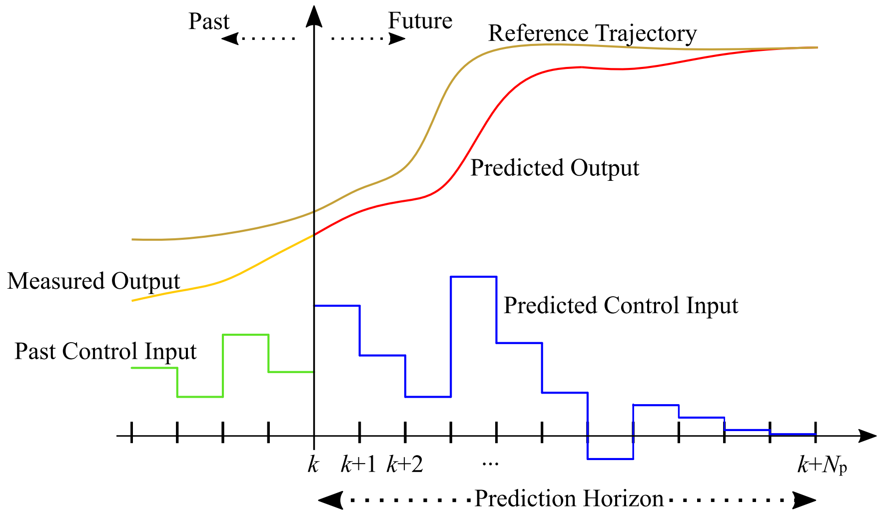


Figure 4.1: MPC working principle

4. observations of the system at each time step, and

5. any available information on upcoming disturbances.

At each time step k, to determine actions, a controller solves the following optimization problem represented in a general mathematical form:

$$\min \sum_{\tau=k}^{k+N_\mathrm{p}-1} J\left(\mathbf{x}(\tau), \mathbf{u}(\tau)\right), \tag{4.1}$$

subject to

$$\mathbf{x}(k+1) = f\left(\mathbf{x}(k), \mathbf{u}(k), \mathbf{d}(k)\right), \tag{4.2}$$

$$\mathbf{y}(k) = g\left(\mathbf{x}(k), \mathbf{u}(k), \mathbf{d}(k)\right), \tag{4.3}$$

$$f_1\left(\mathbf{x}(k), \mathbf{y}(k), \mathbf{u}(k), \mathbf{d}(k)\right) \geq 0, \tag{4.4}$$

$$f_2\left(\mathbf{x}(k), \mathbf{y}(k), \mathbf{u}(k), \mathbf{d}(k)\right) = 0, \tag{4.5}$$

where N_p is the length of the prediction horizon. Value J is a function of system state $\mathbf{x}$ and decisions $\mathbf{u}$ at time step τ. The objective is, without loss of generosity, to minimize the sum of all J from $\tau = k$ to $k + N_\mathrm{p} - 1$. This calculation is made at each time step k, subject to the predicted system dynamics (4.2), (4.3) and constraints (4.4), (4.5). Figure 4.1 shows how a model predictive controller works in general. The process is explained in Alg.4.1.

4.3 MPC example case: Potato starch production

This section provides an example case of MPC for planning potato starch production.

Algorithm 4.1 General MPC principle

1: At time step k, the model predictive controller measures the stages of the system $\mathbf{x}$ and the known disturbances $\mathbf{d}$.
2: The controller solves an optimization problem (4.1)–(4.5), with a certain objective (4.1), represented in Fig. 4.1 as the closeness of the system output from a reference trajectory.
3: Decisions $\mathbf{u}$ for the future N_p time steps have been obtained as predicted control input.
4: The controller executes the decisions for the first upcoming time step $k+1$ only.

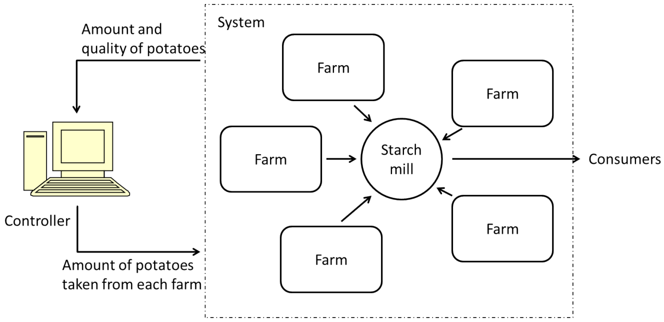


Figure 4.2: A system and control perspective for potato starch production scheduling

4.3.1 Scenario description

Potatoes are one of the main sources for starch production [53]. The extraction of starch from potatoes is an important step in potato starch supply chains. Usually a starch production plant is located near potato farms, producing starch from potatoes during the harvest time of each year. When a starch producing campaign starts, farmers harvest potatoes and store them in their chambers, waiting to transport to the plant for processing. During this waiting time, potatoes start to deteriorate, and starch concentration starts to decrease. Therefore, the scheduling of potato processing can affect the total amount of starch produced. Since farmers get paid for starch and not potato weight, the overall degradation should be minimized.

As discussed in Chapter 3, a system and control perspective is adopted in the general framework. For this potato starch production case, as shown in Fig. 4.2, the system is considered as a starch production plant and several farms that provide potatoes to the plant. The controller is an agent that can measure the amount and quality of potatoes that remain in the storages of each farm, and make decisions on how many and from which farms potatoes should be taken each day. The mathematical representations of the system and the controller are discussed below.

4.3.2 System dynamics

Logistic dynamics

A set of farms $\mathcal{F} = \{1, \ldots, i, \ldots, F\}$ with S_i chambers $\mathcal{S}_i = \{1, \ldots, j, \ldots, S_i\}$ on each farm, and a starch production plant are considered as components of the system. On each day

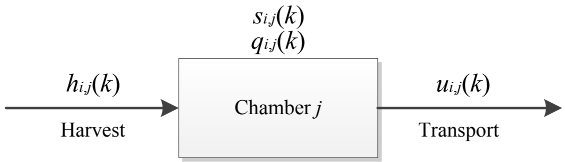


Figure 4.3: Dynamics of potatoes in a chamber

Figure 4.4: Dynamics of potatoes sent to the starch production plant

k in a chamber j of farm i, $h_{i,j}(k)$ represents the amount of potatoes brought in with the harvest, and $u_{i,j}(k)$ represents the amount of potatoes moved out for the plant, where $k \in \mathcal{T} = \{1, \ldots, k, \ldots, T\}$. The amount of potatoes remaining in the chamber is $s_{i,j}(k)$, and $q_{i,j}(k)$ is the quality of them, as shown in Fig. 4.3. Each day during the campaign potatoes from different chambers are transported to the plant, and $P(k)$ is the total starch production on that day, as shown in Fig. 4.4. The dynamics of remaining potatoes in each chamber is then described as follows:

$$s_{i,j}(k+1) = s_{i,j}(k) - u_{i,j}(k) + h_{i,j}(k), i \in \mathcal{F}, j \in \mathcal{S}_i, k \in \mathcal{T} \tag{4.6}$$
$$P(k) = \sum_{i \in \mathcal{F}, j \in \mathcal{S}_i} u_{i,j}(k) q_{i,j}(k). \tag{4.7}$$

Quality dynamics

The starch concentration of stored potatoes decreases over time. This change is also considered in the system. According to an experimental study [111], the degradation of the starch concentration follows a first-order kinetic model. With q_0 the initial quality when harvested, the remaining quality at continuous time t can be denoted as:

$$q(t) = q_0 \exp(-rt). \tag{4.8}$$

where r is a temperature dependent variable derived using Arrhenius Law [139]. This example assumes that r is known from the given temperature. A discrete kinetic model is used as decisions are made at discrete time steps. Let δ be the time interval between time step k and $k+1$. Note that quality at any time step k can be seen as an “initial quality” for time $k+1$, and that r is time-relevant. Let $R(k) = \exp(-r(k)\delta)$, the quality dynamics can be represented as follows:

$$\begin{aligned} q(k+1) &= q(k) \exp(-r(k)\delta) \\ &= q(k) R(k). \end{aligned} \tag{4.9}$$

System state-space representation

Let vector $\mathbf{x}(k)$ denote the state of the system, including the amount of potatoes left in each chamber $s_{i,j}(k)$ and the quality of the potatoes in the chamber $q_{i,j}(k)$. In this instance, the states of the system are assumed measurable, i.e., $\mathbf{y}(k) = \mathbf{x}(k)$. Decision variables are collected in vector $\mathbf{u}(k)$, denoting the amount of potatoes to be transported from each chamber to the plant on day k. The amount of remaining potatoes in the chambers is denoted by $\mathbf{s}(k)$. The qualities of the potatoes are given by $\mathbf{q}(k)$. Vector $\mathbf{h}(k)$ represents the amount of potatoes harvested on day k, which is considered as disturbance of the system $\mathbf{d}(k)$. The element of matrix $\mathbf{H}$ (with the size of $F \times T$) on row i, column k is 1 if there is harvesting for farm i, day k; and 0 otherwise. Denote identical matrix as $\mathbf{I}$, the state-space form of this system can now be represented by:

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A}(k)\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{C}\mathbf{d}(k), \\ &= \begin{bmatrix} \mathbf{I} & 0 \\ 0 & \mathbf{R}(k) \end{bmatrix} \begin{bmatrix} \mathbf{s}(k) \\ \mathbf{q}(k) \end{bmatrix} + \begin{bmatrix} -\mathbf{I} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{u}(k) \\ 0 \end{bmatrix} + \begin{bmatrix} \mathbf{I} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{h}(k) \\ 0 \end{bmatrix} \end{aligned} \tag{4.10}$$

$$\mathbf{y}(k) = \mathbf{x}(k), \tag{4.11}$$

where

$$\mathbf{A}(k) = \begin{bmatrix} \mathbf{I} & 0 \\ 0 & \mathbf{R}(k) \end{bmatrix}, \tag{4.12}$$

$$\mathbf{R}(k) = \begin{bmatrix} R_{1,1}(k) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & R_{F,S}(k) \end{bmatrix}, \tag{4.13}$$

$$\mathbf{x}(k) = [\mathbf{s}^{\mathrm{T}}(k), \mathbf{q}^{\mathrm{T}}(k)]^{\mathrm{T}}, \tag{4.14}$$

$$\mathbf{s}(k) = [s_{1,1}(k), s_{1,2}(k), \ldots, s_{i,j}(k), \ldots, s_{F,S}(k)]^{\mathrm{T}}, \tag{4.15}$$

$$\mathbf{q}(k) = [q_{1,1}(k), q_{1,2}(k), \ldots, s_{i,j}(k), \ldots, s_{F,S}(k)]^{\mathrm{T}}, \tag{4.16}$$

$$\mathbf{u}(k) = [u_{1,1}(k), u_{1,2}(k), \ldots, u_{i,j}(k), \ldots, u_{F,S}(k)]^{\mathrm{T}}, \tag{4.17}$$

$$\mathbf{h}(k) = [h_{1,1}(k), h_{1,2}(k), \ldots, h_{i,j}(k), \ldots, h_{F,S}(k)]^{\mathrm{T}}, \tag{4.18}$$

$$\mathbf{d}(k) = \mathbf{h}(k). \tag{4.19}$$

Constraints

Two constraints are considered in this study case. Firstly, the amount of potatoes $u_{i,j}(k)$ transported is non-negative and not larger than the amount of potatoes left in the chamber. Secondly, the plant has a daily processing capacity $c(k)$. The two constraints are described as follows:

$$0 \leq u_{i,j}(k) \leq s_{i,j}(k), \tag{4.20}$$

$$\sum_{i \in \mathcal{F}} \sum_{j \in \mathcal{S}_i} u_{i,j}(k) \leq c(k). \tag{4.21}$$

Algorithm 4.2 Quality-unaware controller $\mathscr{C}_1$

1: $u_{i,j}(k) \leftarrow 0$ for each $i \in \mathcal{F}$ and $j \in \mathcal{S}_i$.
2: **repeat**
3: Randomly pick a farm $i \in \mathcal{F}$
4: Take away potatoes most recently harvested, $u_{i,j}(k) \leftarrow u_{i,j}(k) + s_{i,j}(k)$.
5: **until** $s_{i,j}(k) \geq c(k) - u_{i,j(k)}$ (the daily capacity reached).

Algorithm 4.3 Quality-aware controller $\mathscr{C}_2$

1: Take measurements $\mathbf{q}(k)$ for all the stored potatoes.
2: Solve the optimization problem (4.22) – (4.26) to get values for $\mathbf{u}(k)$, that maximize the starch production of the day.

Algorithm 4.4 Predictive quality-aware controller $\mathscr{C}_3$

1: Take measurements and predictions for all the stored potatoes within the prediction horizon τ.
2: Solve the problem (4.27) – (4.31) to find the optimal solutions for $\tilde{\mathbf{u}}(k)$.
3: Implement the decision $\mathbf{u}(k)$.

4.3.3 Control approach

The controller takes measurements of the system and makes decisions on when and from which farm potatoes should be transported to the plant for processing. In order to illustrate the performance of MPC, three different control strategies are considered:

- $\mathscr{C}_1$: Quality-unaware controller: scheduling without any knowledge of quality;
- $\mathscr{C}_2$: Quality-aware controller: scheduling with information of quality of the day;
- $\mathscr{C}_3$: Predictive quality-aware controller: scheduling with information of quality over a prediction horizon.

Quality-unaware controller $\mathscr{C}_1$

In a traditional potato starch production scenario, potato quality is often not considered. The postharvest decisions made by growers and starch production plants are irrelevant to the starch content of potatoes. To describe such situation, the quality-unaware controller does not apply any form of optimization and randomly, repeatedly picks a farm on each day, and starts the transport with the most recently harvested potatoes on that farm until the daily capacity is reached, as is shown in Algorithm 4.2.

Quality-aware controller $\mathscr{C}_2$

In a modern starch potato production scenario, potato quality is often estimated by growers or production plants. To describe such situation, the quality-aware controller takes daily measurements of the quality and amount of potatoes in each chamber. It then chooses to transport potatoes that have the best quality first. This controller maximizes the daily production of starch by solving the following optimization problem:

$$\max_{\mathbf{u}(k)} J(\mathbf{x}(k),\mathbf{u}(k),\mathbf{d}(k)) = \sum_{i\in\mathcal{F}} \sum_{j\in\mathcal{S}_i} q_{i,j}(k)u_{i,j}(k), \tag{4.22}$$

subject to

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{C}\mathbf{d}(k), \tag{4.23}$$

$$\mathbf{y}(k) = \mathbf{x}(k), \tag{4.24}$$

$$0 \le u_{i,j}(k) \le s_{i,j}(k), \tag{4.25}$$

$$\sum_{i\in\mathcal{F}} \sum_{j\in\mathcal{S}_i} u_{i,j}(k) \le c(k). \tag{4.26}$$

Algorithm 4.3 shows the steps of this controller.

Predictive quality-aware controller $\mathscr{C}_3$

When potato quality can be predicted, growers and starch production plants can make decisions according to this information. A quality-aware model predictive controller is designed to consider predicted quality over a prediction horizon. The optimal decision can be made at the beginning of each day to maximize the total production. Only the decisions for the first day given by the controller are implemented. A new optimization is carried out each next day until the end of the experiment. The optimization problem solved by the controller is then:

$$\max_{\tilde{\mathbf{u}}(k)} J(\tilde{\mathbf{x}}(k),\tilde{\mathbf{u}}(k),\tilde{\mathbf{d}}(k)) = \sum_{\tau=0}^{\min(N_\mathrm{p}-1,T-k)} \sum_{i\in\mathcal{F}} \sum_{j\in\mathcal{S}_i} q_{i,j}(k+\tau)u_{i,j}(k+\tau) \tag{4.27}$$

subject to

$$\mathbf{x}(k+\tau+1) = \mathbf{A}\mathbf{x}(k+\tau) + \mathbf{B}\mathbf{u}(k+\tau) + \mathbf{C}\mathbf{d}(k+\tau) \tag{4.28}$$

$$\mathbf{y}(k+\tau) = \mathbf{x}(k+\tau) \tag{4.29}$$

$$0 \le u_{i,j}(k+\tau) \le s_{i,j}(k+\tau) \tag{4.30}$$

$$\sum_{i\in\mathcal{F}} \sum_{j\in\mathcal{S}_i} u_{i,j}(k+\tau) \le c(k+\tau) \tag{4.31}$$

where $\tilde{\mathbf{x}}(k) = [\mathbf{x}^\mathrm{T}(k+1),\ldots,\mathbf{x}^\mathrm{T}(k+N_\mathrm{p})]^\mathrm{T}$ is the vector consisting of all system states over the prediction horizon. Similarly, $\tilde{\mathbf{u}}(k)$ and $\tilde{\mathbf{d}}(k)$ are $[\mathbf{u}^\mathrm{T}(k+1),\ldots,\mathbf{u}^\mathrm{T}(k+N_\mathrm{p})]^\mathrm{T}$ and $[\mathbf{d}^\mathrm{T}(k+1),\ldots,\mathbf{d}^\mathrm{T}(k+N_\mathrm{p})]^\mathrm{T}$, respectively. Using this controller, only the first step of the decisions are implemented on the system, i.e. $u(k)$. The procedure of this controller is described in Algorithm 4.4. Because the duration of the experiment is finite, from day $T-N_\mathrm{p}+2$ to day T, the length of the prediction horizon $k+N_\mathrm{p}$ becomes larger than the length of the remaining time steps of the experiment. The controller therefore reduces the prediction horizon if it exceeds the length of the experiments.

Table 4.1: Performance of different controllers

Controller	$\mathscr{C}_1$	$\mathscr{C}_2$	$\mathscr{C}_3$ 5-day	$\mathscr{C}_3$ 10-day	$\mathscr{C}_3$ 30-day	$\mathscr{C}_3$ 60-day
Mean	100.0%	109.9%	111.6%	112.3%	114.1%	114.9%
Deviation	0	0.0324	0.0360	0.0387	0.0460	0.0574

4.3.4 Simulation experiments

The experiments consider 5 farms. Each farm has a storage place of 4 chambers. Each experiment lasts for 60 days in total. Ten scenarios are considered altogether. In each scenario, different strategies are used. The scenario settings are shown as follows:

F = 5,
S_i = 4, $i \in \mathcal{F}$,
T = 60,
$s_{1,1}(1) - s_{5,1}(1)$ = 4400, 4300, 4400, 4500, 4200,
$h_{i,j}(k)$ = $400\mathbf{H}(i,k)$, $i \in \mathcal{F}$, $k \in \mathcal{T}$,
$c(k)$ = 800, $k \in \mathcal{T}$,
$q_{i,j}$ $\sim N(E_{i,j}, d_{i,j})$,
$r_{i,j}(1)$ $\sim N(\mu_{i,j}, \bar{\sigma}_{i,j})$,
$r_{i,j}(k+1)$ $\sim N(r_{i,j}(k), \sigma_{i,j})$,
$E_{1,j} - E_{5,j}$ = 100, 80, 90, 85, 100,
$d_{1,j} - d_{5,j}$ = 1, 1, 1, 0.5, 1,
$\mu_{1,j} - \mu_{5,j}$ = 0.02, 0.03, 0.04, 0.025, 0.03,
$\bar{\sigma}_{i,j}$ = 0.002,
$\sigma_{i,j}$ = 0.001.

The sets of farms (F) and chambers(S), the length of the simulation in days (T), initial amount of potato storage ($s_{i,1}(1)$), amounts and dates of harvesting on each farm ($h_{i,j}(k)$), and the capacity of production plant (c_k) remain the same in all scenarios. The harvesting of farm i happens on day $2+i$, $12+i$, and $22+i$, denoted by binary variables in matrix $\mathbf{H}$. The initial quality of each chamber $q_{i,j}$ and kinetic variables $r_{i,j}(k)$ follow normal distributions.

With each scenario, 3 experiments are conducted using the 3 different control strategies. In each experiment, the results of different controllers are normalized so that they are compared with controller $\mathscr{C}_1$ in percentages. Table 4.1 lists the mean value and standard deviation from the 10 scenarios of relative starch yield of each controller. Controller $\mathscr{C}_1$ yields 100% production, while $\mathscr{C}_2$ has an increase of production by 9.9%. The predictive controller with 5 day's prediction produces 11.6% more starch compared to $\mathscr{C}_1$. With quality prediction of 60 days, the controller has the highest production by an increase up to 14.9% compare to $\mathscr{C}_1$. A chart illustrating the effect of different prediction horizon is presented as Fig. 4.5.

This initial case study investigates the idea of scheduling potato starch production using MPC when considering accurate information on potato quality. The performance of MPC controllers is compared with the performance of a quality-unaware controller and a non-predictive, quality-aware controller. It is illustrated that MPC can use the information of current as well as predicted quality to improve decision making. The example does not include disturbances in quality prediction, thus when the prediction horizon increases, the

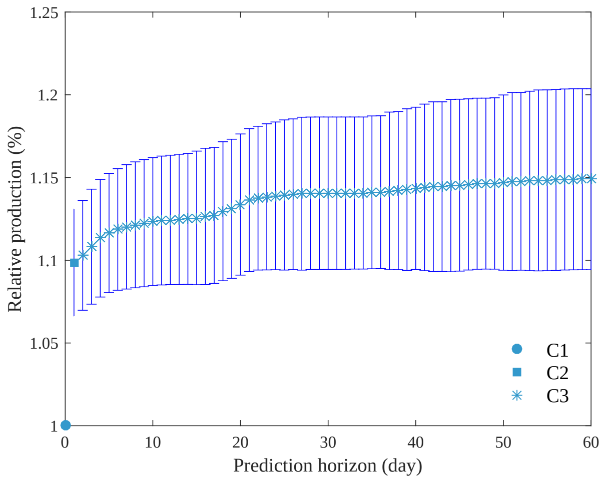


Figure 4.5: Performances of controllers of different prediction horizons

improvements of starch production always become larger.

4.4 Control architectures

The above example shows a centralized control strategy, with one controller holding all information and making all decisions. The advantage of using a centralized control strategy is that the solutions given by the controller are globally optimal (given that the optimization is solved in an optimal manner). However, as Negenborn and Maestre [109] point out, a system can sometimes be difficult for centralized modeling, data collection, and actuation. For instance, a transport network can be too large for a controller to compute the solution. In addition, a supply chain may contain more than one decision makers, who make decisions according to their own knowledge. These situations make it difficult for a centralized controller to be implemented. Moreover, the computational requirements of centralized control strategies can be very high. To avoid these disadvantages, a decentralized control strategy is often used, although a loss of performance may incur compared to a centralized strategy.

Decentralized control strategies can be designed in different architectures, depending on how controllers interact with each other. According to Scattolini [121], architectures include decentralized control architecture, in which each controller controls one of the subsystems and do not communicate with each other; distributed control architecture, in which each controller is responsible for each of the subsystems, and communicate with other controllers; hierarchical control architecture, in which controllers are organized in a hierarchical way with different levels. Each of the architectures can be applied according to the features and relationships of the considered decision makers.

4.5 MPC design steps for perishable goods logistics

This section lists the general steps for designing a control strategy, once the model of the logistic system is known.

1. Identify the number of supply chain players and their goals in the supply chain, individually or collectively.
2. Determine the control architecture according to the relationships amongst the players. This includes how controllers communicate with each other.
3. Determine the length of the prediction horizon based on the available future information and computational requirements.
4. For each controller, determine the objective function and constraints, forming an optimization problem.
5. For each controller, determine an appropriate solving technique for the optimization problem.

4.6 Conclusions

This chapter focuses on the controller component of the general framework. In this chapter, the Research Question 3 is addressed by proposing the use of MPC. In an example of potato starch production scheduling, the MPC strategy proves to have its strength in dealing with real-time and predicted quality information in scheduling perishable goods logistics. In addition, distributed MPC is briefly introduced. The steps needed in general to implement MPC in a perishable goods supply chain is listed. Chapters 5, 6, and 7 implement the general framework in supply chains with different commodities.

Chapter 5

Quality-aware modeling in a banana distribution network

In Chapter 3, a quality-aware modeling approach is proposed to describe perishable goods logistics. This chapter follows Chapter 3 by applying the proposed modeling approach to a banana distribution network. The network considers a port-based cool warehouse, a ripening facility, and retailers in hinterland. Bananas' quality is used as reference for decision making. The quality-aware model also considers quality-related decisions on ripening.

This chapter is organized as follows: Section 5.1 introduces a typical banana supply chain. Section 5.2 describes mathematically using the proposed quality-aware modeling approach, with an objective of maximizing the total revenue generated by the banana distribution network. Section 5.3 presents the simulation experiments to evaluate the proposed approach. Section 5.4 concludes the chapter.

Parts of this chapter have been published in [93].

5.1 Introduction

Bananas are one of the most traded agricultural products in the world. The total export of bananas was 17.5 million tonnes in 2016 and were expected to reach 18.1 million tonnes in 2017 [50]. EU imported 5.8 million tonnes of bananas in 2017 [44].

The amount of wasted bananas is huge. In UK alone, 83000 tonnes of bananas become wasted per year [133]. Wastage can happen in households or supply chains. For instance, failing to meet quality requirements imposed by downstream supply chain players can result in wastage of a whole container of bananas [140].

5.1.1 Life cycle of bananas

Bananas slowly go through a climacteric period after being taken from trees. This period is often referred to as "ripening". During this climacteric period, bananas' respiration rate and ethylene production increase. The time period prior to ripening is referred to as a green-life period [148], for peels of bananas are green during this period. As the ripening process

Table 5.1: Seven-stage scale for assessing banana ripeness [126].

Stage	Description
1	Green
2	Green with traces of yellow
3	More green than yellow
4	More yellow than green
5	Yellow with green tip
6	Completely yellow
7	Yellow with brown flecks

initiates, bananas start to gradually turn from green to yellow. Although bananas can ripen naturally, in today's supply chain it is preferred that bananas are ripened in ripening facilities through ethylene treatment. Because this helps bananas develop a bright-yellow peel color which appeals to the consumers [39]. After the ripening treatment, bananas are transported from the ripening facility to nearby retailers.

If storage temperature is too high during green-life period, bananas may start to ripen before reaching a ripening facility. This undesired situation is referred to as "early ripening". Ripe bananas have a very short shelf-life before they turn too ripe. Therefore, during shipping, the temperature in reefer containers should be kept at about 13 °C in order to reduce the risk of early ripening.

The ripeness of bananas can be assessed by visual inspection of the color of banana peel. A seven-stage scale is mostly used in commercial banana supply chains [126]. As shown in Table 5.1, the larger the number, the more ripe bananas become. Usually retailers require the bananas to be at stage 3 or 4 of ripeness.

5.1.2 Typical banana supply chain

In a typical intercontinental supply chain, bananas are harvested at farms in tropical regions (e.g., Central America), then cut, washed, quality-checked and put into boxes. Then these boxes are prepared for shipping by sea, stowed in reefer containers and transported to a port terminal by truck. These procedures take less than a day. After being loaded onto a vessel, the intercontinental journey takes about two weeks for the reefers to reach terminals in Europe. Figure 5.1 shows a banana distribution network in Europe. Bananas from Costa Rica are shipped to several ports in Europe. They are then transported by truck to local ripening facilities and afterwards to retailers. Upon arrival at the destination continent, bananas are stored in warehouses for up to 1 week. Before being distributed to retailers, bananas go through a forced ripening procedure using ethylene treatment in a sealed chamber with temperature and atmosphere control. This procedure takes about 4 to 8 days depending on the temperature before bananas can be taken to retail stores or supermarkets and finally consumed by customers in a few days.

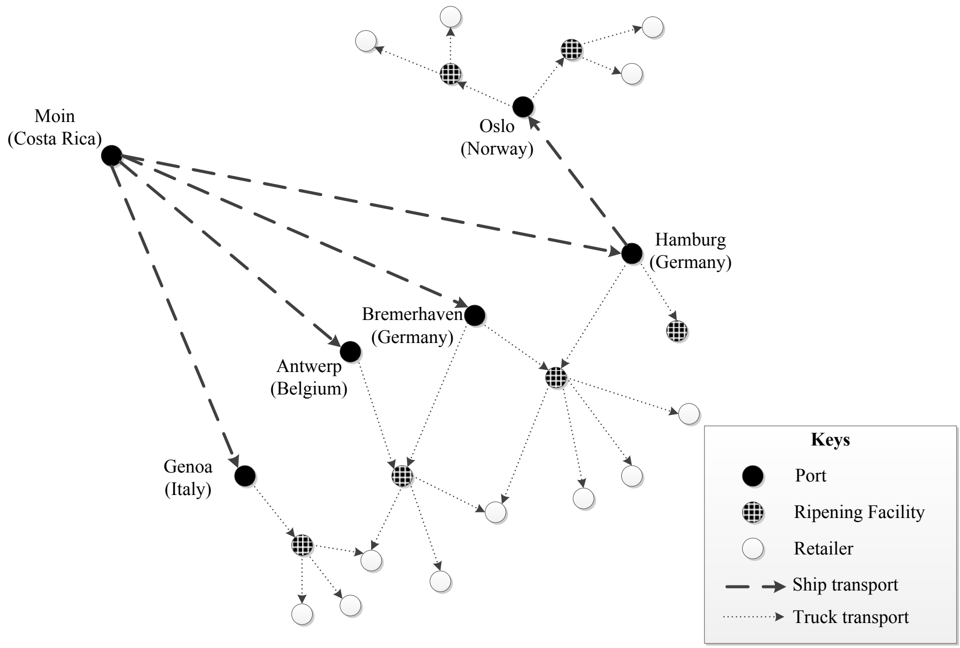


Figure 5.1: A banana distribution network (adapted from [100]).

5.1.3 Previous research focusing on banana distribution

Banana supply chain is a mature industrial sector. However, very limited research addresses the changes that can be brought by the real-time quality awareness provided by recently developed technologies.

Jedermann *et al.* [69] study the impact of awareness of banana quality change on an international banana supply chain. They conclude that remote quality monitoring has high potential in improving supervision of transport processes to reduce losses in a banana supply chain. Furthermore, techniques of ripening bananas in reefer containers can be made available with remote monitoring and supervision. Recent development of sensor technology [66], communication technology [68] and understanding of banana physiology [69] can contribute to better coordinations amongst supply chain players with the objective of reducing the wastage of bananas [79].

One promising aspect is to use quality information to optimize logistics activities. Some previous research has focused on this aspect of a banana distribution system. Lütjen *et al.* [100] consider an assignment problem to allocate containers to fulfill customer orders considering the risk of bananas' early ripening. Haass *et al.* [56] design a coordination strategy for intelligent containers to automatically adjust destinations according to demand of customers and quality of bananas being held inside containers. They demonstrate the potential of quality driven distribution of perishable foods by intelligent containers. Both papers assume that quality information of bananas can be acquired and shared using communication technology.

This chapter examines the capability of a quality-aware model by describing a banana logistics system using such method. Subsequently an optimization of banana logistics activities from a terminal to retailers is carried out. Bananas are scheduled in containers, taking into consideration of quality before and after ripening.

5.2 Scheduling with quality information for a banana logistics system

This section firstly formalizes the research problem. Then assumptions considered in this study are discussed. Subsequently, the quality-aware model is developed for scheduling in a banana logistics system.

5.2.1 Problem statement and assumptions

Figure 5.1 shows a banana distribution network in Europe. Bananas grown in tropical countries are shipped to several ports in Europe. They are then transported by truck to local ripening facilities and afterwards to wholesalers and retailers. In a ripening facility, bananas receive ethylene treatment to be ripened, which takes about 4–8 days. In today's banana supply chain, the latest quality information is only available when bananas reach certain check points. If bananas are found with bad quality at a check point, they should be discarded, or a secondary customer who is willing to receive them should be contacted. If real-time information would be available, adjustments could be made in time to proactively handle such situations.

The quality change of bananas can be divided into two periods: the green-life period and the ripe period. The relationship between the length of the green-life period t^{GP} and temperature T is derived from [69] as follows:

$$t^{\mathrm{GP}}(T) = 159.86e^{-0.124T}. \tag{5.1}$$

When $T = 13.5$°C, t^{GP} = 30 days. This temperature can be used as a reference temperature T_0, so that a reduction of green-life Δg^{T_0} is 1 day. When T has other values, Δg^T varies based on the following rate:

$$\Delta g^T = \frac{t^{\mathrm{GP}}(T_0)}{t^{\mathrm{GP}}(T)}. \tag{5.2}$$

For instance, when $T = 16.8$°C, t^{GP} = 20 days, meaning that the bananas have their green-life decreasing 1.5 times as fast as when considering T_0. Therefore, $\Delta g^{16.8} = 1.5\Delta g^{T_0}$. For bananas in the ripe period, consider an indicator of ripeness r, which increases after bananas have received ethylene treatment. The ripeness is checked at retailers when making the decision of whether to accept the bananas.

The objective of this chapter is to propose a scheduling method for banana supply chains, based on the quality-aware modeling approach. Decisions are made on distribution and ripening of bananas with the consideration of quality information, aiming at reducing losses in banana supply chains, which could be useful for banana trading companies or

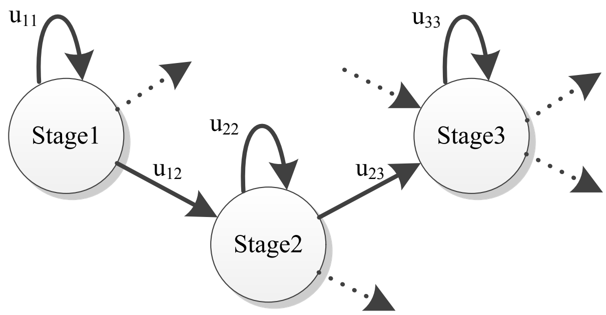


Figure 5.2: A typical example of the logistics representation. Each node represents a stage that a container could be at; each arc represents a possible transition from one stage to another.

logistics service providers. The following general assumptions in the modeling are considered:

- Bananas have homogeneous quality within each container.
- The time bananas can remain green does not affect the time needed for ripening.
- Information regarding the quality of bananas is available and predictable.
- Demand from retailers is known in advance.
- Bananas that ripen early are considered spoiled and thus discarded.

Next, the quality-aware model for the banana logistics is presented.

5.2.2 Quality-aware modeling for banana logistics

Consider a container of bananas as a minimum controllable unit $m \in \mathcal{M}$, with $\mathcal{M}$ being the collection of considered containers. Each container goes through different stages $i \in \mathcal{N}$ as it is transported in the supply chain over a discrete time horizon $\mathcal{K} = \{1, 2, \dots\}$. Container m can be at a certain stage i (e.g., at a port) at time step $k \in \mathcal{K}$ (denoted by $l_{mi}(k) = 1$, otherwise $l_{mi}(k) = 0$); and if a decision at time step k is made to move this container to another stage j (e.g., loaded on a truck), $u_{mij}(k) = 1$ and $l_{mj}(k+1) = 1$. The collections of stages (nodes) and transitions (arcs) form a graph $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$, as shown in Figure 5.2. Note that a unit m can stay at a stage i over multiple time steps ($u_{mij}(k) = 1$, $i = j$). The collections of origin stages (where containers start from) and destination stages (where containers should end up) are denoted by $\mathcal{O}$ and $\mathcal{D}$, respectively.

Variables related to each unit m are linked by three types of constraints, namely logistics, demand from retailers, and quality constraints. Next, the constraints of the model are listed followed by their explanations:

$$\sum_{j\in S(i)\cup\{i\}} u_{mij}(k) = l_{mi}(k), \qquad \forall m\in\mathcal{M}, i\in\mathcal{N}, k\in\mathcal{K} \quad (5.3)$$

$$\sum_{i\in P(j)\cup\{j\}} u_{mij}(k) = l_{mj}(k+1), \qquad \forall m\in\mathcal{M}, j\in\mathcal{N}, k\in\mathcal{K} \quad (5.4)$$

$$\sum_{i\in\mathcal{N}} l_{mi}(k) = 1, \qquad \forall m\in\mathcal{M}, k\in\mathcal{K} \quad (5.5)$$

$$\sum_{j\in S(i)\cup\{i\}} \left(t_{mi}^{\text{lead}} u_{mij}(k)\right) - a_{mj}(k) - Q u_{mjj}(k+1) \le 0, \qquad \forall m\in\mathcal{M}, i\in\mathcal{N}, k\in\mathcal{K} \quad (5.6)$$

$$a_{mj}(k) = \sum_{\tau=1}^{k} \sum_{i\in P(j)\cup\{j\}} u_{mij}(\tau), \qquad \forall m\in\mathcal{M}, j\in\mathcal{N}, k\in\mathcal{K} \quad (5.7)$$

$$\sum_{m\in\mathcal{M}} \sum_{j\in P(i)\cup\{i\}} u_{mji}(k) \le C_i^{\text{node}}(k+1), \qquad \forall i\in\mathcal{N}, k\in\mathcal{K} \quad (5.8)$$

$$\sum_{m\in\mathcal{M}} \sum_{j\in S(i)} u_{mij}(k) \le C_i^{\text{arc}}(k), \qquad \forall i\in\mathcal{N}, k\in\mathcal{K} \quad (5.9)$$

$$s_i(k) = \sum_{m\in\mathcal{M}} \sum_{j\in P(i)} u_{mij}(k), \qquad \forall i\in\mathcal{D}, k\in\mathcal{K} \quad (5.10)$$

$$\sum_{\tau=0}^{l_{\text{w}}-1} f_i^{\tau}(k) + f_i^{\text{C}}(k) = d_i(k), \qquad \forall i\in\mathcal{D}, k\in\mathcal{K} \quad (5.11)$$

$$s_i(k) = \sum_{\tau=0}^{\min(l_{\text{w}}-1,k-1)} f_i^{\tau}(k-\tau), \qquad \forall i\in\mathcal{D}, k\in\mathcal{K} \quad (5.12)$$

$$g_m(k+1) = g_m(k) - \Delta g_m^T(k), \qquad \forall m\in\mathcal{M}, k\in\mathcal{K} \quad (5.13)$$

$$r_m(k+1) = r_m(k) + \Delta r_m(k), \qquad \forall m\in\mathcal{M}, k\in\mathcal{K} \quad (5.14)$$

$$\Delta r_m(k) \le Q d_m^{\text{ripe}}(k), \qquad \forall m\in\mathcal{M}, k\in\mathcal{K} \quad (5.15)$$

$$Q\Delta r_m(k) \ge d_m^{\text{ripe}}(k), \qquad \forall m\in\mathcal{M}, k\in\mathcal{K} \quad (5.16)$$

$$\Delta r_m(k) \le 1 + Q \sum_{j\in N_{\text{RF}}} \sum_{i\in P(i)} u_{mij}(k), \qquad \forall m\in\mathcal{M}, k\in\mathcal{K} \quad (5.17)$$

$$\sum_{i=P(j)} u_{mij}(k) \le Q g_m(k), \qquad \forall m\in\mathcal{M}, j\in\mathcal{N}_{\text{RF}}, k\in\mathcal{K} \quad (5.18)$$

$$\sum_{k\in\mathcal{K}} d_m^{\text{ethy}}(k) \le 1, \qquad \forall m\in\mathcal{M} \quad (5.19)$$

$$\sum_{j\in\mathcal{N}_{\text{RF}}} \sum_{i\in P(j)} u_{mij}(k) \ge d_m^{\text{ethy}}(k+1), \qquad \forall m\in\mathcal{M}, k\in\mathcal{K} \quad (5.20)$$

$$Q(d_m^{\text{ethy}}(k) - 1) \le g_m(k+1), \qquad \forall m\in\mathcal{M}, k\in\mathcal{K} \quad (5.21)$$

$$d_m^{\text{ripe}}(k+1) = d_m^{\text{ripe}}(k) + d_m^{\text{ethy}}(k), \qquad \forall m\in\mathcal{M}, k\in\mathcal{K} \quad (5.22)$$

$$Q(1 - \sum_{j\in\mathcal{D}} \sum_{i\in P(j)} u_{mij}(k)) \ge r_m(k+1) - r^{\text{high}}, \qquad \forall m\in\mathcal{M}, k\in\mathcal{K} \quad (5.23)$$

$$Q(1 - \sum_{j\in\mathcal{D}} \sum_{i\in P(j)} u_{mij}(k)) \ge r^{\text{low}} - r_m(k+1), \qquad \forall m\in\mathcal{M}, k\in\mathcal{K}. \quad (5.24)$$

Logistics. Constraints (5.3)-(5.9) belong to the aspects related to the logistics. Constraints (5.3) and (5.4) denote that when changing stages, containers follow the directed arcs. In the constraints, $P(i)$ and $S(i)$ are the collections of predecessor and successor nodes of node i excluding i itself. Constraint (5.5) ensures that each container can only be at one of the stages for each time step. Constraint (5.6) ensures that a lead time t_{mi}^{lead} is given to container m when it enters a node i and can only move out after the lead time is reached. Here (also for the rest of the constraints) Q is a big number. In (5.7), $a_{mj}(k)$ is a counter that calculates the number of time steps for which container m has stayed in node j up to time step k. Constraint (5.8) limits the number of containers at node i at time step k, and (5.9) limits the number of containers moving from node i to any other successive nodes.

Demand from retailers. Constraints (5.10)-(5.12) belong to this aspect. Logistics planners need to fulfill retailers' demand by sending them ripe bananas from ripening facilities. Constraint (5.10) explains the relation between number of containers received by wholesaler $i \in \mathcal{D}$ and decisions of the logistics planners. Constraint (5.11) specifies how demand from retailer $i \in \mathcal{D}$ at time step k can be responded in different ways: $f_i^{\tau}(k)$ represents the number of containers that fulfills the demand with a τ days' delay ($0 \leq \tau \leq l_{\text{w}} - 1$), and $f_i^{\text{C}}(k)$ denotes the number of containers in the demand $d_i(k)$ that cannot be fulfilled. Constraint (5.12) links fulfillments of demand f_i^{τ} to supply $s_i(k)$. Note that a supply of container on day k can respond to the demand from day $k - l_{\text{w}+1}$ to day k.

Quality. Constraints (5.13)-(5.24) belong to the aspect of quality. Constraint (5.13) describes the decreasing of green-life period $g_m(k)$ of bananas in container m in days, with $\Delta g_m^T(k)$ derived from (5.2). Constraint (5.14) describes quality change of bananas after ripening. Variable $r_m(k)$ represents ripeness of bananas. Integer decision variable $\Delta r_m(k)$ represents the increasing of ripeness, which can be one of the values from $\{0,1,2\}$ for each day, each container. When bananas are not ripe, $\Delta r_m(k) = 0$, which is described by (5.15). When bananas are in ripening facilities, $\Delta r_m(k)$ can be 1 or 2 depending on how fast they need to be ripened but cannot be 0, limited by (5.16). After moving out of ripening facilities $\Delta r_m(k) = 1$ in a static environment, ensured by (5.17). Constraint (5.18) enforces that only containers with unripe bananas ($g_m(k) \geq 0$) can be moved to a ripening facility $j \in \mathcal{N}_{\text{RF}}$. Constraint (5.19) makes sure that each container m can go through ripening process no more than once. Constraint (5.20) indicates that the decisions to start ripening can only be made when container m is in a ripening facility. Constraint (5.21) ensures that containers holding ripe bananas cannot go through ripening process. In Constraint (5.22), an indicator d_m^{ripe} becomes 1 from 0 at time step k when bananas in container m go through an ethylene treatment at time step k ($d_m^{\text{ripe}}(k) = 1$). Wholesalers need bananas within a certain ripeness range, which is ensured by (5.23) and (5.24) with a maximum and minimum acceptable range of ripeness r^{high} and r^{low}.

5.2.3 Scheduling objective

Consider an objective function over a finite time period ($\mathcal{K} = \{1, \ldots, N_{\text{s}}\}$) as follows:

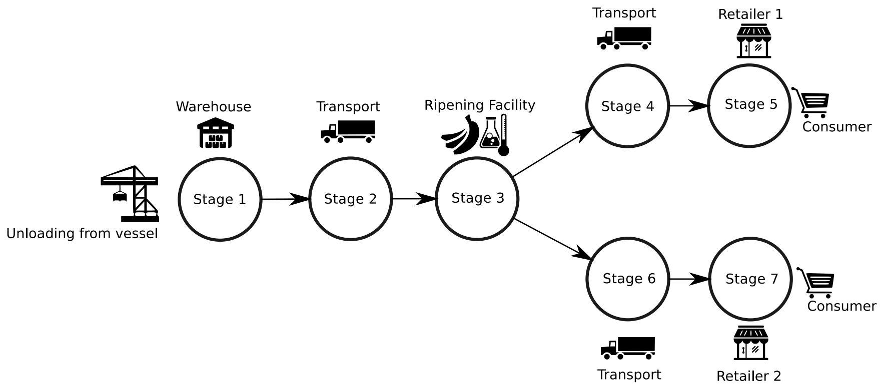


Figure 5.3: Considered supply chain.

$$
\begin{aligned}
J = & \sum_{k=1}^{N_\mathrm{s}} \sum_{i \in \mathcal{D}} s_i(k)\alpha - \sum_{k=1}^{N_\mathrm{s}} \sum_{m \in \mathcal{M}} \sum_{(i,j) \in \mathcal{E}} u_{mij}(k)\beta_{ij} \\
& - \sum_{k=1}^{N_\mathrm{s}} \sum_{i \in \mathcal{D}} \sum_{\tau=0}^{\min(l_\mathrm{w}-1,k-1)} (f_i^\tau(k-\tau)\gamma\tau) - \sum_{k=1}^{N_\mathrm{s}} \sum_{i \in \mathcal{D}} f_i^\mathrm{C}(k)\delta,
\end{aligned}
\tag{5.25}
$$

in which α is the price for delivering a container to a wholesaler; β_{ij} is the cost for a container to transit from stage i to stage j (e.g., cost for transport); γ is the penalty for delaying an order of a container by 1 day; δ is the penalty for not fulfilling a demand of a container.

In summary, the quality-aware model considers three aspects. First, it considers the decisions in logistics activities including movements of the containers (5.3)–(5.9). Secondly, demand-supply coupling is considered in Constraints (5.10)–(5.12). Thirdly, the model includes bananas' two-period quality changing process (5.13)–(5.14), and how quality affects decision making in logistics (5.18)–(5.24). The objective function considers income for selling bananas to retailers, transition costs, and penalties for delays and lost sales. The combination of the objective function and the constraints forms a mixed integer linear programming (MILP) problem: $\max J$, subject to Constraints (5.3)-(5.24). The decision variables are $u_{mij}(k)$, $f_i^\tau(k)$, $f_i^\mathrm{C}(k)$, $\Delta r_m(k)$, and $d_m^\mathrm{ethy}(k)$, for all $k \in \{1,2,\ldots,N_\mathrm{s}\}$.

5.3 Simulation experiments

In this section, simulation experiments are carried out to illustrate the potential of the proposed scheduling method. In the experiments, a typical supply chain shown in Figure 5.3 is considered. There are seven stages that each container with bananas could be located in. Stage 1 represents the container being stored in the warehouse at the port of destination. Stage 2 represents the transportation from the port to a ripening facility by truck. Stage 3 is when the container being at the ripening facility. Stage 4 and 6 are the container being transported to different retailers (denoted by stage 5 and 7).

Table 5.2: Scenario settings

Variable	Value
M	5
N	7
N_s	16
l_w	3
t^{lead}	$t_3^{lead} = 4, t_6^{lead} = 2$
C_3^{node}	2
$d_i(k)$	$d_5(7) = 3, d_5(10) = 3, d_5(14) = 1$ $d_7(1) = 1, d_7(8) = 1$
$\Delta g_m(k)$, $\Delta r_m(k)$	1
$g_m(1)$	$[7, 3, 2, 8, 10]$
r_5^{high}, r_7^{high}	12, 11
r_5^{low}, r_7^{low}	8, 7
α	10
β	0
γ	1
δ	5

In order to illustrate the performance of the proposed scheduling method, two experiments are performed: one inspired by the current handling procedures, the other based on the proposed modeling method. In the current case experiment, quality information is only available at certain check points. The ripening facilities identify early ripened bananas upon their arrival and discard the containers that do not meet the requirement; the retailers examine the ripeness of bananas upon arrival and make decisions on accepting or rejecting bananas; reefer containers are moved according to a pre-defined sequence.

5.3.1 Scenario description

The details of a typical scenario setting are shown in Table 5.2. Assume that five of the reefer containers are assigned to a particular ripening facility. The lead times for the transport from the port to the ripening facility (Stage 2) and from the ripening facility to the two retailers (Stage 4 and 6) are 1, 1, and 2, respectively. The capacity of the ripening facility is two containers. The demand of retailer 1 and retailer 2 falls on different days given in the table. Consider the temperature in containers to be static, but the initial remaining green-life can vary among containers, and quality requirements of the retailers can also differ as shown in the table. Fulfilling a container of bananas with the right quality brings €10,000, while each day's delay of an order costs the supply chain planner €1,000. Canceling the order results in a penalty of €5,000. Assume that the ripening facilities and transport companies are contracted, so that transporting and ripening costs are not considered. The experiments are carried out using Matlab 2015b, on a desktop with Intel Core 2 CPU Q8400, 4GB RAM, and Windows 7-64bit. The optimization problems are solved using the CPLEX (v12.5.1) MILP solver. Next section compares the results given by the current case experiment and the experiment with the proposed method.

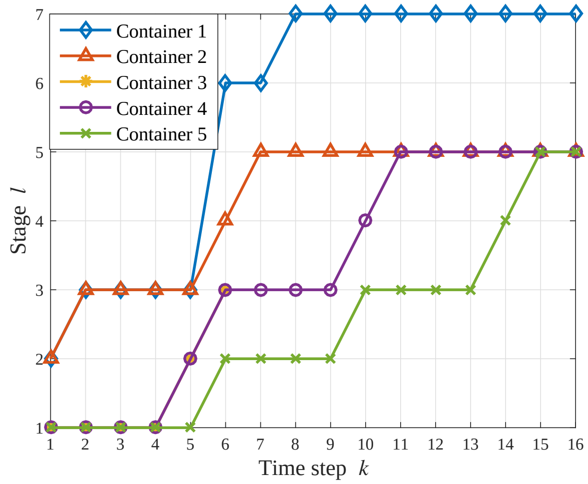


Figure 5.4: Movements of each container over time in the current case experiment.

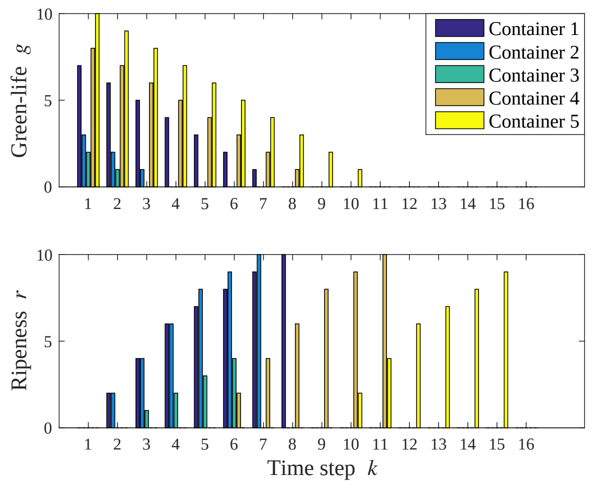


Figure 5.5: Quality of each container over time in the current case experiment. (Only positive green-life is shown.)

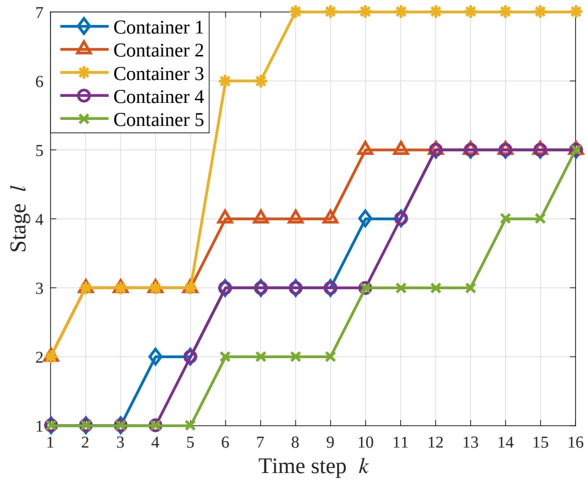


Figure 5.6: Movements of each container over time by the proposed method.

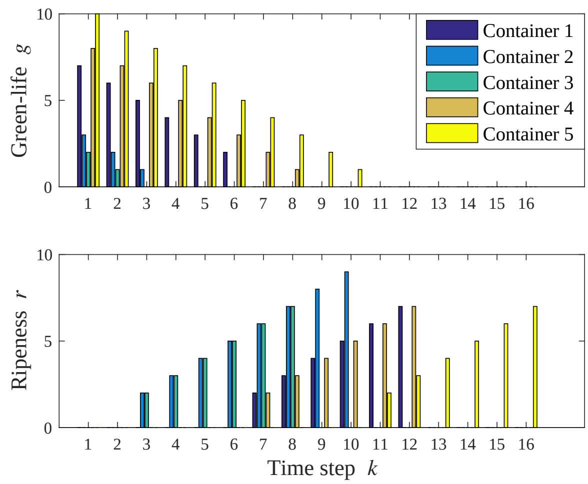


Figure 5.7: Quality of each container over time with the proposed method. (Only positive green-life is shown.)

5.3.2 Results and discussion

Solving the MILP problem takes only a few seconds. The results are shown in Figures 5.4–5.11. Figure 5.4 shows the scheduled container movements over time for the current case experiment. In the current case experiment, Figure 5.4 shows that container 1 and 2 are given priority to move to the ripening facility while container 3, 4, and 5 await for the call. Note that container 3 (overlaps with Container 4) no longer moves forward after reaching the ripening facility (stage 3) at time step 6. The reason is shown in Figure 5.5: the green-life

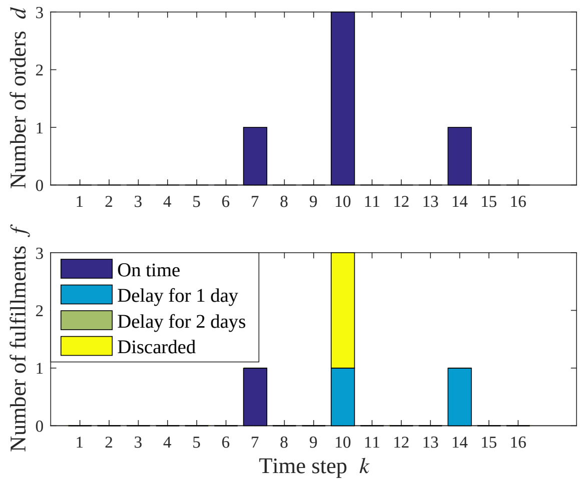


Figure 5.8: Fulfillments of Retailer 1 in the current case experiment.

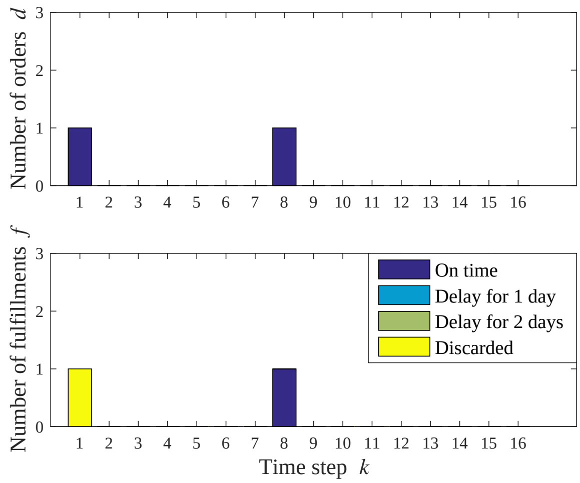


Figure 5.9: Fulfillments of Retailer 2 in the current case experiment.

of bananas in container 3 is the lowest amongst the five containers. However, the ripening facility only becomes aware of this on time step 6 and has to discard the bananas.

For the future case experiment, using the proposed method, Figure 5.6 shows the scheduled movements according to the optimization. Considering the quality conditions, container 2 and 3 receive the priority to be transported to the ripening facility before early ripening takes place (see Figure 5.7). This method saves the bananas in container 3 from being discarded.

Figure 5.8 and 5.9 show how demands from the two retailers are fulfilled (or discarded) in the current case experiment. In this experiment, two orders are fulfilled on time, two

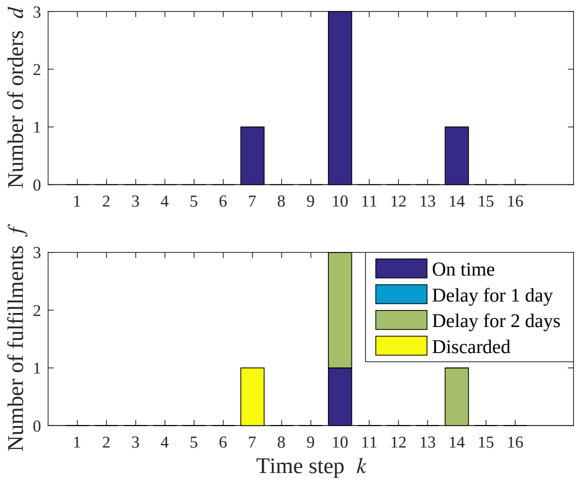


Figure 5.10: Fulfillments of Retailer 1 with the proposed method.

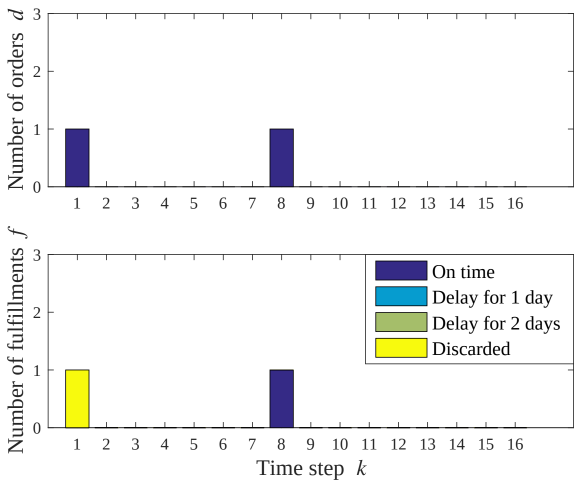


Figure 5.11: Fulfillments of Retailer 2 with the proposed method.

orders delayed for a day, and three orders are not fulfilled, resulting in a total profit of €23,000. Figure 5.10 and 5.11 show how demands from the two retailers are fulfilled (or discarded) in the experiment with the proposed method. In this experiment, two orders are fulfilled on time, three orders delayed for two days and two orders discarded, resulting in a total profit of €34,000. Comparing this result to the one from the previous experiment, it can be noticed that for Retailer 1, there are 2 containers being delayed for 1 more day so that another container, although delayed, could still get through. This scheduling saves one of the 3 containers (33%) of bananas from being wasted, and resulted in €11,000 (48%) more profit.

From the comparison of the two experiments, the conclusion could be drawn that the efficiency of logistics activities could be improved by considering quality information in the optimization of logistics activities. Especially in a banana supply chain, the potential wastage due to early ripening could be reduced.

5.4 Conclusions

Bananas are grown, traded and consumed in huge amount in the world. The amount of waste bananas is also large due to the perishing nature and effectiveness of supply chain activities. This chapter investigates opportunities provided by modern technologies to improve decision making process in scheduling banana logistics by considering quality of bananas. This chapter addresses Research Question 4, based on descriptions of remaining green-life and ripeness, a quality-aware model is used to describe and optimize the quality evolution and logistics process of bananas when going through a supply chain from a port to retailers. Simulation experiments illustrate that decisions can be made with bananas' quality taken into account, and thus the wastage can be reduced by up to 14% in banana distribution networks. The next chapter presents another case study, which combines the modeling approach and the control strategies that can take into account of disturbances occur in perishables logistics.

Chapter 6

Starch production scheduling

In Chapter 4, an MPC strategy is proposed for controlling operations of perishable goods logistics. In that chapter, an illustrative example of potato starch production scheduling is carried out. This chapter focuses on the same example with more details considered, where a starch potato postharvest event takes place each year. In this scenario, a starch production plant and several farms work together to maximize the seasonal starch production, forming a logistics. This chapter combines the quality-aware modeling and the MPC strategy as the general framework to aid decision making for the production plant as well as farms.

This chapter is organized in five sections. Section 6.1 introduces the background of the problem. Section 6.2 focuses on quality and logistic aspects of starch potatoes and models the system using quality-aware method. In Section 6.3, one centralized controller and one distributed controller are designed to control the postharvest activities. Section 6.4 describes simulation experiments used to demonstrate the effectiveness of the quality-aware modeling and model predictive control methods. Section 6.5 concludes the chapter and provides future research directions regarding the case study.

Parts of this chapter have been published in [95].

6.1 Introduction

Potato starch is widely used in food, paper, and textile industries [53]. In 2014, 6.9 million tonnes of potatoes were harvested and processed for starch in Europe [128]. The harvest in Europe takes place between August and April of the next year. The harvest is often referred to as the starch campaign [53]. During this campaign, starch production plants receive potatoes produced by local farms. The largest starch processing plant today can process about 250 tonnes potatoes per hour [53]. Nevertheless, usually not all potatoes can be processed immediately due to the large volume of harvested potatoes. As shown in Fig. 6.1, if potatoes are not sent to a processing plant immediately after harvest, they are stored in barns or in pits of the farm, waiting for their time to be transported and processed [20].

In Chapter 3, such scenarios are studied as an example. In that chapter, an MPC strategy is used to aid decision making with the change of quality and new harvests. This chapter investigates the combination of quality-aware modeling and MPC in the general framework, considering more details compared to the example in Chapter 3. The system aspect con-

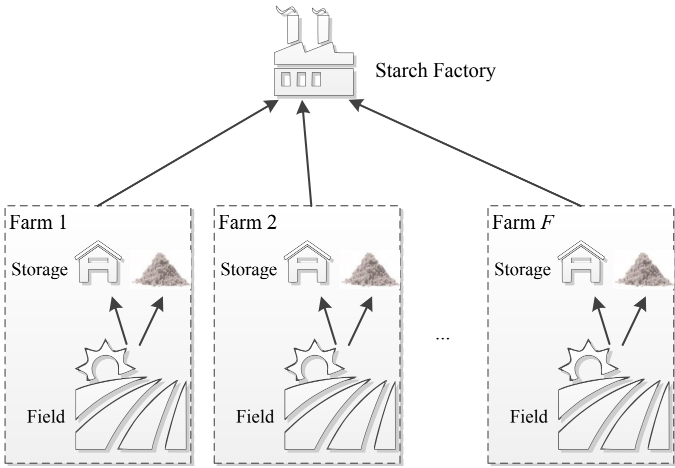


Figure 6.1: Movements of potatoes during a starch campaign. Growers of each farm move harvested starch potatoes to the on-farm storages and the starch plant.

siders not only the turning-in to the starch plant, but also the harvesting operations. The quality is considered as the feature of the potatoes instead of the feature of the storages. Labor availability as well as storage capacity are also included. The controller aspect considers two control strategies: centralized and distributed. The two strategies can represent different types of cooperation among growers and the starch plant.

According to Wustman and Struik [151], stored potatoes lose weight and starch content over time, as they have an active metabolism. The loss can be caused by several factors: evaporation, respiration, sprouting, changes in the chemical composition, damage by extreme temperature, and spread of diseases. Uncertainties in storage conditions can also affect the weight and quality loss. For instance, a too low storage temperature can cause more starch conversing into reducing sugars. Therefore, managing stored potatoes in uncertain environments is important for reducing loss of quality during the starch campaign.

As discussed in Chapter 2, good decision support systems can be beneficial for players in perishable goods supply chains. Since the end product is starch in the logistic operations, this chapter defines quality of potatoes as their starch content. Therefore, this section focuses on the monitoring and preservation of starch content. There are two approaches by which information on starch content from potatoes can be obtained: direct measurements and indirect estimation.

Direct measurements take samples of potatoes and physically measure the starch content. Under water weight (UWW) is the most commonly used method for determining starch content [125]. What is more, a near infrared approach is studied and is reported to be accurate in measuring starch content [55]. Because the near infrared approach is not destructive to the samples, it is suitable for rapid, on-line measurements [114]. This approach has great potential to be further developed into fully automatic measuring systems [17, 60]. In addition, it can also be used to estimate the harvest time for potatoes, by monitoring the chemical composition in potato tubers [114].

Indirect methods obtain environmental information (e.g., temperature or humidity) to estimate the quality change of fresh products. This can be achieved by installing temperature/humidity sensors in storages where potatoes are placed. Compared to direct measurements, indirect methods are less accurate but very efficient if used properly. Quality models are powerful tools to describe the way in which environmental factors affect chemical changes in fresh products. These models are widely used in estimating the quality of fresh food products [139]. For instance, kinetic models can be used to calculate the conversion rate from starch to reducing sugar, given the temperature over time and the initial quality [111].

As can be seen from the aforementioned literature, a number of approaches are available to measure or estimate quality of potatoes. With new technologies, opportunities are enabled to improve supply chain operations with the consideration of products' quality information. This chapter proposes to use the general framework discussed in Chapter 3, to further investigate the case study of starch potato postharvest scheduling. Compared with the initial case study, in this chapter, decisions made for both the plant operators and the growers are considered. Two control strategies are developed to improve the overall starch productivity and to cope with uncertainties with the consideration of real-time quality information. One strategy is designed for a fully cooperative farm-plant structure and the other for a partially cooperative structure. The proposed approaches could be implemented in a decision support system for potato growers and starch production plants.

6.2 Dynamics of starch potato postharvest system

In this section, the dynamics of potatoes are discussed in a starch campaign using a quality-aware modeling approach. This approach builds on the previous research, of which an initial case study is carried out in Chapter 3. First, the discussion focuses on how quality information can be estimated and acquired in a potato farm. Second, the considered scheduling problem and assumptions are introduced. Then, a model is build to represent potatoes' dynamics in a starch production campaign, with the consideration of both quality and logistic features of potatoes.

6.2.1 Obtaining quality of starch potatoes

To obtain quality information, a technical framework is designed for monitoring potatoes and the environment they are exposed to. Potatoes on each farm could be located at different places. When potatoes are harvested, they are put in a pit or a barn, or directly transported to the plant [150]. When potatoes are still in the fields, the starch content first rises and then decreases [28]. In the literature, no model has been found that estimates and predicts starch content in their growing stage. Therefore, the content of starch from them should be directly measured, which requires constant operations by growers. After potatoes have been harvested and put into storage in a pit or a barn, a quality model can be used to represent the relationship between starch content and temperature in storage [111]. The quality change of potatoes can be automatically estimated using the temperatures measured in storages.

6.2.2 Problem statement and assumptions

Starch content in potatoes changes during the time of harvest and storage [28, 111]. Although factors such as mechanical damage, humidity, and micro-organisms can also influence potatoes' quality [75], this section focuses only on the effect of temperature on the decreasing rate of starch content during storage [111].

The problem defined in this section is how real-time quality information can help make decisions in a starch campaign and to cope with disturbances of environmental factors and quality. Similar to the instance in Chapter 3, an area with a starch production plant and several farms nearby is considered in this chapter. During a starch campaign, the plant takes a limited number of potatoes from the growers each day for processing. The growers gather potatoes in the field or in a barn, getting ready to send potatoes to the plant [150]. While being stored, potatoes' starch content may differ from farm to farm due to varying conditions of farming and storage. Therefore, it is the question how to make decisions regarding harvesting, storing, and transporting potatoes in order to have the maximum overall starch production.

Some assumptions are considered in this research. First, sensing and communication technologies are assumed ready to implement real-time estimating of potatoes' starch content. Second, this chapter assumes that factors other than temperature have the same influence on potatoes from different farms, by which the kinetics model presented in [111] can be used to estimate and predict starch content.

6.2.3 Description of system variables

In order to structure the scheduling design, this chapter adopts the general framework from a system and control perspective. The system consists of all potatoes in the considered area. The control strategies contain one or more controllers, which take in information of the state of the system and make decisions accordingly. This section focuses on the modeling of the system. The control strategies are presented in Section 6.4.

In order to apply the quality-aware modeling approach, potatoes on each farm are divided and handled by units. Each unit of potatoes can fill up a truckload (5 tonnes), and is moved as a minimal controllable entity as discussed in Chapter 3. The status of the system consists of state variables of all units. Variables of each unit are twofold: the location of the unit over time as logistic state variables, and average quality of potatoes in the unit as biological state variables. The logistic variables consider units that physically go through different phases in order to move from origins to destinations. The biological variables consider the dynamics of quality of the units over time. These variables evolve over a discrete time line, depending on decisions taken at each time step. Possible decisions are considered at two levels: a starch plant operation level, where units are called by the plant and moved from farms; and a farm operation level, where units are harvested and put into different types of storages. The mathematical representations are explained in the following.

Logistic variables

The logistic variables of the units represent the places where the units are located. Consider a set of farms $\mathcal{F} = \{1, \dots, f, \dots, F\}$ and a starch plant. Fig. 6.2 shows an illustration with a plant and two farms. A unit of potatoes can be in one of several locations

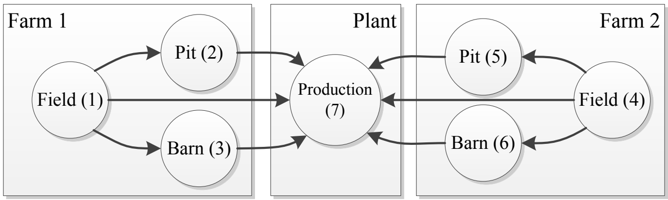


Figure 6.2: Possible location (nodes) and transition (arcs) of each unit from different farms.

$\mathcal{N} = \{1,\ldots,i,\ldots,N\}$, including being in the field, being in a pit, being in a barn of different farms, and being processed in the plant. Let M_f be the number of units of potatoes on farm f. Binary variable $l_{fmi}(k)$ represents whether unit m from farm f is at location i at time step k:

$$l_{fmi}(k) = \begin{cases} 1, & \text{unit } m \text{ is at location } i \text{ of farm } f \text{ at time step } k; \\ 0, & \text{otherwise.} \end{cases} \tag{6.1}$$

Decisions made on the units include moving from one location to another, or staying at a particular location for a time step. The possible movements of each unit between locations can then be represented by a set of arcs $\mathcal{E} = \{(1,1),\ldots,(i,j),\ldots\}$, where (i,j) is a directed arc from i to j. Together, the nodes and arcs form a directed graph $\mathcal{G} = \{\mathcal{N},\mathcal{E}\}$. Binary variable $u_{fmij}(k)$ represents whether unit m from farm f is moved from i to j at time step k (in which $i = j$ is allowed, as it represents that unit stays at location i). The decision of taking action $u_{fmij}(k)$ is made at time step k, and results in a new location for unit m at time step $k+1$. The logistic variable $u_{fmij}(k)$ therefore is defined as follows:

$$u_{fmij}(k) = \begin{cases} 1, & \text{unit } m \text{ moves from } i \text{ towards } j \text{ at the end of time step } k; \\ 0, & \text{otherwise.} \end{cases} \tag{6.2}$$

To give an example using Fig. 6.2, unit 1 is from farm 1. At time step 1, it is located in the field (node 1). Therefore, $l_{111}(1) = 1$. Then farm 1 receives the call from the plant, and moves unit 1 to the plant for production after time step 1, which is represented by $u_{1117}(1) = 1$. This leads to the fact that unit 1 is at node 7 at time step 2, represented by $l_{117}(2) = 1$.

Logistics conditions of potatoes may affect the environment that potatoes are exposed to. Decisions of moving units to different locations may result in new environmental conditions. The following section discusses how different environmental conditions may affect quality of starch potatoes.

Biological variables

After potatoes have been transported to a starch production plant and have been processed into dry starch, the quality stops changing. But before that, quality of stored potatoes follow the so-called first-order kinetics. Consider the change rate of starch content at location i, time step k as $\rho_i(k)$ in a unit of potatoes, denoting the remaining percentage of starch; and represent the average quality of the potatoes in unit m from farm f at time step k as $q_{fm}(k)$.

Therefore, the quality of unit m from farm f at location i time step $k+1$ is given by:

$$q_{fm}(k+1) = q_{fm}(k)\rho_{fi}(k). \tag{6.3}$$

In food engineering, kinetic models (discussed in Chapter 2) are widely used to describe temperature-related chemical reactions and quality parameters in food [139]. In stored potatoes, starch is transforming into sugar. Previous research has shown that the rate of this transformation can be described using a first-order kinetic model [111]:

$$\frac{\mathrm{d}A(t)}{\mathrm{d}t} = -rA(t), \tag{6.4}$$

where $A(t)$ is the starch concentration at time t, r is the temperature-dependent rate of starch decomposing. In the case of starch in potatoes, $r_i(k)$ represents the decreasing rate of starch of storage i at time step k [111]. This reaction happens more rapidly when the temperature is lower. According to Arrhenius' law [139], this temperature dependent relation is:

$$\ln\frac{r}{r_0} = \frac{E_a}{RT}, \tag{6.5}$$

where $r_0 = 8.75\times10^{-9}$ is a pre-exponential factor, $E_a = 34.2$kJ/mol the activation energy, $R = 8.314$J/mol°K the gas constant, T the absolute temperature. Note that the term on the right-hand-side of (6.5) can also be negative in other cases when a raising of temperature increases the reaction rate. For potato starch, although a higher temperature makes sprouting more likely to happen [111], it slows down the decreasing of starch.

Since a discrete-time kinetic model is used in this chapter, let τ be an equally divided time interval between two adjacent time steps, and represent reaction rate r as function of time. The kinetic model can then be represented as the following discrete model:

$$A(k+1) = A(k)e^{-r(k)\tau}. \tag{6.6}$$

When considering the quality evolution of units at location i, define $\rho_i(k) = e^{-r_i(k)\tau}$ as the rate of decomposition of starch, following the first-order kinetic model. When stored, the rate of decreasing starch ρ_i can then be described as a function of location dependent temperature T_i as:

$$\rho_i(T_i) = \exp\left(-r_0\tau\exp(\frac{E_a}{RT_i})\right). \tag{6.7}$$

6.2.4 Dynamics and constraints of the system

Based on the variables introduced above, this section formalizes the dynamics and constraints of the units in the farm-plant system.

System dynamics

Let $\mathbf{x}(k)$ be the vector for all the state variables of the system at time step k. As mentioned above, the state variables consist of a logistic part and a biological part. Let $\mathbf{l}(k) = [l_{111}(k),\ldots,l_{fmi}(k),\ldots]^{\mathrm{T}}$ be the logistic part, i.e., the vector for all the location variables of the system at time step k; let $\mathbf{q}(k) = [q_{11}(k), \ldots, q_{fm}(k), \ldots]^{\mathrm{T}}$ be the biological part, i.e., the vector for all the quality variables of the units in the system at time step k; then define $\mathbf{x}(k) = [\mathbf{l}(k)^{\mathrm{T}}, \mathbf{q}(k)^{\mathrm{T}}]^{\mathrm{T}}$.

Let $\mathbf{u}(k) = [u_{1111}(k), \ldots, u_{fmij}(k), \ldots]^{\mathrm{T}}$ be the vector for all the decision variables of the system at time step k. The evolution of the locations of all units can then be represented as follows:

$$\mathbf{l}(k+1) = \mathbf{l}(k) + \mathbf{K}\mathbf{u}(k). \tag{6.8}$$

where $\mathbf{K}$ is an $FMN \times FME$ matrix determined by the topology of the graph $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$. The approach to get $\mathbf{K}$ from $\mathcal{G}$ is given in the last part of this section:"Evolution of system location states".

The quality evolution of unit m of farm f from time step k to $k+1$ can be represented by:

$$q_{fm}(k+1) = q_{fm}(k) \sum_{i \in \mathcal{N}} \rho_{fi}(k) l_{fmi}(k). \tag{6.9}$$

Let $\mathbf{d}(k) = [\rho_{11}(k), \ldots, \rho_{fi}(k), \ldots]^{\mathrm{T}}$ be the vector for the deterioration rates at all locations at time step k. Then the evolution of the quality states of all units can be represented by:

$$\mathbf{q}(k+1) = \mathbf{P}(k)\mathbf{q}(k), \tag{6.10}$$

where

$$\mathbf{P}(k) = \mathrm{diag}\left(\sum_{i \in \mathcal{L}_1} \rho_{fi}(k) l_{11i}(k), \ldots, \sum_{i \in \mathcal{L}_F} \rho_{fi}(k) l_{FMi}(k) \right) \tag{6.11}$$

$$= \mathrm{diag}\left(\mathbf{d}_1^{\mathrm{T}}(k)\mathbf{l}_{11}(k), \ldots, \mathbf{d}_f^{\mathrm{T}}(k)\mathbf{l}_{fm}(k), \ldots, \mathbf{d}_F^{\mathrm{T}}(k)\mathbf{l}_{FM}(k) \right), \tag{6.12}$$

and

$$\mathbf{d}_f(k) = [\rho_{f1}(k), \ldots, \rho_{fi}(k), \ldots, \rho_{fN}(k)]. \tag{6.13}$$

Therefore, both biological and logistic aspects can be described simultaneously as the evolution of the system as follows:

$$\mathbf{x}(k+1) = g\left[\mathbf{x}(k), \mathbf{u}(k), \mathbf{d}(k)\right] \tag{6.14}$$

Constraints of the system

For mathematical modeling, constraints regarding the network topology assure that the model adequately represents the transport dynamics. Several physical constraints also need to be considered: the plant can only process a certain amount of potatoes per day; the amount of potatoes stored in a barn is limited by the capacity of the barn; the speed of harvesting potatoes from the field depends on the amount of labor available on that farm.

Network topology On each day the growers can relocate potatoes from fields to warehouses or to the plant. The following constraint represents that each unit can only appear at one location at each time step:

$$\sum_{i\in\mathcal{N}} l_{fmi}(k) = 1,\ \forall f \in \mathcal{F}, m \in \mathcal{M}, k \in \{1,2,\ldots\}. \tag{6.15}$$

Let $\mathcal{P}(j)$ be the collection of predecessors of a location j (i.e., the collection of all the nodes that are connected to node j by a directed arc pointing to j) and let $\mathcal{S}(i)$ be the collection of successors of a location i (i.e., the collection of all the nodes that are connected to node i by a directed arc pointing from i). Then the following two constraints represent that each unit of potatoes can either travel through the directed connection or stay at its location:

$$\sum_{i\in\mathcal{P}(j)\cup\{j\}} u_{fmij}(k) = l_{fmj}(k), \forall f \in \mathcal{F}, m \in \mathcal{M}, j \in \mathcal{N}, k \in \{1,2,\ldots\}, \tag{6.16}$$

$$\sum_{j\in\mathcal{S}(i)\cup\{i\}} u_{fmij}(k+1) = l_{fmi}(k), \forall f \in \mathcal{F}, m \in \mathcal{M}, i \in \mathcal{N}, k \in \{1,2,\ldots\}. \tag{6.17}$$

Storage capacity The constraint on storage capacity represents that the amount of potatoes stored in storages cannot exceed the capacity of the storages. Let $C^{\mathrm{s}}_{fi}(k)$ be the capacity of location i, farm f, at time step k, the constraint for storage capacity is then represented as follows:

$$\sum_{m\in\mathcal{M}} l_{fmi}(k) \leq C^{\mathrm{s}}_{fi}(k),\ \forall f \in \mathcal{F}, i \in \mathcal{N}, k \in \{1,2,\ldots\}. \tag{6.18}$$

Labor availability The constraint on labor availability represents that during each time period, the amount of potatoes being harvested and moved from the ground to be stored or to the plant are limited for each farm. Let o be the location of fields at each farm, and $C^{\mathrm{l}}_{f}(k)$ be the maximum number of units that can be harvested on farm f at time step k:

$$\sum_{m\in\mathcal{M}} \sum_{j\in S(o)} u_{fmoj}(k) \leq C^{\mathrm{l}}_{f}(k), \forall f \in \mathcal{F}, k \in \{1,2,\ldots\}. \tag{6.19}$$

Capacity of processing facility The constraint on processing capacity limits the amount of potatoes that can be processed by the plant at each time step. Let the plant in the network be denoted as $d \in \mathcal{N}$, and let $i \in P(d)$ denote a location i that is connected to the plant by a directed arc (i,d). Let $C^{\mathrm{p}}(k)$ be the processing capacity of time step k, the processing facility has the following constraint:

$$\sum_{m\in\mathcal{M}} \sum_{f\in\mathcal{F}} \sum_{i\in P(d)} u_{fmid}(k) \leq C^{\mathrm{p}}(k), \forall k \in \{1,2,\ldots\}. \tag{6.20}$$

In summary, the system dynamics of the model include (6.8), (6.10), and (6.14). Constraints of the system are (6.15)–(6.20).

Evolution of system location states

This part explains how logistic decisions affect the states of the system. The evolution of location (6.8) represents how each unit moves from one location to another. The matrix **K** is related to the locations and possible movements between locations. It applies decisions to the current locations, resulting in the locations at the next time step. Divide $\mathbf{l}(k)$ and $\mathbf{u}(k)$ into FM blocks:

$$\mathbf{l}(k) = [\mathbf{l}_{11}^{\mathrm{T}}(k), \ldots, \mathbf{l}_{fm}^{\mathrm{T}}(k), \ldots \mathbf{l}_{FM}^{\mathrm{T}}(k)]^{\mathrm{T}} \tag{6.21}$$

$$\mathbf{u}(k) = [\mathbf{u}_{11}^{\mathrm{T}}(k), \ldots, \mathbf{u}_{fm}^{\mathrm{T}}(k), \ldots \mathbf{u}_{FM}^{\mathrm{T}}(k)]^{\mathrm{T}}, \tag{6.22}$$

where $\mathbf{l}_{fm}(k)$ and $\mathbf{u}_{fm}(k)$ have the length of N and E, respectively. Substitute $\mathbf{l}(k)$ and $\mathbf{u}(k)$ in (6.8):

$$\begin{bmatrix} \mathbf{l}_{11}(k+1) \\ \vdots \\ \mathbf{l}_{fm}(k+1) \\ \vdots \\ \mathbf{l}_{FM}(k+1) \end{bmatrix} = \begin{bmatrix} \mathbf{l}_{11}(k) \\ \vdots \\ \mathbf{l}_{fm}(k) \\ \vdots \\ \mathbf{l}_{FM}(k) \end{bmatrix} + \mathbf{K} \begin{bmatrix} \mathbf{u}_{11}(k) \\ \vdots \\ \mathbf{u}_{fm}(k) \\ \vdots \\ \mathbf{u}_{FM}(k) \end{bmatrix}. \tag{6.23}$$

Matrix $\mathbf{K}$ can then also be divided into blocks:

$$\mathbf{K} = \mathrm{diag}(\mathbf{K}_{11}, \ldots, \mathbf{K}_{fm}, \ldots, \mathbf{K}_{FM}). \tag{6.24}$$

Then $\mathbf{K}$ can be derived from $\mathbf{K}_{fm}$, which represents the relations between $\mathbf{l}_{fm}(k)$, $\mathbf{l}_{fm}(k+1)$, and $\mathbf{u}_{fm}(k)$:

$$\mathbf{l}_{fm}(k+1) = \mathbf{l}_{fm}(k) + \mathbf{K}_{fm}\mathbf{u}_{fm}(k), \tag{6.25}$$

where $\mathbf{K}_{fm}$ is an $N \times E$ matrix determined by graph $\mathcal{G}$. Since the constraints (6.15) – (6.17) are considered, every of the sums of all elements in $\mathbf{l}_{fm}(k+1)$, $\mathbf{l}_{fm}(k)$, and $\mathbf{u}_{fm}(k)$ should be one. Then, separate $\mathbf{K}_{fm}$ into two parts:

$$\mathbf{l}_{fm}(k+1) = \mathbf{K}_{fm}^{+}\mathbf{u}_{fm}(k), \tag{6.26}$$

$$\mathbf{l}_{fm}(k) = \mathbf{K}_{fm}^{-}\mathbf{u}_{fm}(k). \tag{6.27}$$

Therefore, $\mathbf{K}_{fm} = \mathbf{K}_{fm}^{+} - \mathbf{K}_{fm}^{-}$.

Let $\mathbf{TP}_{\mathcal{G}}$ be an $N \times N$ matrix that represents the topology of the graph $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$. Each element TP_{ij} in the matrix $\mathbf{TP}_{\mathcal{G}}$ is binary and determined by the following rule:

$$TP_{ij} = \begin{cases} 1, & (i,j) \in \mathcal{E}; \\ 0, & \text{otherwise.} \end{cases} \tag{6.28}$$

Then E is determined by the number of ones in matrix $\mathbf{TP}_{\mathcal{G}}$. The process of getting $\mathbf{K}_{fm}^{+}$ and $\mathbf{K}_{fm}^{-}$ from $\mathbf{TP}_{\mathcal{G}}$ is listed in the Alg. 6.1 and Alg. 6.2.

6.3 Scheduling with quality information using model predictive control

The cooperation between farms and starch processing plants can take different forms. In this chapter, two types of cooperations are considered. To coordinate actions among the

Algorithm 6.1 Getting $\mathbf{K}_{fm}^{+}$ from $\mathbf{TP}_{\mathcal{G}}$

$n \leftarrow 1$, $\mathbf{K}_{fm}^{+} \leftarrow \mathbf{0}$
for i=1 **to** N **do**
  for j=1 **to** N **do**
    if $TP_{ij} = 1$ **then**
      The element on the n-th column and i-th row of $\mathbf{K}_{fm}^{+}$ gets value 1.
      $n \leftarrow n + 1$
    end if
  end for
end for

Algorithm 6.2 Getting $\mathbf{K}_{fm}^{-}$ from $\mathbf{TP}_{\mathcal{G}}$

$n \leftarrow 1$, $\mathbf{K}_{fm}^{-} \leftarrow \mathbf{0}$
for i=1 **to** N **do**
  for j=1 **to** N **do**
    if $TP_{ij} = 1$ **then**
      The element on the n-th column and j-th row of $\mathbf{K}_{fm}^{-}$ gets value 1.
      $n \leftarrow n + 1$
    end if
  end for
end for

two types of players, namely plant operators and growers, two coordination strategies are proposed. A centralized strategy can be used in a fully cooperative scenario, where growers agree to share all the information of their farms with the processing plant and to accept its instructions on farm operations. In this strategy, one controller is used to schedule the movements of all potatoes in every considered farm (as shown in Fig. 6.3) in a centralized way. A distributed strategy can be used in a partially cooperative scenario (as shown in Fig. 6.4). In the distributed strategy, growers share part of the information to the processing plant and can make decisions at the farm level. The distributed strategy considers one farm controller for each farm, and one plant controller for the plant. In this distributed control architecture, the plant controller communicates with every farm controller. To assess the performance of these control strategies, a traditional approach is added to the experiments. The traditional approach is to call farms according to a fixed sequence and does not make any adjustments once the plan is made.

Both control strategies adopt the model predictive control strategy, as introduced in Chapter 4, and decisions are made at each time step over a prediction horizon of N_{p} steps, based on predicted information and system dynamics over the same horizon. The MPC approach makes decisions using the latest information, with the expectation that the effectiveness of scheduling in changing environments can be enhanced.

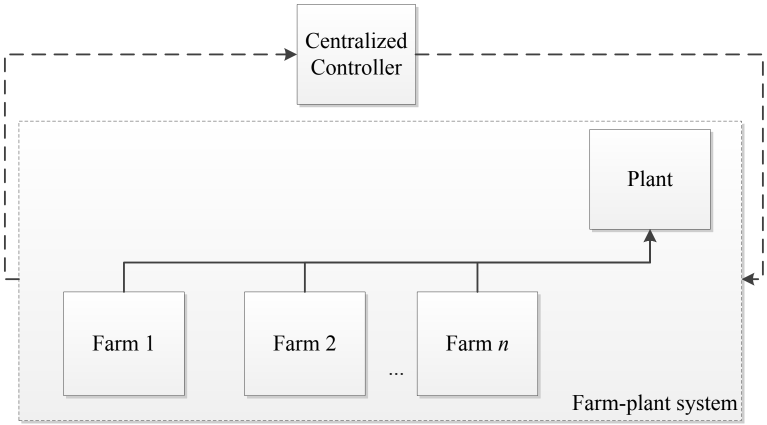


Figure 6.3: Centralized control architecture. Solid lines represent the flows of potatoes, and dashed lines represent the flows of information.

6.3.1 Centralized control strategy

In the centralized control architecture, one controller gathers information from the complete system and makes decisions on the movements of units as shown in Fig. 6.3. The controller predicts the quality of potatoes in future days based on weather forecasts. Then it makes decisions on the movements of units of each farm over the whole scheduling horizon. A centralized controller needs to know all the information of the system, including the location and quality of each unit on each farm. It requires every piece of detail in order to determine an optimal plan.

At time step k, the controller evaluates the total amount of starch left in the whole system from the next time step $k+1$ until the end of the prediction horizon N_p. For this, it maximizes the following objective function:

$$J = \sum_{f \in \mathcal{F}} \sum_{m \in \mathcal{M}} q_{fm}(k) \prod_{\tau=k+1}^{N_\text{p}} \sum_{i \in \mathcal{N}} l_{fmi}(\tau) \rho_{fi}(\tau), \tag{6.29}$$

subject to constraints (6.8), (6.10), (6.14), and (6.15)–(6.20). In this objective function, the quality of each unit after the final movements is calculated considering all the possible locations l_{fmi} and all the relating deterioration rates ρ_{fi}. The summation is the total amount of starch in the system including potatoes that have already been processed, at the end of the prediction horizon. Note that the prediction horizon N_p should not exceed the scheduling horizon N_s.

The algorithm used by the centralized controller is listed in Alg. 6.3. This strategy requires the information flows to be unrestricted, which is under the assumption that the growers are willing to share all their information. If the growers do not accept a fully cooperative strategy, the lack of communication can make it infeasible for a centralized controller to do all the scheduling by itself. A distributed control strategy that does not require all information in a single controller is then required.

Algorithm 6.3 Centralized control algorithm at time step k

1: Predict deterioration rate $\mathbf{d}(\tau)$ for the coming N_p time steps using kinetic model and temperature forecasts $T_{fi,\tau}(k)$ on time step k, where $\tau \in \{k, \ldots, k+N_p-1\}$.
2: Maximize J in (6.29) by solving the optimization problem with the constraints (6.8)–(6.19) to determine $\mathbf{u}(\tau)$, where $\tau \in \{k, \ldots, k+N_p-1\}$.
3: Implement to the system the decisions for upcoming time step $\mathbf{u}(k)$.

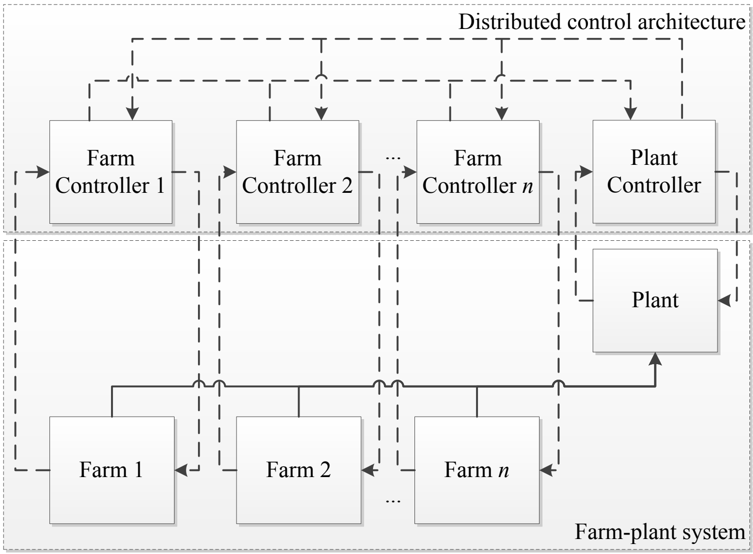


Figure 6.4: Distributed control architecture. Solid lines represent the flows of potatoes, and dashed lines represent the flows of information.

6.3.2 Distributed control strategy

In the distributed control architecture, as shown in Fig. 6.4, each farm and the plant is managed by a controller. A farm controller measures the situation of the farm, communicates with the plant controller and makes decisions on farm operations. The plant controller gathers information from all the farm controllers and inform farm controllers regarding the amount of potatoes to be transported from each farm to the plant. In this strategy, both types of controllers use model predictive control, with a prediction horizon of N_p that can be smaller than scheduling horizon N_s. In the following, the plant controller and the farm controllers are discussed in detail, and the algorithms are listed to demonstrate how the two types of controllers coordinate their decisions.

Plant controller

The plant controller interacts with all farm controllers at each time step. From each farm, the plant controller receives the information on the average quality of potatoes, number of units that are available, and how much labor for each farm at each time step. This is to

Algorithm 6.4 Plant control strategy at time step k in the distributed architecture

1: Request the information on average predicted quality $q_f^{\mathrm{a}}(\tau)$, potatoes remained in the field $\sum_{m \in M} l_{fmo}(\tau)$, and available labor on each farm $\sum_{\bar{\tau}=k}^{\tau} C_f^{l}(\bar{\tau})$, where $f \in \mathcal{F}$ and $\tau \in \{k, \ldots, k+N_{\mathrm{p}}-1\}$
2: Decide on $y_f(k)$ for each farm by solving the MILP problem in (6.30), with constraints (6.31) and (6.32), where $f \in \mathcal{F}$ and $\tau \in \{k, \ldots, k+N_{\mathrm{p}}-1\}$
3: Deliver the call over the prediction horizon N_{p} to farm controllers

ensure that it will not make demands that farms cannot fulfill. Then the plant controller maximizes the starch yield over the upcoming N_{p} time steps, by deciding on the number of units that each farm should send to the plant for processing. Let $q_f^{\mathrm{a}}(k)$ be the average quality of potatoes in farm f at time step k, and let $y_f(k)$ denote the decision on the number of units in farm f that should be sent to the plant at time step k. The plant controller can then make the decisions by solving the following optimization problem:

$$\max J = \sum_{f \in \mathcal{F}} \sum_{\tau=k}^{k+N_{\mathrm{p}}-1} y_f(\tau) q_f^{\mathrm{a}}(\tau), \tag{6.30}$$

subject to:

$$\sum_{f \in \mathcal{F}} y_f(\tau) \leq C^{\mathrm{p}}(\tau), \qquad \forall \tau \in \{k, \ldots, k+N_{\mathrm{p}}-1\}, \tag{6.31}$$

$$\sum_{\tau'=k}^{\tau} y_f(\tau') \leq \sum_{\tau'=k}^{\tau} C_f^{\mathrm{Q}}(\tau'), \qquad \forall f \in \mathcal{F}, \tau \in \{k, \ldots, k+N_{\mathrm{p}}-1\}, \tag{6.32}$$

where the objective for the plant is to maximize the estimated starch production over the horizon of N_{p} steps. For each time step within the horizon, the maximum amount of potatoes that the plant can accept from the farms in $\mathcal{F}$ is $C^{\mathrm{P}}(\tau)$, which limits the daily total demand that the plant can request from the farms as shown in (6.31). For each farm, the request from the plant should be no more than what the farm has, as shown in (6.32), in which $C_f^{\mathrm{Q}}(k)$ is the number of units that farm f can provide at time step k. This value is calculated by farm controllers for each of the farms, as detailed below, and is then sent to the plant controller.

Farm controller

At each time step, farm controllers supply information on average quality of the potatoes and number of available units in the farm to the plant controller. Based on that, the plant controller can make decisions to maximize the overall starch production by determining the number of units that should be moved from each farm to the plant at every future steps. After being informed about the decisions, farm controllers then decide on which specific units should be moved within their own farms to fulfill the requests from the plant.

The average quality of units on farm f at time step $\tau \in \{k, \ldots, k+N_{\mathrm{p}}-1\}$ is calculated

Algorithm 6.5 Farm f control strategy at time step k in the distributed architecture

1: Predict deterioration rate $\rho_{fi}(\tau)$ and average quality of all the available units on the farm $q_f^{\mathrm{a}}(\tau)$ for the upcoming $N_{\mathrm{p}}-1$ steps according to temperature forecasts from time step k, $\tau \in \{k,\ldots,k+N_{\mathrm{p}}-1\}$.
2: Calculate number of available units $C_f^{\mathrm{Q}}(\tau)$ using (6.34)–(6.36).
3: The information regarding quality and availability of potatoes is then sent to the plant controller.
4: Stand by until the plant controller returns a call to the farm controller.
5: Compute the movements for the upcoming N_{p} steps, by solving the optimization problem with (6.37) the objective function, and subject to (6.38)–(6.43).
6: Implement the decisions $\mathbf{u}_f(k)$ for the upcoming time step.

by the farm controller before the information is sent to the plant controller as follows:

$$q_f^{\mathrm{a}}(\tau) = \begin{cases} \dfrac{\sum_{m\in\mathcal{M}}\sum_{i\in\mathcal{N},i\neq d} q_{fm}(\tau)l_{fmi}(\tau)}{\sum_{i\in\mathcal{N},i\neq d} l_{fmi}(\tau)}, & \sum\limits_{i\in\mathcal{N},i\neq d} l_{fmi}(\tau)\neq 0, \\ 0, & \sum\limits_{i\in\mathcal{N},i\neq d} l_{fmi}(\tau) = 0. \end{cases} \tag{6.33}$$

As discussed above, $C_f^{\mathrm{Q}}(\tau)$ is the number of units that farm f can provide at time step τ. Two aspects determine this parameter: how many units farm f has at time step τ (denoted as $C_f^{\mathrm{S}}(\tau)$), and how many units have already been, or can be harvested ($C_f^{\mathrm{H}}(\tau)$). The number of available units is the smaller one of the two variables:

$$C_f^{\mathrm{S}}(\tau) = \sum_{m\in\mathcal{M}}\sum_{i\in\mathcal{N}} l_{fmi}(\tau) - \sum_{m\in\mathcal{M}} l_{fmd}(\tau), \tag{6.34}$$

$$C_f^{\mathrm{H}}(\tau) = \sum_{m\in\mathcal{M}}\sum_{i\in\mathcal{N}} l_{fmi}(\tau) - \sum_{m\in\mathcal{M}} \big(l_{fmo}(\tau)+l_{fmd}(\tau)\big) + C_f^{\mathrm{I}}(\tau), \tag{6.35}$$

$$C_f^{\mathrm{Q}}(\tau) = \min\Big(C_f^{\mathrm{S}}(\tau), C_f^{\mathrm{H}}(\tau)\Big). \tag{6.36}$$

After a call plan has been generated, the plant controller informs every farm controller about the requests of the number of units requested by the plant. Each farm controller then starts to make decisions on how to organize the activities for each farm to fulfill the demand from the plant, with the aim of maximizing the starch content of units produced by the farm at the end of the prediction horizon:

$$\max J = \sum_{m\in\mathcal{M}} q_{fm}(k) \prod_{\tau=k}^{k+N_{\mathrm{p}}-1} \sum_{i\in\mathcal{N}} l_{fmi}(\tau)\rho_{fi}(\tau), \tag{6.37}$$

subject to for $\tau \in \{k,\ldots,k+N_{\mathrm{p}}-1\}$,

$$\sum_{i\in\mathcal{N}} l_{fmi}(\tau) = 1, \forall m \in \mathcal{M}, \tag{6.38}$$

Algorithm 6.6 Traditional approach for the plant to make calls on farms at time step k

$f \leftarrow 1$
while $f \leq F$ **do**
  The plant enquires farm f whether they have potatoes available for turning in.
  if Yes **then**
    The plant takes potatoes from farm f.
  else
    if No **then**
      $f \leftarrow f+1$
    end if
  end if
end while

$$\sum_{i \in P(j) \cup \{j\}} u_{fmij}(\tau) = l_{fmj}(\tau), \forall m \in \mathcal{M}, j \in \mathcal{N}, \tag{6.39}$$

$$\sum_{j \in S(i) \cup \{i\}} u_{fmij}(\tau+1) = l_{fmi}(\tau), \forall m \in \mathcal{M}, i \in \mathcal{N}, \tag{6.40}$$

$$\sum_{m \in \mathcal{M}} l_{fmi}(\tau) \leq C^{s}_{fi}(\tau), \forall i \in \mathcal{N}, \tag{6.41}$$

$$\sum_{m \in \mathcal{M}} \sum_{j \in S(o)} u_{fmoj}(\tau) \leq C^{l}_{f}(\tau), \tag{6.42}$$

$$\sum_{m \in \mathcal{M}} \sum_{i \in P(d)} l_{fmi}(\tau) = y_f(\tau). \tag{6.43}$$

Similar to the centralized strategy, the farm controllers are subject to constraints (6.38)–(6.43). Constraints (6.38), (6.39), and (6.40) ensure that the movements of units follow the topology of the network. Constraint (6.41) limits the number of units stored in locations with capacities. Constraint (6.42) limits the number of units harvested each time step by growers due to the availability of labor. Constraint (6.43) indicates that the call from the plant has to be fulfilled by each farm controller. Note that the capacity of the plant is not considered as a constraint for the farm controllers, since in the distributed control architecture, the plant controller already makes calls considering this limit. The algorithm for each farm controller in the distributed control architecture is listed in Alg. 6.5. The actions taken at each time step by the controllers of the plant and the farms and the interactions among them are shown in Fig. 6.5.

6.3.3 Traditional approach

Apart from the two proposed control strategies, for comparison, a currently used approach is also considered. In this approach, growers agree upon a certain sequence of moving potatoes within the farms and to the plant, regardless of the upcoming weather conditions. Without loss of generosity, consider a sequence that gives priority to farm 1, as long as it has enough potatoes harvested and ready to be transported. If farm 1 does not have potatoes ready for transport, the opportunity moves to the next farm. This calling sequence is illustrated in Alg. 6.6. In addition, each of the farms operates to harvest potatoes as fast as possible and

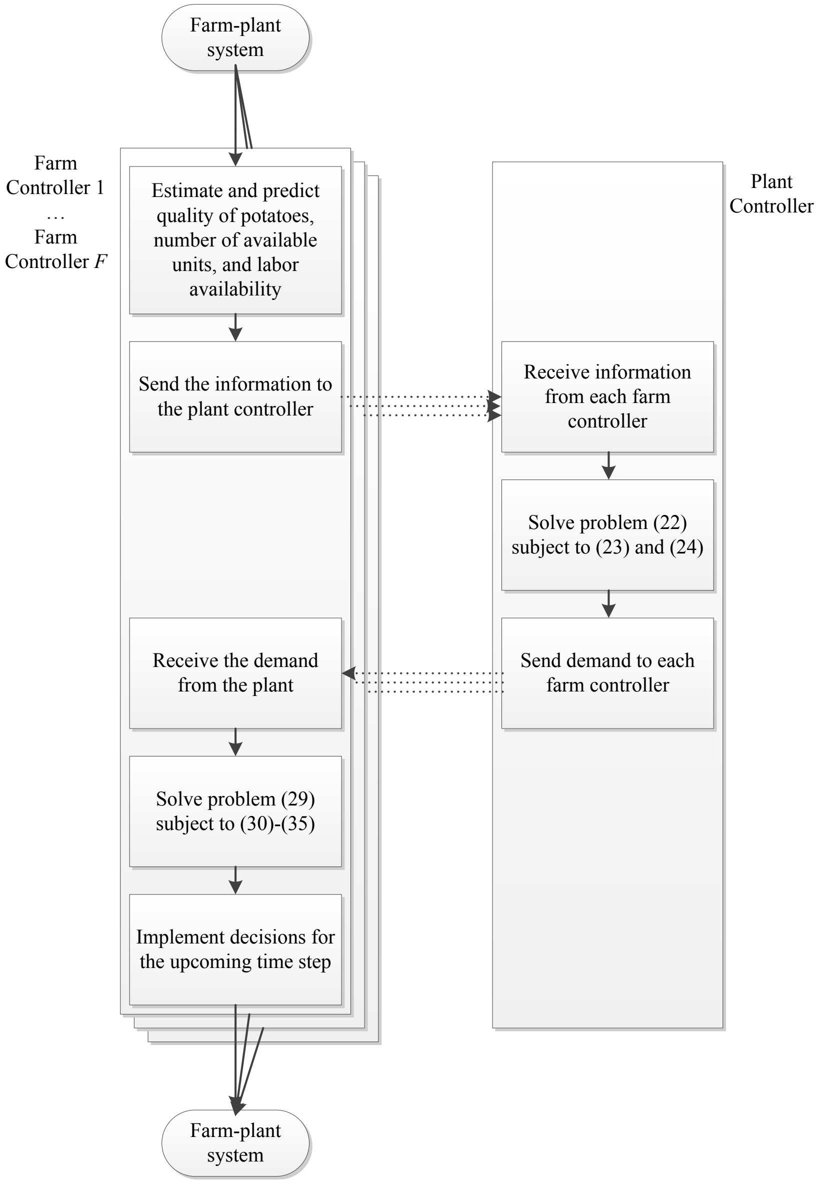


Figure 6.5: Actions taken by the two types of controllers in a distributed control strategy at each time step k.

responds to calls from the plant.

6.4 Simulation experiments

This section presents simulation experiments in order to evaluate the effectiveness of the proposed scheduling methods. Scenarios with different environmental conditions are considered. The performance of the strategies in different weather conditions are also compared.

The experiments are carried out on a desktop with Intel(R) Xeon(R) E5-1620 3.70 GHz CPU and 32 GB RAM, using Matlab 2014b. For the centralized control strategy, the controller solves the optimization problems using SCIP (v3.2.0) [2], a mixed integer non-linear programming (MINLP) solver provided by Opti toolbox (v2.21) [30]. For the distributed control strategy, the plant controller solves its optimization problems using the mixed integer linear programming (MILP) solver provided by Matlab in the optimization toolbox. The farm controllers solve their MINLP optimization problems using SCIP.

6.4.1 Scenario description

We set up several scenarios to evaluate our control strategies. Parameters of the system and the controllers are introduced. Different environmental conditions are simulated in order to evaluate the performance of the proposed control strategies.

System parameters

Table 6.1 shows the system parameters used in the experiments. To distinguish differences in temperature and labor availability, consider 12 hours as the time interval for decision making. Then, each day consists of two time steps: one time step in the morning, the other in the evening. Potatoes can be transported from the farms to the plant at each time step. The plant runs all the time but can only accept one unit of potatoes from these farms per 12 hours (C^{p}=1). Harvest only takes place during day time due to the labor availability. Each barn has the capacity of storing one unit of potatoes. A system with three farms and three units of potatoes on each farm is considered. We assume that potatoes in the ground follow a fixed deterioration rate. Meanwhile, the reduction of starch content in stored potatoes follows the first-order kinetics, described by equation (6.4) and (6.5). When potatoes are transported to the plant, they are processed and thus are no longer perishable. The temperature that affects the quality of stored potatoes are considered as out-door temperature $T^{\mathrm{Out}}(k)$ and in-door temperature $T^{\mathrm{In}}(k)$. The actual out-door temperature being used in the simulation is shown in the table. The prediction of out-door temperature $T^{\mathrm{Out}}_{k+\tau}(k)$, from the forecast on time step k for time step $k+\tau$ follows a normal distribution. The in-door temperature T^{In} is different from the out-door temperature by a difference of T^{Diff}, which is also chosen from a normal distribution.

To assess the potential of the proposed strategies when it comes to handling environmental disturbances, a scenario with an extreme environmental condition is included, in which potatoes can suffer from loss of starch. This can happen due to unwanted weather conditions (e.g., low temperature or frost). Being aware of such conditions in the upcoming days, a decision support system can update decisions to avoid such loss as much as possible.

Table 6.1: Parameters of the system

Parameter	Value
C^{p}	1
C^{l}_{f}	Day: 1, Night: 0
C^{s}_{f}	1 (when $i=$ barn), ∞ (otherwise)
$\rho_{fi,k}(k+\tau)$	0.95 ($i=o$), follows kinetic model ($i=$ pit or barn), 1 ($i=d$)
F	3
M_f	3
$q_{fm}(1)$ in %	$(q_{11}(1),\dots,q_{21}(1),\dots,q_{33}(1)) = (12,13,14,15,16,17,14,15,16)$
T^{Out}	$T^{\mathrm{Out}}_{k+\tau}(k) \sim N(T^{\mathrm{Out}}_{k+\tau}(k+\tau), 0.02\tau)$
T^{In}	$T^{\mathrm{Out}} + T^{\mathrm{Diff}}$, $T^{\mathrm{Diff}} \sim N(1, 0.2)$

Unwanted weather conditions can take on many forms and can affect potatoes in different storage conditions. This chapter assumes that a bad weather condition occurs on time step 7 of the simulation experiment. This information becomes known from time step 3. The impact of this weather condition is that all potatoes stored in pits will suffer from a starch loss of 50%:

$$\rho_{f2,7}(k) = 0.5, k \in [3,7], f \in \mathcal{F}. \tag{6.44}$$

Note that this percentage is not based on any prediction models, rather, it is manually chosen. However, it shows that the controllers can react accordingly through re-scheduling based on the predictive information to let potatoes avoid being affected by the weather condition.

Controller parameters

Parameters regarding control strategies include the length of the simulation horizon, length of the prediction horizon, and features regarding the graph. The length of the simulation horizon is 21 time steps, i.e., $N_{\mathrm{s}} = 21$ and the prediction horizon $N_{\mathrm{p}} = 10$.

In the centralized control strategy, on each farm there are three locations: field, pit, and barn. So together with the plant, the total number of locations in the graph $\mathcal{G}$ is $N = 3F + 1$.

In the distributed control strategy, each controller considers operations on one farm, in which there are 4 possible locations for each unit: field, pit, barn, and the plant. Therefore, for each farm controller, $\mathcal{G}$ contains $N = 4$ nodes.

6.4.2 Results and discussion

We compare the performance of the three approaches, i.e., the traditional, the centralized, and the distributed strategy. The experiments are carried out with a normal weather scenario, and with a scenario with the bad weather condition, respectively. Fig. 6.6 and Fig. 6.7 show the total amount of remaining starch, including the starch left in potatoes and the starch that has already been processed by the plant. Table 6.2 shows the computation time required to solve the problem and the amount of starch recovered using different approaches.

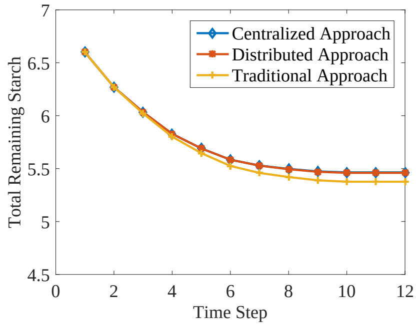


Figure 6.6: Normal weather scenario.

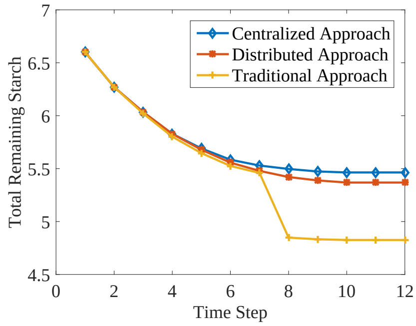


Figure 6.7: Bad weather scenario.

Table 6.2: Computation time and recovered starch of the three approaches in the normal weather scenario and the bad weather scenario

Control strategy	Computation time (hh:mm:ss)	Recovered starch (tonnes) Normal weather	Recovered starch (tonnes) Bad weather
Centralized strategy	01:48:34	5.4644	5.4638
Distributed strategy	00:00:05	5.4600	5.3685
Basic approach	-	5.3763	4.8256

Quality of solutions

In the normal weather scenario, the centralized strategy has a gain of 1.64% and the distributed strategy has a gain of 1.56% compared to the traditional approach. The centralized strategy has a slightly higher starch production than the distributed strategy. The performance of the traditional approach was also very close to the two control strategies. In the bad weather scenario, the gap between the two control strategies become larger. While the traditional approach was heavily affected by the weather condition, the centralized and distributed strategies show the capability in coping with the upcoming change. The centralized strategy, with a gain of 13.23%, is more capable to cope with major changes in environmental conditions than the distributed strategy, which has a gain of 11.25% compared to the traditional approach.

The traditional approach uses a fixed scheduling plan that does not change throughout the starch campaign. The two control strategies could both benefit from real-time quality information by means of MPC. As a result, they yield higher starch production than the traditional approach, especially in the bad weather scenario. This illustrates the value of real-time and predicted quality information when making decisions in the starch campaign. A scheduling strategy considering this information could support growers and plant operators to respond to possible changes of environmental disturbances and quality changes.

Complexity of the problem and computation time

Although the centralized strategy performs better than the distributed one in both scenarios, at each time step, it takes the centralized strategy a much longer timeto solve the centralized optimization problem. To solve a 3-farm problem, the centralized strategy takes 1 hour 48 minutes while the distributed strategy takes only 5 seconds.

The advantage of the centralized strategy is that it has all the information of each farm and can find better solutions than distributed strategy, especially when disturbances occur. However, the computation time required by the centralized strategy can drastically expand because the size of the optimization problem grows exponentially. Therefore, the centralized strategy can be used in smaller businesses with fewer farms included.

On the other hand, although the distributed strategy divides the problem into smaller subproblems, it can still find solutions that are close to the solution of the centralized strategy. Moreover, the time for the distributed control strategy does not increase significantly if the number of farms increases. Note that in the simulations, the distributed controllers operate one after another, while in the real world they can carry out computation in parallel, which suggests that even less time would be needed for computation. As a result, the distributed strategy suits larger settings where more farms are to be considered in the scheduling.

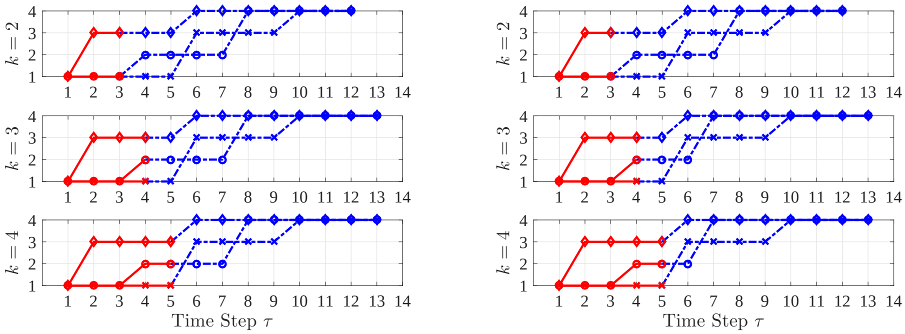
Nevertheless, if more units of potatoes are considered in each farm (which happens if there are more potatoes in one farm, or if fewer potatoes are considered as a unit), the complexity of the problem does increase even in the distributed strategy, because each farm controller makes decisions for more units. In that case, it is necessary to consider relatively good solutions instead of exact solutions by including heuristics solving methods.

Impact of disturbances environmental conditions

The awareness of the potential quality change can affect decisions made by predictive controllers. From Fig. 6.7 it can be observed that the performance of the traditional approach suffers from a drastic drop from time steps 7 and 8. Apparently, the traditional operational procedure causes some potatoes being affected by the bad weather in this scenario. On the other hand, this fall is not seen from either in centralized or distributed control strategy. Still, controllers have to come up with alternative plans when they are aware of the weather condition in the upcoming days. Analysis is then made about the performance of the two control strategies when zooming in to one of the farms.

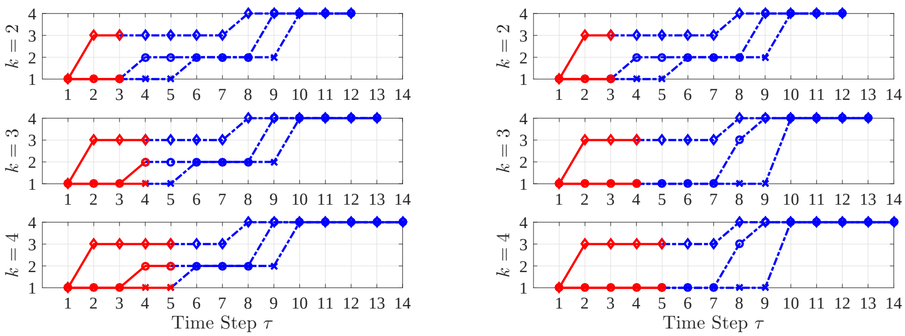
Fig. 6.8 and Fig. 6.9 show the plans and the actual movements of units on farm 1 under different weather condition generated by the centralized and the distributed control strategies. In Fig. 6.8(a) and Fig. 6.8(b), the centralized control strategy is used in normal and bad weather condition. While in Fig. 6.9(a) and Fig. 6.9(b), the distributed control strategy is used in normal and bad weather condition, respectively. In each figure there are two subfigures, for the normal and the bad weather condition, respectively. In each sub-figure there are three charts, showing actual movements (red solid lines) as well as the updated plans (blue dashed lines) at time steps 2, 3, and 4. Units in the farm are marked with different markers on the plots. The horizontal axis is the time steps, while the vertical axis represents the locations of units (1, in the field; 2, in the pit; 3, in the barn; 4, in the plant).

In Fig. 6.8(a) and Fig. 6.8(b), when $k = 2$ the centralized controller gives the same plan, since it is not yet aware of the upcoming bad weather condition. One unit will be staying in the field (location 2) time step 7. The plan change happens at time step 3 in the bad weather condition, at which the centralized controller forces this unit to leave location 2 before time step 7. Similarly, when the distributed control strategy is applied in these two scenarios, the



(a) Normal weather (b) Bad weather

Figure 6.8: Actual movements (solid lines) and plans (dashed lines) produced by the centralized strategy



(a) Normal weather (b) Bad weather

Figure 6.9: Actual movements (solid lines) and plans (dashed lines) produced by the distributed strategy

plans are the same before the bad weather can be detected. Two units will enter location 2 at time steps 4 and 6, and will stay till time steps 8 and 9, as planed from time step 2, as can be seen from Fig. 6.9(b). However, after time step 3, the bad weather condition becomes known, and the controllers manage to prevent potatoes from entering location 2, so that they will not be affected by this condition.

From the results of the different control architectures in different scenarios, the effectiveness of applying model predictive control strategy can be seen. When future disturbances become predictable, such as a change of weather, the model predictive control strategy has the ability to deal with disturbances by updating the plan for upcoming time steps.

6.5 Conclusions

This chapter focuses on a starch potato scheduling problem for starch production. Approaches to acquire real-time information are discussed. To answer the Research Question 5, a quality-aware modeling approach is applied to effectively describe the operation with quality considered. A centralized control and a distributed control strategy are designed taking into account different growers' willingness to share information. The modeling method and the proposed control strategies are tested using simulation experiments. The results illustrate that the proposed methods can increase starch production and have a better response to disturbances compared to the traditional method. In particular, the different control strategies work well in different situations. The centralized strategy suits smaller scale, cooperative supply chains with fewer farms, having a 1.64% gain and a 13.23% gain compared to the traditional approach in normal and unexpected weather conditions, respectively. The distributed strategy has improved the starch production by 1.56% and 11.25% in normal and unexpected weather conditions. Although disturbances may cause less production compared to the centralized strategy, the distributed strategy works well with more farms and allows more autonomy for growers in their decision making.

This chapter presents the basis for the control strategies that can be implemented in quality-aware scheduling for potato starch campaigns. The modeling approach and control strategies could also be used for other kinds of agricultural products. The next chapter discusses another commodity's supply chain where the quality dynamics is different and participants of logistic activities do not share the same interest relationships.

Chapter 7

Cut rose logistics

The proposed general framework has shown its potential at the supply side in a scenario of starch potato postharvest in Chapter 6. This chapter focuses on the consumption side, with a specific application domain in a cut rose supply chain. The commodity, the business mode, and its supply chains have different features in both biological and logistic dynamics and thus the general framework needs to be further extended to adapt to this application.

This chapter is organized as follows: Section 7.1 gives background information regarding cut rose supply chains. Section 7.2 defines the scope and objective of the study. Section 7.3 presents the formulation of the quality-aware model for the cut rose supply chain. A distributed model predictive control strategy is developed in Section 7.4 for several supply chain players. Section 7.5 concludes the chapter.

Parts of this chapter have been published in [94].

7.1 Introduction

Cut flowers and foliage are some of the most traded commodities in the world. In the year 2014 alone, the amount of these perishable goods imported to Europe from developing countries is worth almost €1.2 billion according to the Centre for the Promotion of Imports from developing countries [21]. The Netherlands is the largest cut flower trader in Europe, with an annual total value of €2.9 billion exported to other countries.

A typical international cut flower supply chain consists of growers, forwarders, importers, retailers, and customers. In the Netherlands, Royal FloraHolland, the Dutch auction house, is the main hub for cut flower trades. In 2016, the turnover of cut roses for instance, had a value of €746 millions, making it largest part of the cut flower trade in [117].

Cut roses are highly perishable and vulnerable to high temperatures. Efficiencies of the supply chain are often affected by uncertainties from the weather-dependent perishing nature, as well as from the dynamics of supply and demand [143]. The nature of this fragile product, the fast moving feature of the supply chain, and the complexity of supply-demand interactions create the need for close coordination among different parties within the supply chain.

The transport of cut roses is a race against time due to their perishing nature. In [141], it is pointed out that temperature is one of the most important factors in rose quality control, and that modeling temperature and quality relations is beneficial for rose supply chains. Tromp *et al.* [136] have examined two different models for rose quality prediction, namely, a kinetic model and a time-temperature model. Through analysis of experiments, they prove that the time-temperature model has practical value in predicting the remaining vase life of roses during transport and storage. To implement this model in rose supply chain optimization and coordination, temperature is the key indicator that needs to be monitored alone with roses during transport. Since this information can be made available in real-time by the advancing sensor and communication technologies (see, e.g.,[1]), this chapter focuses on how real-time quality information can be used to increase the effectiveness of supply chain activities and reduce cost and spoilage.

7.1.1 Research background

Limited research addresses logistic scheduling in a rose supply network with the consideration of the decreasing quality of fresh products. Verdouw *et al.* [144] make an initial step regarding this topic by designing a conceptual framework for the Dutch horticultural supply chain virtualization. The paper proposes that by means of Internet of Things technology, a dynamic, connected, intelligent, and quality controlled supply chain can be realized. De Keizer *et al.* [35] perform a quantitative study by designing a network for flower distribution. A network flow model is applied to represent the amount of flowers being transported from auctions to wholesalers and finally to retailers. Quality aspects are considered with index of time-temperature summation attached to nodes (locations) and arcs (transportations) in the network model. As discussed in Chapter 2, network flow models do not consider quality attributes and logistic attributes as independent features, and thus do not have adequate capacity to consider quality of cut flowers.

Chapter 3 and 4 proposes that the general framework can make the information of demand and quality more beneficial. A combination of quality-aware models and MPC is used to schedule logistic activities in Chapter 6. The quality-aware model is developed to represent the logistic activities and quality change when commodities are going through during their life cycle. The MPC strategy is applied to assist supply chain participants regarding decisions on postharvest, distribution, or inventory control, with the consideration of possible disturbances of quality or environmental factors.

Being different from the previous case study in Chapter 6, this chapter focuses on the demand part, i.e., the part of the supply chain after the auction house, including wholesalers, florists, and customers. In today's business mode, a common practice of florists and wholesalers is to maintain a certain stock of roses. However, in this business mode, uncertainties of demand and degradation rate often leads to demand not responded to or spoilage. To reduce the unmet demand and spoilage, a different business mode is considered in which customers can subscribe to florists to have continuous fresh roses supply. When a bouquet at a customer is not fresh any more, another fresh bouquet is supplied to the customer. Meanwhile, with the quality information of roses made available to suppliers by sensing and communication technologies, the demand from customers can be predicted.

In previous chapters, the general framework of quality-aware modeling and MPC is proposed and implemented in scheduling postharvest activities in starch campaigns. However, a cut rose supply chain has different dynamics from starch campaigns in the following aspects: First, a cut rose supply chain is a distribution network with multiple destinations

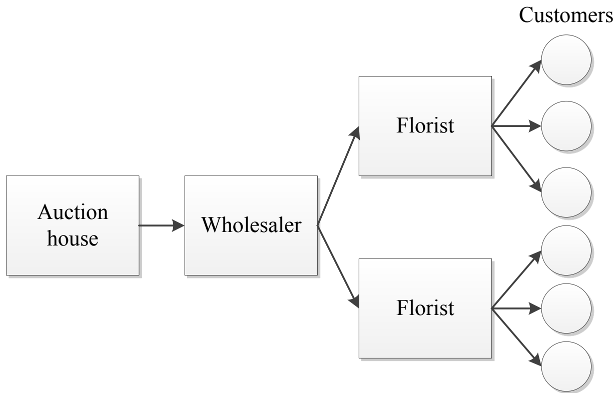


Figure 7.1: Supply network for cut roses considered in this study.

(different end customers); second, players at this section of the supply chain interact in a demand-driven way; third, the deterioration rate of roses affect demand in the future; last but not least, roses are fast moving commodities, and new roses keep flowing through the whole supply chain. Therefore, new components that have not been discussed in the previous chapters are introduced to adjust the general framework for better modeling and controlling.

7.1.2 Objective and contributions

The objective of this chapter is to develop a decision making strategy for cut rose supply chain players with the consideration of roses' quality. This strategy controls the supply chain in a coordinated way to reduce unmet demand and spoilage. By utilizing real-time and predicted information on the vase life of roses, the strategy can assist supply chain players to make informed decisions on amounts and time of purchasing.

The contribution of this chapter is twofold. From the theoretical perspective, the general framework is implemented with new features. A rotating unit method is added to the quality-aware modeling approach to tackle the inbound (fresh roses) and outbound (decayed roses) movements. A partially coordinated distributed control strategy is proposed to reflect objectives and operations of the various supply chain players. From the practical perspective, it can be demonstrated that the quality-aware modeling method and the MPC strategy are capable of handling decision making processes for supply chain players in the considered supply chain.

7.2 Problem statement and assumptions

This chapter considers a cut rose supply network from auction house to end customers. Involved players are the auction house, a wholesaler, several florists and customers (see Figure 7.1). From the auction house the wholesaler purchases roses, which are kept dry at a low temperature. The florists buy roses from the wholesaler and put them in water. Because roses are highly perishable, and the demand is often not known in advance, it is difficult for florists and the wholesaler to determine a proper number of roses in stock, which has no loss of sales or spoilage of roses.

In this study, end customers are also seen as supply chain players – if they prefer to have continuous supply of rose bouquets. When their roses perish, they will soon need another bouquet. This chapter considers a future scenario where supply chain players adopt sensing technology so that roses' remaining vase life can be predicted. Customers can subscribe to a local florist who keeps their houses decorated with bouquets of roses. Thus the demand can be considered known to the florist via estimation of the vase life of roses.

Assumptions

The following assumptions are considered in this study:

- Vase life of roses can be estimated and predicted by the wholesaler and florists;
- Auction has unlimited amount of flowers available to the wholesaler at any time;
- Wholesalers and florists discard roses with low quality according to their standards;
- Wholesalers purchase roses in boxes, and florists purchase roses in bouquets. Each box contains several bouquets.
- The wholesalers can always satisfy demands from florists, while florists only purchase at fixed days per week. A penalty is imposed on florists if they do not fulfill the demand from customers.

7.3 Quality-aware model for cut rose supply chains

This study focuses on the decisions and operations of the wholesaler and florists. Below each supply chain element is described in a quality-aware modeling method, consisting of a logistic aspect and a quality aspect.

7.3.1 Logistic and quality evolution in a quality-aware model

Using the quality-aware modeling method, roses are considered as units. As discussed in the assumptions considered in this chapter, a wholesaler operates on boxes of roses, and a florist operates on bouquets of roses. A box contains roses that can be made into several bouquets. (The interaction between two types of units will be discussed later in this section.) Each unit goes through different stages in the supply chain, denoted by a directed graph $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$. The nodes in collection $\mathcal{N}$ stand for possible locations of each unit, and the directed arcs in collection $\mathcal{E}$ stand for possible transitions between locations. Notation $l_{mi}(k) = 1$ represents that at time step k unit m is at node i. A transition from one node to another takes place if $u_{mij}(k) = 1$, where a decision is made at time step k, that unit m moves from location i to location j at the next time step. Note that every node has a self-directed arc ($i = j$), which allows units to stay at the same location for several time steps.

From the quality aspect, consider the quality of a unit of rose q_m as its remaining vase life t_{VL}. The vase life can be predicted using a time-temperature model [136] with temperature T and time period in days for storage t_{Day}.

The logistic and quality evolution of each unit $m \in \mathcal{M}$ is described as follows:

$$l_{mi}(k) = \begin{cases} 1, & \text{if unit } m \text{ is at node } i \text{ at time step } k, \\ 0, & \text{otherwise,} \end{cases} \tag{7.1}$$

$$u_{mij}(k) = \begin{cases} 1, & \text{if unit } m \text{ moves from node } i \text{ to node } j \text{ after time step } k, \\ 0, & \text{otherwise,} \end{cases} \tag{7.2}$$

$$l_{mj}(k+1) = \begin{cases} 1, & \text{if } l_{mi}(k) = 1 \text{ and } u_{mij}(k) = 1, \\ 0, & \text{otherwise,} \end{cases} \tag{7.3}$$

$$t_{\mathrm{VL}} = A - \frac{1}{20}(T - 273.15)t_{\mathrm{Day}}, \tag{7.4}$$

$$\Delta q_i = \frac{1}{20}(T_i - 273.15), \tag{7.5}$$

$$q_m(k+1) = q_m(k) - \sum_{(i,j)\in\mathcal{E}} \Delta q_i(k) u_{mij}(k), \tag{7.6}$$

in which (7.1), (7.2), and (7.3) represent the evolution of logistic attributes (locations and movements) of unit m. Equations (7.4), (7.5), and (7.6) are the evolution of quality attributes, in which (7.5) and (7.6) illustrate that deterioration rate per day Δq_i is related to the temperature T_i at node i. Parameter A represents the initial vase life, which is estimated by [136] to be 10 days.

Equations (7.1)–(7.6) describe the two aspects of the dynamics (logistic and quality) of a unit of roses in a quality-aware model. With this, models specifically for the wholesaler and the florists can be formulated next.

7.3.2 Quality-aware logistic model for the florists

Each florist purchases roses from a wholesaler, stores them in water, and then supplies them to subscribed customers. The graphical representation ($\mathcal{G}_f = \{\mathcal{N}_f, \mathcal{E}_f\}$) of the connections between a florist $f \in \mathcal{F}$ and other parties is shown in Figure 7.2. In this graph, node $o_f = 1$ represents the location of the wholesaler; node $b = 2$ represents the location of the florist; node $c \in \mathcal{C} = \{3, 4, 5\}$ represent different customers that subscribed to this florist. Node $z_f = 6$ is a virtual node for disposing roses that are not fresh anymore.

Consider the dynamics of each bouquet unit m in the collection of cut roses $\mathcal{M}_f$ under control of a florist f at step k, and the dynamics of all roses at the florist f at time step k as follows:

$$\sum_{(i,j)\in\mathcal{E}_f} u_{mij}(k) = 1, \qquad \forall m \in \mathcal{M}_f, k \in \{1, 2, \ldots\}, \tag{7.7}$$

$$\sum_{p\in\mathcal{P}(i)\cup\{i\}} u_{mpi}(k) = \sum_{j\in\mathcal{S}(i)\cup\{i\}} u_{mij}(k+1), \qquad \forall m \in \mathcal{M}_f, i \in \mathcal{N}_f, k \in \{1, 2, \ldots\}, \tag{7.8}$$

$$\sum_{j\in\mathcal{S}(i)\cup\{i\}} u_{mij}(1) = l_{mi}(1), \qquad \forall m \in \mathcal{M}_f, i \in \mathcal{N}_f, \tag{7.9}$$

$$\sum_{m\in\mathcal{M}_f} \sum_{i\in\mathcal{P}(j)} u_{mij}(k) \leq C_j, \qquad \forall j \in \mathcal{N}_f, k \in \{1, 2, \ldots\}, \tag{7.10}$$

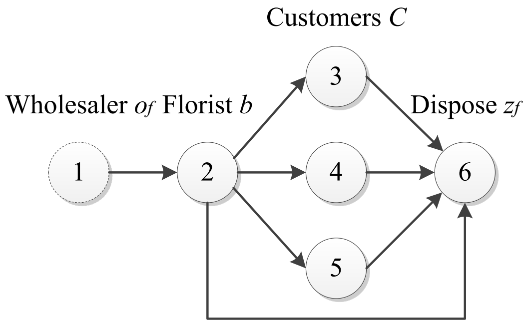


Figure 7.2: The graph $\mathcal{G}_f$ for a florist.

$$q_m(k+1) = q_m(k) - \sum_{(i,j)\in\mathcal{E}_f} \Delta q_i(k) u_{mij}(k), \qquad \forall m \in \mathcal{M}_f, k \in \{1,2,\dots\}, \quad (7.11)$$

$$Q(1-u_{mbc}(k)) \geq q_f^{\text{low}} - q_m(k), \qquad \forall m \in \mathcal{M}_f, k \in \{1,2,\dots\}, c \in \mathcal{C}, \quad (7.12)$$

$$Q(1-u_{mbb}(k)) \geq q_f^{\text{low}} - q_m(k), \qquad \forall m \in \mathcal{M}_f, k \in \{1,2,\dots\}, \quad (7.13)$$

$$Q(1-u_{mcc}(k)) + q_m(k) \geq 0, \qquad \forall m \in \mathcal{M}_f, k \in \{1,2,\dots\}, c \in \mathcal{C}, \quad (7.14)$$

$$\sum_{m\in\mathcal{M}_f} u_{mo_f b}(\tau) \leq Q B_k^f(\tau), \qquad \forall \tau \in \{1,\dots,N_{\text{P}}\}, k \in \{1,2,\dots\}. \quad (7.15)$$

$$\mathbf{l}_f(k) = \{l_1(k),\dots,l_m(k),\dots,l_{M_f}(k)\}^{\text{T}}, \quad (7.16)$$

$$\mathbf{q}_f(k) = \{q_1(k),\dots,q_m(k),\dots,q_{M_f}(k)\}^{\text{T}}, \quad (7.17)$$

$$\Delta\mathbf{q}_f(k) = \{\Delta q_1(k),\dots,\Delta q_i(k),\dots,\Delta q_{N_f}(k)\}^{\text{T}}, \quad (7.18)$$

$$\mathbf{u}_f(k) = \{u_{111}(k),\dots,u_{mij}(k),\dots\}^{\text{T}}, \quad (7.19)$$

$$\mathbf{x}_f(k) = \{\mathbf{l}_f^{\text{T}}(k), \mathbf{q}_f^{\text{T}}(k)\}^{\text{T}}, \quad (7.20)$$

$$\mathbf{x}_f(k+1) = g_f\left(\mathbf{X}_f(k), \mathbf{u}_f(k), \Delta\mathbf{q}_f(k)\right), \quad (7.21)$$

in which (7.7) enforces that at any time step, the transition of locations of a unit/bouquet m should follow only one arc; (7.8) makes sure that the unit always follows the directed arcs when being moved ($\mathcal{P}(i)$ and $\mathcal{S}(i)$ are the collection of the predecessor and successor nodes of node i, respectively); (7.9) enforces that the decisions for movements of the upcoming time step $k+1$ should be from the current location i at time step k; (7.10) guarantees that the number of units at a certain location j at the same time step k does not exceed the capacity of this location C_j; (7.11) keeps track on quality of each unit. In the following constraints, Q is a large, positive value. (7.12) and (7.13) forces roses with their vase life less than q^{low} at florists to be discarded, and thus customers ($c \in \mathcal{C}$) will not receive roses with too low quality; (7.14) describes that roses at customers are discarded when running out of vase life. Constraint (7.15) describes that the purchases made by florists from the wholesaler follows a pattern B, an array denoting on which in the N_{P} upcoming days the florists visit the wholesaler. For instance, $B_k^f = \{0,1,0,0,0,0,0\}$ represents whether the florist f will have purchasing plans on the following days seen from day k, and the second element in the array ($B_k^f(2) = 1$) indicates that on day $k+2$, florist f has a purchase plan. In (7.16)–(7.21),

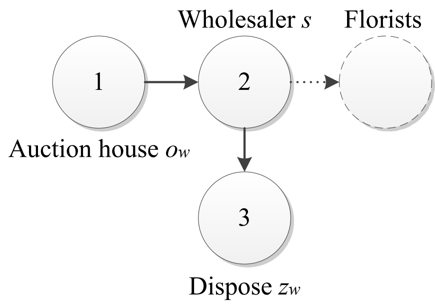


Figure 7.3: The graph $\mathcal{G}_w$ for the wholesaler.

vectors $\mathbf{l}_f(k)$, $\mathbf{q}_f(k)$, $\Delta\mathbf{q}_f(k)$, $\mathbf{u}_f(k)$ represent locations, qualities, deterioration rates, and decisions of all the units at time step k, respectively. $\mathbf{x}_f(k)$ represents the current system state at time step k. Function g_f is the state transition of the system of the future system state $\mathbf{x}_f(k+1)$ based on the current state $\mathbf{x}_f(k)$ and decisions of movements $\mathbf{u}_f(k)$. Note that the vectors in $\mathbf{x}_f(k+1)$ can be derived from (7.3) and (7.6), respectively.

7.3.3 Quality-aware logistic model for the wholesaler

The part of the logistic system for the wholesaler w is represented by graph $\mathcal{G}_w$ in Figure 7.3. The wholesaler receives demand information from the florists and purchases roses from the auction house. The wholesaler also discards roses with low quality according to its own regulation. In $\mathcal{G}_w$ the auction house is represented by node $o_w = 1$, the wholesaler by node $s = 2$, and dispose by node $z_w = 3$.

Note that the wholesaler buys roses in boxes but sells them to florists in bouquets. Therefore, a box of roses can be sold to different florists. Introduce a variable $h_m(k)$, which denotes the quantity (of bouquets) of roses left in a box m at the wholesaler, at time step k. Decision variable $r_m(k)$ represents the number of bouquets required by florists from the box m at time step k from the wholesaler.

Next the dynamics of each box of roses $m \in \mathcal{M}_w$ under control of the wholesaler w and the dynamics of all the boxes of roses is demonstrated in a state-space fashion as follows:

$$\sum_{(i,j)\in\mathcal{E}_w} u_{mij}(k) = 1, \qquad \forall m \in \mathcal{M}_w, k \in \{1,2,\ldots\}, \tag{7.22}$$

$$\sum_{p\in\mathcal{P}(i)\cup\{i\}} u_{mpi}(k) = \sum_{j\in\mathcal{S}(i)\cup\{i\}} u_{mij}(k+1), \qquad \forall m \in \mathcal{M}_w, i \in \mathcal{N}_w, k \in \{1,2,\ldots\}, \tag{7.23}$$

$$\sum_{j\in\mathcal{S}(i)\cup\{i\}} u_{mij}(1) = l_{mi}(1), \qquad \forall m \in \mathcal{M}_w, i \in \mathcal{N}_w, \tag{7.24}$$

$$q_m(k+1) = q_m(k) - \sum_{(i,j)\in\mathcal{E}_w} \Delta q_i(k) u_{mij}(k), \qquad \forall m \in \mathcal{M}_w, k \in \{1,2,\ldots\}, \tag{7.25}$$

$$Q(1-u_{mss}(k)) \geq q_w^{\text{low}} - q_m(k), \quad \forall m \in \mathcal{M}_w, k \in \{1,2,\ldots\}, \tag{7.26}$$

$$h_m(k+1) = h_m(k) - r_m(k), \quad \forall m \in \mathcal{M}_w, k \in \{1,2,\ldots\}, \tag{7.27}$$

$$\sum_{\tau=0}^{N_P-1} r_m(\tau) \leq h_m(k), \quad \forall m \in \mathcal{M}_w, k \in \{1,2,\ldots\}, \tag{7.28}$$

$$r_m(k) \leq Q\left(u_{mo_ws}(k) + u_{mss}(k)\right), \quad \forall m \in \mathcal{M}_w, k \in \{1,2,\ldots\}, \tag{7.29}$$

$$\sum_{m\in\mathcal{M}_w} r_m(k) = \sum_{f\in\mathcal{F}} d_f(k), \quad \forall k \in \{1,2,\ldots\}, \tag{7.30}$$

$$u_{mss}(k) \leq Q\left(h_m(1) - \sum_{\tau=1}^{k} r_m(\tau)\right), \quad \forall m \in \mathcal{M}_w, k \in \{1,2,\ldots\}, \tag{7.31}$$

$$\mathbf{l}_w(k) = \{l_{11}(k),\ldots,l_{mi}(k),\ldots\}^{\mathrm{T}}, \tag{7.32}$$

$$\mathbf{q}_w(k) = \{q_1(k),\ldots,q_m(k),\ldots,q_{M_w}(k)\}^{\mathrm{T}}, \tag{7.33}$$

$$\Delta\mathbf{q}_w(k) = \{\Delta q_1(k),\ldots,\Delta q_i(k),\ldots,\Delta q_{N_w}(k)\}^{\mathrm{T}}, \tag{7.34}$$

$$\mathbf{h}(k) = \{h_1(k),\ldots,h_m(k),\ldots,h_{M_w}(k)\}^{\mathrm{T}}, \tag{7.35}$$

$$\mathbf{u}_w(k) = \{u_{111}(k),\ldots,u_{mij}(k),\ldots\}^{\mathrm{T}}, \tag{7.36}$$

$$\mathbf{r}(k) = \{r_1(k),\ldots,r_m(k),\ldots,r_{M_w}(k)\}^{\mathrm{T}}, \tag{7.37}$$

$$\mathbf{d}(k) = \{d_1(k),\ldots,d_f(k),\ldots,d_F(k)\}^{\mathrm{T}}, \tag{7.38}$$

$$\mathbf{x}_w(k) = \{\mathbf{l}_w^{\mathrm{T}}(k),\mathbf{q}_w^{\mathrm{T}}(k),\mathbf{h}^{\mathrm{T}}(k)\}^{\mathrm{T}}, \tag{7.39}$$

$$\mathbf{x}_w(k+1) = g_w\left(\mathbf{x}_w(k),\mathbf{u}_w(k),\mathbf{r}(k),\Delta\mathbf{q}_w(k),\mathbf{d}(k)\right), \tag{7.40}$$

in which (7.22), (7.23) are the topology constraints that ensure units appear at one place at each time step and move along the directed arcs of the graph; (7.24) enforces that the decisions for movements of the upcoming time step $k+1$ should be from the current location i at time step k; (7.25) keeps track on quality of each unit; constraints (7.26) keep the quality of roses at wholesaler by discarding the ones that have quality lower than q_w^{low}; (7.27) explains how quantity of roses in a box m can change over time; (7.28) ensures that the number of bouquets taken from each box m over the horizon N_P should be no more than the number of bouquets that are left at each time step k; (7.29) enforces that florists can only purchase roses from boxes arriving or stored at the wholesaler; (7.30) ensures that roses taken out from boxes at the wholesaler equals the demand from the florists. (7.31) ensures that once all the roses are taken out from the box, the unit for the box moves to the next stage (dispose). In Equations (7.32) – (7.40), vectors $\mathbf{l}_w(k)$, $\mathbf{q}_w(k)$, $\Delta\mathbf{q}_w(k)$, $\mathbf{h}(k)$, $\mathbf{u}_w(k)$, $\mathbf{r}(k)$, and $\mathbf{d}(k)$ represent locations, qualities, deterioration rates, quantities left in boxes, decisions of all the movements, decisions of all the numbers of bouquets taken from each box, and demand from all the florists at time step k, respectively. $\mathbf{x}_w(k)$ is the current system state for all roses considered at the wholesaler at time step k. Function g_w is the state transition to the future state $\mathbf{x}_w(k+1)$.

7.4 Control strategy for real-time coordination

The previous section presents the quality-aware models for rose handling at the wholesaler and florists. This section introduces the control strategy for each supply chain player to make optimal decisions, and to coordinate with others in the supply chain. Firstly, this section introduces the objective functions of controllers at the wholesaler and the florists. Subsequently, a rotating units method is adopted in order to cope with a fast moving rose supply chain. Then, control algorithms for each controller and inter-controller communication are described.

7.4.1 Objectives of the controllers

The controller at each florist f aims at minimizing the cost for buying roses and the unmet demand. Each bouquet costs α_1 and the penalty for each unmet demand per day is α_2. Similarly, the controller at the wholesaler seeks to minimize the cost for purchasing roses. Each box of roses costs $\beta(k)$, as this price may vary from day to day. Consider an upcoming time period $\{1,\ldots,k,\ldots,N_\mathrm{P}\}$. The objective functions for controllers at florists (J_f) and the wholesaler (J_w) are as follows:

$$\min \; J_f = \alpha_1 \sum_{k=1}^{N_\mathrm{P}} \sum_{m\in\mathcal{M}_f} u_{mo_f b}(k) + \alpha_2 \sum_{k=1}^{N_\mathrm{P}} \sum_{j\in C} \left(1 - \sum_{m\in\mathcal{M}_f} \sum_{i\in\mathcal{P}(j)\cup\{j\}} u_{mij}(k) \right), \tag{7.41}$$

$$\min \; J_w = \sum_{k=1}^{N_\mathrm{P}} \sum_{m\in\mathcal{M}_w} \beta(k) u_{mo_w s}(k). \tag{7.42}$$

7.4.2 Rotating unit method and communication between controllers

In the quality-aware model method, the number of units in a system needs to be defined prior to optimization. However, roses are fast moving goods as they are going through the supply chain all the time. This feature requires controllers to be capable of introducing new units and disposing consumed/spoiled units. A rotating unit method is applied: when a bouquet/box enters a part of the supply chain, the player registers it to a unit with the new attributes (quality and location). When the bouquet/box is disposed, it is unregistered and the unit moves to the beginning of the supply chain to be registered to a new bouquet/box of roses. Therefore, given a pre-determined number of units, these units can be "reused" over time, instead of trying to include every future unit in the model. Consider any unit m in the wholesaler/florist, the following equations show how this method is applied:

$$\begin{aligned} &q_{m_f}(k+1) = q_{m_w}(k+1), \text{if } u_{m_f o_f b}(k) = 1 \text{ and } \; r_{m_w} \geq 0, \\ &\forall m_f \in \mathcal{M}_f, m_w \in \mathcal{M}_w, f \in \mathcal{F}, k \in \{1,2,\ldots,N_\mathrm{P}\}, \end{aligned} \tag{7.43}$$

Algorithm 7.1 Algorithm for florist f

1: Examine the current system state $\mathbf{x}_f(k)$ and the purchase pattern B_k^f.
2: Solve the binary integer linear programming problem with the objective function (7.41) and constraints (7.7)-(7.15). Compute the optimal solution over the horizon: $(\hat{\mathbf{u}}_f(k),\ldots,\hat{\mathbf{u}}_f(k+N_\mathrm{P}-1))$.
3: Send purchase plans $\left(\sum_{m\in\mathcal{M}_f} u_{mo_fb}(k)\right)$ for the time steps $k+1$ to $k+N_\mathrm{P}$ to the wholesaler.
4: After receiving confirm from the wholesaler, purchase roses from wholesaler with certain qualities, update qualities of newly purchased bouquets in $\mathbf{q}_f(k+1)$ using (7.43).
5: Execute the decisions $\hat{\mathbf{u}}(k)$ using (7.21), and rotate units that are disposed, and register qualities to these units according to (7.43)–(7.45). This results in the new system state $\mathbf{x}_f(k+1)$.

$$\begin{aligned}&q_{m_f}(k+1)=q_w^{\mathrm{low}}, \text{if } u_{m_fiz_f}(k)=1,\\&\forall m_f\in\mathcal{M}_f, f\in\mathcal{F}, i\in P(z_f), k\in\{1,2,\ldots,N_\mathrm{P}\},\end{aligned}\tag{7.44}$$

$$\begin{aligned}&l_{m_fo_f}(k+1)=1, l_{m_fz_f}(k+1)=0, \text{if } u_{m_fiz_f}(k)=1,\\&\forall m_f\in\mathcal{M}_f, i\in P(z_f), k\in\{1,2,\ldots,N_\mathrm{P}\},\end{aligned}\tag{7.45}$$

$$\begin{aligned}&q_{m_w}(k+1)=q_{m_w}^{\mathrm{ini}}(k+1), \text{if } u_{m_wo_ws}(k)=1,\\&\forall m_w\in\mathcal{M}_w, k\in\{1,2,\ldots,N_\mathrm{P}\},\end{aligned}\tag{7.46}$$

$$\begin{aligned}&l_{m_wo_w}(k+1)=1, l_{m_wz_w}(k+1)=0, \text{if } u_{m_wiz_w}(k)=1,\\&\forall m_w\in\mathcal{M}_w, k\in\{1,2,\ldots,N_\mathrm{P}\}.\end{aligned}\tag{7.47}$$

$$\begin{aligned}&h_{m_w}(k+1)=h^{\mathrm{ini}}, \text{if } u_{m_wiz_w}(k)=1,\\&\forall m_w\in\mathcal{M}_w, k\in\{1,2,\ldots,N_\mathrm{P}\},\end{aligned}\tag{7.48}$$

where (7.43) describes the communication of quality between the wholesaler and a florist when purchases happen: the quality of a new bouquet moving into a florist f is updated with the quality of the box from which the bouquet is taken. If from more than 1 boxes the bouquets are taken, their qualities should be updated respectively according to the qualities of the boxes. Note that units are indexed here (as m_f and m_w) to discriminate a "box unit" of the wholesaler from a "bouquet unit" from a florist. Equations (7.44) and (7.45) show that when a bouquet is disposed, the unit is unregistered with the bouquet, moved to node 1, and registered with newly registered minimum acceptable quality from wholesaler. Although the quality information of the new bouquet is not yet available to the florist before the purchase, it is guaranteed with a minimum quality (ensured by constraint (7.26)). Similarly, wholesalers apply the same principle with the rotating unit method. In (7.46) and (7.48), the quality and initial quantity is updated with information from the auction house. Equation (7.47) takes care of the re-registration of units to new boxes of roses.

7.4.3 Distributed control algorithms

In Figure 7.4, a flow chart is used that represents how and when inter-controller communication is carried out within a control loop at time step k. When florists have generated

Algorithm 7.2 Algorithm for wholesaler w

1: Examine the current system state $\mathbf{x}_w(k)$.
2: Receive the total demand from florists $\mathbf{d}(k)$ over the prediction horizon.
3: Solve the mixed integer linear programming problem with the objective function (7.42), constraints (7.22)-(7.31), and the daily update of the price $\beta(k)$. Compute the optimal solution over the horizon: $(\hat{\mathbf{u}}_w(k),\ldots,\hat{\mathbf{u}}_w(k+N_\mathrm{P}-1))$ and $(\hat{\mathbf{r}}(k),\ldots,\hat{\mathbf{r}}_M(k+N_\mathrm{P}-1))$.
4: Sell roses to florists with certain qualities according to $\hat{\mathbf{r}}(k)$. Update with the florists about the qualities of the sold items using (7.43).
5: Execute the decisions $\hat{\mathbf{u}}_w(k)$ and $\hat{\mathbf{r}}_m(k)$; rotate units that are disposed; and register qualities to these units according to (7.46)–(7.48). This results in the new system state $\mathbf{x}_w(k+1)$.

purchase plans, they send this information to the wholesaler. The wholesaler then decides which roses to sell to the florists. The quality information is updated with the florists, as these bouquets being traded are registered with units at each florist. Alg. 7.1 and 7.2 provide the details of the algorithms of the control sequences for the florists and the wholesaler, respectively.

7.4.4 A traditional approach

Apart from the proposed control strategy, a traditional approach is also explained. To demonstrate the potential of the proposed approach in the business mode, a comparison is made with respect to its performance with a simulation of a reference group without the proposed approach. The supply chain players in the reference group apply the strategy of maintaining their stocks at certain levels that are time-invariant.

7.5 Simulation experiments

In this section, simulation experiments are carried out to compare the effectiveness of the current handling method and the proposed approach.

7.5.1 Scenario description

This section assumes that florists 1 and 2 aim to maintain their stock at 2 and 3 bouquets, respectively; the wholesaler maintains the stock at no less than 5 bouquets. Consider the scenario of one wholesaler, 2 florists and 6 customers (as shown in Figure 7.1). The parameters and initial system states are given in Table 7.1. In the scenario, consider $N_\mathrm{total} = 16$ days as the total time period. The purchase pattern of each florist of each week stays the same. The price of purchasing a box of roses from auction houses can varying from day to day. Denote $\beta^t(k)$ as the price of day $t+k-1$ seen from day t (e.g., $\beta^3(1)$ is the price of day 3 seen from day 3). Since the auction price can not be predicted, the wholesaler uses the average price (€15) as a reference for the predictive controller. Similarly, $\Delta\mathbf{q}^t_f(k)$ and $\Delta\mathbf{q}^t_w(k)$ are the degradation rates for day $t+k-1$ seen from day t. Initial locations of each unit $\mathbf{l}_f(1)$ and $\mathbf{l}_w(1)$ are denoted as the node numbers of the locations, instead of the binary indicators (e.g., if $l_{mi}(1) = 1$ then the m-th number in the value is i).

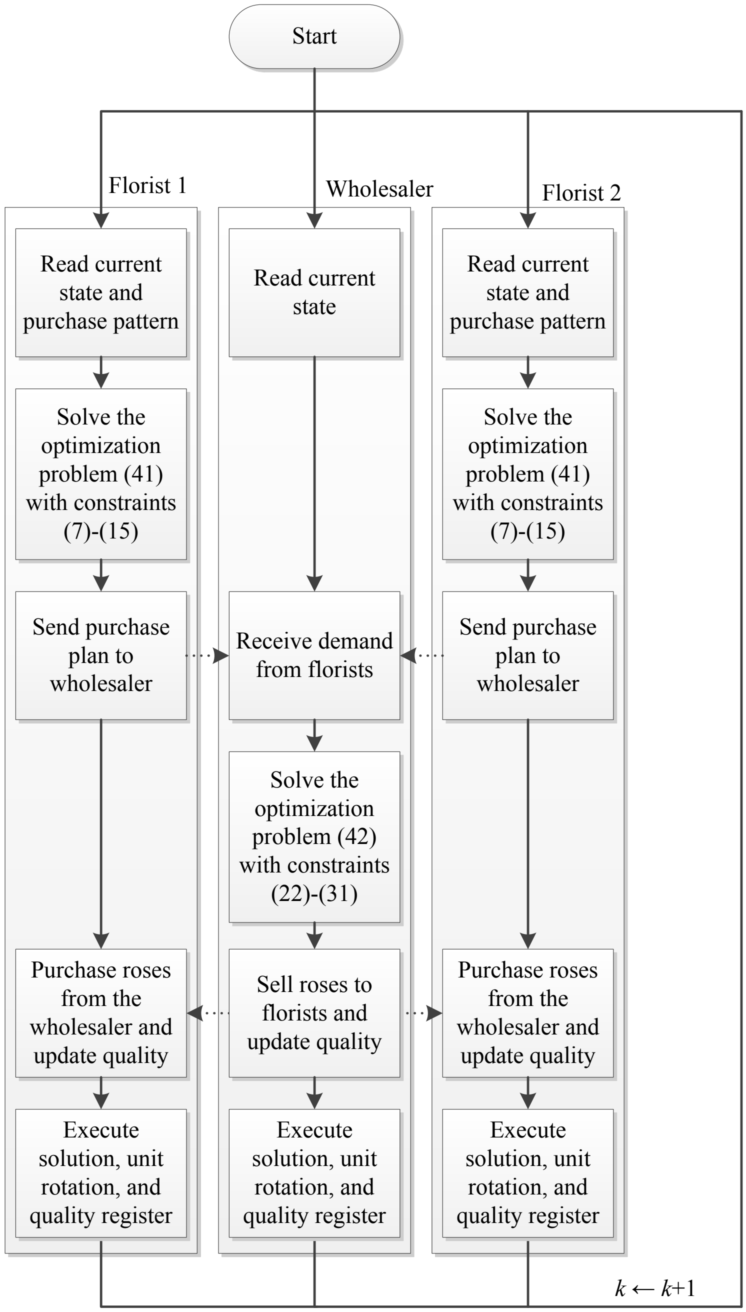


Figure 7.4: Flowchart of the coordinated control strategy at time step k.

Table 7.1: Scenario considered in the experiments

	Parameter	Value
System	N_{P}	7
	N_{total}	16
	M	$M_f = 12$, $M_w = 8$
	N	$N_f = 6$, $N_w = 3$
	q^{low}	$q_f^{\text{low}} = 6$, $q_w^{\text{low}} = 8$
	W	1
	F	2
	C	3
	α_1	€5
	α_2	€25
	$\beta^t(k)$	$\beta^t(1) = \text{N} \sim (€15, 1.5)$, $\beta^t(k)\|_{k\geq 2} = €15$, $t \in \{1,\ldots,N_{\text{total}}\}$
Florist 1	$\mathbf{l}_f(1)\|_{f=1}$	$\{1,1,1,1,1,1,1,1,2,3,4,5\}$
	$\mathbf{q}_f(1)\|_{f=1}$	$\{7,7,7,7,7,7,7,7,7,3,1,2\}$
	$B_1^f(1)\|_{f=1}$	$\{1,0,0,1,0,0,0\}$
	$\Delta\mathbf{q}_f^t(k)\|_{f=1}$	$\Delta q_i^t\|_{i=1,6}(k) = 0$,$\Delta q_2^t(k) = 0.8$, $\Delta q_3^t(k) = 1$, $\Delta q_i^1\|_{i=4,5}(1) = 1.2$ $\Delta q_i^{t+1}\|_{i=4,5}(1) = \text{N} \sim (\Delta q_i^t\|_{i=4,5}(1), 0.1)\,, \forall t \in \{1,\ldots,N_{\text{total}}-1\}$ $\Delta q_4^t(k) \sim \text{N}\,(\Delta q_4^t(1), 0.05 + 0.003k)\,, \forall k \in \{2,\ldots,N_{\text{P}}\}$ $\Delta q_5^t(k) \sim \text{N}\left(\Delta q_5^t(1), 0.06 + 0.005k\right), \forall k \in \{2,\ldots,N_{\text{P}}\}$
Florist 2	$\mathbf{l}_f(1)\|_{f=2}$	$\{1,1,1,1,1,1,1,1,1,3,4,5\}$
	$\mathbf{q}_f(1)\|_{f=2}$	$\{7,7,7,7,7,7,7,7,7,3,1,2\}$
	$B_1^f(1)\|_{f=2}$	$\{0,1,0,0,1,0,0\}$
	$\Delta\mathbf{q}_f^t(k)\|_{f=2}$	$\Delta q_i^t\|_{i=1,6}(k) = 0$, $\Delta q_3^t(k) = 1.1$, $\Delta q_i^1\|_{i=4,5}(1) = 1.1$ $\Delta q_i^{t+1}\|_{i=4,5}(1) = \text{N} \sim (\Delta q_i^t\|_{i=4,5}(1), 0.12)\,, \forall t \in \{1,\ldots,N_{\text{total}}-1\}$ $\Delta q_4^t(k) \sim \text{N}\,(\Delta q_4^t(1), 0.05 + 0.003k)\,, \forall k \in \{2,\ldots,N_{\text{P}}\}$ $\Delta q_5^t(k) \sim \text{N}\left(\Delta q_5^t(1), 0.06 + 0.005k\right), \forall k \in \{2,\ldots,N_{\text{P}}\}$
Wholesaler	$\mathbf{l}_w(1)$	$\{1,1,1,1,1,1,1,2\}$
	$\mathbf{q}_w(1)$	$\{9,10,10,10,10,10,10,10\}$
	$\mathbf{h}(1)$	$\{5,5,5,5,5,5,5,2\}$
	$\Delta\mathbf{q}_w^t(k)$	$\Delta q_i^t\|_{i=1,3}(k) = 0$, $\Delta q_2^1(1) = 0.3$ $\Delta q_2^{t+1}(1) \sim \text{N}\,(\Delta q_2^t(1), 0.02)\,, \forall t \in \{1,\ldots,N_{\text{total}}-1\}$ $\Delta q_2^t(k) \sim \text{N}\,(\Delta q_2^t(1), 0.01 + 0.002k)\,, \forall k \in \{2,\ldots,N_{\text{P}}\}$

The optimization problems are solved by CPLEX v12.5.1 in a Matlab 2015b, Windows 7 64-bit environment, on a desktop with Intel Core 2 Q8400 2.66 GHz and 4 GB RAM. Running the whole program takes about 19 seconds.

7.5.2 Results and discussion

The results of the two simulations (the current approach and the proposed approach) are shown in Table 7.2 and Table 7.3, respectively. In each table, the results from florist 1, 2, and the wholesaler are listed in 3 sections (Florist 1, 2, and Wholesaler), from day 1 to day 15. In each section, "Florist 1 st.", "Florist 2 st.", and "Wholesaler" represent the number of stocks in units for each player in the supply chain. In the two florist sections, “Customer *c*” shows whether the customer possesses a bouquet of roses. “C*c* Quality” is the quality, or estimated remaining vase life of the bouquet at the customer. “Purchase”, “Spoilage”, “Unmet” are the numbers of units purchased from the upper stream, spoiled, or customers not supplied with bouquets, respectively. In the section for the wholesaler, “Unit *m*” assigns a unit at the wholesaler to keep track its quality “U*m* Quality” and quantity “U*m* Quantity”. “Price” is the daily price of purchasing each box of roses from auction in €. Note that “Spoilage” in the wholesaler’s section shows roses spoiled in bouquets instead of boxes. Quality and price are shown in 2 significant digits.

The performances of florists in the two simulations are compared. In the simulation with the current approach, Florist 1 purchased 8 bouquets in 15 days, 3 of them spoiled and 3 customers are left without a bouquet, each for a day. Florist 2 purchased 11 bouquets in 15 days, with a spoilage of 4 of them, and there is 1 lost sale. In the simulation with the proposed approach, Florist 1 purchased 7 bouquets and has 1 customer left unserved. No bouquet is wasted in 15 days. Florist 2 purchased 7 bouquets and has 1 demand not met. Also bouquets are all sent to customers for the simulation period.

Next the performance of wholesalers is compared. In the simulation without the proposed approach, the wholesaler purchased 6 boxes of roses. The total cost for purchasing these roses is €94 and the spoiled roses could have been made into 5 bouquets. In the simulation with the proposed approach, the wholesaler purchased 4 boxes roses from auction house. No spoilage is observed during the simulation period. The total cost is only €56, a reduction of 40% in cost from the experiment of the current approach. The unmet demand is reduced by 60%. The wholesaler with the proposed approach purchases roses at the most suitable time: when there is foreseen demands from customers and auction price is low. In contrast, the wholesaler in the current approach purchases whenever roses are needed, resulting in a much higher price.

Compared with the current approach, florists in the proposed approach have number of spoiled bouquets reduced to 0. Unmet demands from subscribed customers are also much fewer. The wholesaler has 1 spoiled bouquet but has fewer costs making purchases from the auction house. Although the auction price per box of roses of the upcoming days is assumed unknown in advance, considering an average price of €15 is helpful for the wholesaler in making purchasing plans.

7.5.3 Sensitivity analysis

A sensitivity analysis is carried out regarding α_1 (the cost of buying from the wholesaler), α_2 (penalty of spoiling cut roses), β (cost of buying from the auction), and uncertainty in prediction of Δq. Experiments are conducted with the adjusted parameter values in different scenarios, with results shown in Table 7.4. A scenario with a static bid price assumes that the cost of each box from the auction house is static ($\beta^t(k) = 15, k \in \{1,\dots,N_\mathrm{P}\}, t \in \{1,\dots,N_\mathrm{total}\}$). A dynamic environment refers to the scenario introduced by Table 7.1, where prediction of vase life change may not be accurate. A static environment assumes that the prediction of quality change is accurate.

When the price for a box of roses from the auction house is static and predictable, the wholesaler only buys roses when necessary, spending less in purchasing roses and making less spoilage. When the price fluctuates, the wholesaler needs to compare the current auction

Table 7.2: Results from supply chain players in the current approach

	Days														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Florist 1 st.	2	1	0	2	1	1	1	2	2	2	2	0	0	0	2
Customer 1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0
C1 Quality	2.0	1.0	0	-*	8.3	7.3	6.3	5.3	4.3	3.3	2.3	1.3	0.3	0	-
Customer 2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C2 Quality	0	8.2	7.2	6.2	5.2	4.2	3.1	1.9	0.5	0	6.4	5.3	4.2	3.2	2.2
Customer 3	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
C3 Quality	0.8	0	8.2	7.0	5.9	4.6	3.3	2.0	0.8	0	-	8.0	6.8	5.6	4.6
Purchase	1	0	0	2	0	0	0	2	0	0	1	0	0	0	2
Spoilage	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0
Unmet	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1
Florist 2 st.	0	3	1	0	3	3	3	3	3	3	1	3	1	1	1
Customer 1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1
C1 Quality	1.9	0.8	0	8.1	7.0	5.9	4.8	3.7	2.6	1.5	0.3	0	7.6	6.5	5.4
Customer 2	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1
C2 Quality	0	-	8.7	7.6	6.4	5.0	3.7	2.1	0.5	0	6.8	5.5	4.3	3.0	1.6
Customer 3	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1
C3 Quality	0.8	0	8.9	7.6	6.2	4.9	3.5	2.1	0.6	0	6.8	5.2	3.8	2.5	1.2
Purchase	0	3	0	0	3	0	0	0	3	0	0	2	0	0	0
Spoilage	0	0	0	0	0	0	0	0	3	0	0	0	1	0	0
Unmet	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Wholesaler	2	3	2	2	3	2	2	3	2	1	2	2	2	2	2
Unit 1	1	1	0	0	1	1	1	1	1	0	1	1	1	1	1
U1 Quality	9.7	9.4	-	-	10	9.6	9.2	8.8	8.4	-	10	9.6	9.2	8.8	8.4
U1 Quantity	1	0	-	-	5	5	5	3	0	-	5	5	5	5	3
Unit 2	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1
U2 Quality	10	9.7	9.4	9.1	8.7	-	-	10	9.6	9.2	8.8	8.4	8.0	7.6	10
U2 Quantity	5	3	3	1	0	-	-	5	5	5	4	2	2	2	5
Unit 3	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0
U3 Quality	-	10	9.7	9.4	9.0	8.6	8.2	7.8	-	-	-	-	-	-	-
U3 Quantity	-	5	5	5	3	3	3	3	-	-	-	-	-	-	-
Purchase	1	1	0	0	1	0	0	1	0	0	1	0	0	0	1
Price	16	14	15	15	17	16	16	16	15	15	16	12	16	17	15
Spoilage	0	0	0	0	0	0	0	3	0	0	0	0	0	2	0

*: *A dash "-" means that quality or quantity of units is not available because there is no unit at the location.*

Table 7.3: Results from supply chain players with the proposed approach

	Days														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Florist 1	2	1	0	0	0	0	0	2	1	1	2	1	1	0	1
Customer 1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C1 Quality	6.2	5.2	4.2	3.2	2.2	1.2	0.2	0	7.6	6.6	5.6	4.6	3.6	2.6	1.6
Customer 2	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
C2 Quality	0	8.9	7.9	6.8	5.8	4.8	3.7	2.5	1.1	0	-*	8.4	7.2	6.2	5.2
Customer 3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C3 Quality	0.8	0	8.1	6.9	5.8	4.5	3.3	2.0	0.8	0	6.0	4.9	3.7	6.8	5.8
Purchase	2	0	0	0	0	0	0	2	0	0	2	0	0	0	1
Spoilage	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Unmet	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Florist 2	0	3	1	0	0	0	0	0	3	2	0	1	1	1	0
Customer 1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C1 Quality	1.9	0.8	0	8.4	7.3	6.2	5.1	4.0	6.4	5.3	4.2	3.1	2.0	7.3	6.2
Customer 2	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
C2 Quality	0	-	9.2	8.0	6.8	5.4	4.0	2.4	0.9	0	6.4	5.1	3.9	2.6	1.2
Customer 3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C3 Quality	0.8	0	9.2	7.8	6.4	5.1	3.7	2.3	0.8	0	6.4	4.8	3.4	2.1	0.8
Purchase	0	3	0	0	1	0	0	0	2	0	0	1	0	0	0
Spoilage	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Unmet	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Wholesaler	1	1	1	1	1	1	1	1	2	1	1	2	2	2	1
Unit 1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1
U1 Quality	9.7	10	9.8	10	9.6	9.2	8.8	8.4	8.1	-	-	10.1	9.7	9.2	8.8
U1 Quantity	0	2	2	5	4	4	4	2	0	-	-	5	5	5	4
Unit 2	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0
U2 Quality	-	-	-	-	-	-	-	-	10	9.7	9.3	8.9	8.5	8.1	-
U2 Quantity	-	-	-	-	-	-	-	-	5	5	3	1	1	1	-
Purchase	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0
Price	16	14	15	15	17	16	16	16	15	15	16	12	16	17	15
Spoilage	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

*: *A dash "-" means that quality or quantity of units is not available because there is no unit at the location.*

Table 7.4: Comparing results from the current approach with the proposed approach and sensitivity analysis

Scenarios	Parameters	Florist 1		Florist 2		Wholesaler	
		Unmet	Spoil	Unmet	Spoil	Cost	Spoil
Current Approach	$\alpha_1 = 5, \alpha_2 = 25$	3	2	1	4	94	5
Proposed Approach	$\alpha_1 = 5, \alpha_2 = 25$	1	0	1	0	56	0
Static bid price	$\alpha_1 = 5, \alpha_2 = 25$	0	0	1	0	30	0
Dynamic Environment	$\alpha_1 = 0, \alpha_2 = 25$	0	2	1	5	113	2
	$\alpha_1 = 5, \alpha_2 = 0.5$	36	0	42	0	0	2
	$\alpha_1 = 5, \alpha_2 = 500$	0	0	1	0	57	2
Static Environment	$\alpha_1 = 5, \alpha_2 = 25$	0	0	1	0	41	0
	$\alpha_1 = 0, \alpha_2 = 25$	0	2	1	4	83	0
	$\alpha_1 = 5, \alpha_2 = 0.5$	36	0	42	0	0	2
	$\alpha_1 = 5, \alpha_2 = 500$	0	0	1	0	42	0

price with the average value and buys roses in advance if the auction offers a good deal, which can result in increased buying frequency. In a dynamic environment, when the cost of each bouquet $\alpha_1 = 0$, the wholesaler buys more roses from auction house and thus more roses flow into this part of the supply network, which results in an increase of spoilage. When $\alpha_1 = 5$, $\alpha_2 = 0.5$, as the penalty for unmet demand is so low, that florists would rather pay the penalty instead of purchasing roses to fulfill the demand from customers. If the penalty, on the other hand, is very high (e.g., $\alpha_2 = 500$), the florists will sometimes supply bouquets to the customers before the previous bouquet deteriorate to reduce the possibility of having demands unsatisfied. In addition, experiments in static circumstances result in lower unmet demand, spoilage, and cost with the accurate quality information.

In summary, the results illustrate that the approach of quality-aware modeling and model predictive control can largely benefit supply chain players in a cut rose supply chain, even though participants do not share the same interest. The application of the new business mode brings wholesalers, florists, and customers in a closer coordination. In this way, purchased roses are being used better with reduced prices, unmet demand, and spoilage. A closer analysis shows that higher penalty for unmet demand or lower price of bouquets may result in a higher flow volume, and more accurate prediction of vase life may help stakeholders make even better decisions in logistic operations.

7.6 Conclusions

Cut roses are traded and transported in significant amounts across continents. Nevertheless, the high perishing nature and complexity in supply-demand relations often bring challenges to supply chain players in reducing waste and loss sales at the same time. This chapter considers a business mode that brings end customers into the rose supply chain as participants, together with wholesalers and florists. In this business mode, customers can subscribe to a florist to get continuous supply of fresh bouquets of roses. Decision making in this business mode can be supported by sensor and communication technologies, which makes remaining vase life known to other players in the supply chain. In order to fully benefit from this business mode, the general framework is proposed combining a quality-aware modeling method and a model predictive control approach. A partially coordinated distributed control strategy is designed to coordinate several players in a fast moving perishable goods supply chain with uncertainties. Simulation experiments illustrate that the realization of this business mode via the proposed approach could significantly reduce unmet demand (60% reduction) and spoilage (100% reduction) in a cut rose supply chain.

This chapter addresses the Research Question 6, and has contributions in two main aspects. First, it applies the general framework to a part of a cut rose supply chain, and illustrates the applicability of the quality-aware modeling and MPC in a specific business scenario. Second, the general framework is extended with some new features. A rotating unit method is proposed to enable more flexibility of quality-aware models. A partially coordinated control strategy in this chapter, which reflects the objective and operations with different players in the cut rose supply chain. Comparing to the hierarchical control architecture used in Chapter 6, in this partially coordinated distributed control strategy, all controllers operate at the same level, allowing each supply chain participant to reduce wastage while accomplishing their own objectives, and yet keeping each player's autonomy.

Chapter 8

Conclusions and future research

In this thesis we have discussed the value of real-time information and coordination in perishable goods logistics. Quality-aware modeling methods and model predictive control strategies are discussed for use in several typical supply chains with different commodities.

This last chapter concludes the thesis. Firstly the key questions and the main research question are answered. Subsequently, directions for future research are recommended.

8.1 Conclusions

8.1.1 Key research questions

1. *How does perishability of products affect logistic processes in perishable goods supply chains?*

   Through the literature review chapter, the physiology, technology, and methodology aspects are analyzed. In the physiology aspect, reviewed literature includes: 1. factors that can *affect* the deteriorating rate; 2. indicators that can *reflect* the freshness of perishable goods; and 3. mathematical models that can *estimate* and predict the quality of perishable goods. In the technology part, the technological development of perishable goods supply chains is discussed. This includes the application of infrastructures, sensors, and communication technologies. In the methodology part, the discussion focuses on scheduling and control strategies for improving the efficiency of logistic operations in perishable goods supply chains.

   The physiological knowledge on how perishables lose their value over time and how they can be preserved is the very first step to determine what will be required of the supply chain to deliver fresh products. Technologies provide solutions such as reefer containers to realize temperature controlled transportation that preserve commodities in accordance to their physiological features. The literature review points out that technologies have far more potentials in improving logistics if real-time quality information is considered. Methods need to be developed in order to bring more benefit of considering perishability by better modeling and controlling logistic operations.

2. *In what way can mathematical models be built to represent both quality and logistics of perishable goods when planning logistic processes?*

   From Chapter 2 the conclusion is drawn that making better use of physiological features and technologies, especially real-time awareness, can improve the effectiveness of logistic operations for perishable goods supply chains. In Chapter 3, a methodological general framework is proposed for supply chain players to consider novel, more comprehensive perspectives in planning logistic activities. The general framework adopts a system and control fashion. The system consists of all the goods being transported in the considered supply chain, with both logistic and quality features. Chapter 3 focuses on a quality-aware modeling method. Unlike other models such as network flow models or job shops, a quality-aware model focuses on *goods*, rather than *networks*, which can explicitly represent both features. In this way, better decisions can be made via optimization and control strategies that consider real-time quality information.

3. *Given the information of incoming disturbances on both quality and logistic side of a perishable good supply chain, in what way can decision makers respond?*

   Chapter 2 points out that the inaccuracy of measurements and disruptions in quality or logistic conditions are sources of disturbances in planning of a perishable goods supply chain. These disturbances can cause changes of planned course of operations. Given the information of incoming disturbances, decisions can be updated in time in order to achieve the best possible performance in dynamic environments. Chapter 4 proposes to use model predictive control strategy. This strategy considers the most recent information and can adjust decisions accordingly, which gives decision makers the ability to act pro-actively on foreseen disturbances of supply chains. Chapter 4 uses a numerical example of starch potato postharvest scheduling to show model predictive control strategy is suitable for real-time control of logistic activities in perishables supply chains.

4. *How can the logistic process of a supply chain be optimized using a mathematical model that considers perishability?*

   Chapter 5 takes the quality-aware modeling approach to an example of a banana distribution network. An optimization problem is designed for improvements of decision making, using mix-integer programming. The objective is to maximize the total profit of the considered distribution network. The constraints include customer demands on quantity and quality. Decisions include movements of containers, ethylene treatments on bananas, and the rate bananas are being ripened. All decisions can directly or indirectly affect quality of bananas. Numerical experiments are conducted to examine the effectiveness of the proposed approach. Results show that the optimized decisions reduce the amount of waste by 33%, and increase the revenue by 48%. This example demonstrates that quality-aware modeling approach can be used to optimize the logistic operations including decisions that directly affects quality of products.

5. *How to design real-time control strategies for perishable goods logistics where supply chain players share the same interest?*

In Chapter 6, a potato starch production scheduling problem is considered in more detail compared to the example shown in Chapter 4. The several decision makers (starch production plant, and farms that grows potatoes) share the same interest: to maximize the production of starch. Potatoes are divided into units and the quality-aware modeling is used to describe the starch content and location change of units of potatoes. A centralized control strategy and a distributed control strategy are designed for the scheduling. In the centralized control strategy, one controller gathers all information from every farm and makes overall decisions for each growers. The limitation of this method is that it requires information of each farm to be fully shared, and when the size of the problem grows, the computation time to solve the optimization problems grows exponentially. The distributed control strategy on the other hand, does not have those downsides. In Chapter 6, the distributed control architecture is designed in a two-layer, hierarchical way that a master controller divides the overall problem into several parts and assigns the subproblems to slave controllers at each farm (Hierarchical Control Architecture shown in Fig. 8.1). Simulation experiments illustrate that the centralized control architecture has better solution quality, and thus is suitable for small scale production scheduling. The distributed control strategy uses less computation time and does not require information to be fully shared, which makes this strategy excel in larger scale production operations. The amount of starch production can be increased by up to 13.23% and 11.25% via centralized and distributed control architecture, respectively.

6. *How to design real-time control strategies in a perishable goods supply chain where supply chain players coordinate but do not share the same interest?*

   A case study of cut roses logistics is presented in Chapter 7, focusing on a part of the cut rose supply chain from the auction house to the household. In this part of the supply chain, a wholesaler and several florists are the decision makers. Each florist interacts with the wholesaler, but have different interests. A wholesaler maximizes its own revenue and guarantee enough roses for florists, and a florist is to satisfy the need of its customers. The chapter assumes that the quality of roses can be obtained in real-time, so that decisions can be made according to customers' demand as well as the quality of roses. With this information, a new business mode is proposed, in which consumers can subscribe to a florist and get continuous supplies of rose bouquets. The florist provides a new bouquet to the subscribed customer when the old one is not fresh. To assist wholesalers and florists in making better decisions in this business mode, the chapter uses the general framework. The quality-aware modeling method is used to represent quality and movements of cut roses in boxes and in bouquets. Each wholesaler or florist is supported by a controller in decision making. A single-layer, partially coordinated control architecture is developed (Partially coordinated architecture in Fig. 8.1), with one controller deployed at each decision maker (i.e., the wholesaler or a florist). Simulation experiments are carried out to demonstrate the approach's potential in supporting the new business mode. Results show that with the proposed approach, unmet demand and wastage can be reduced by 60% and 100% respectively in the business mode.

Table 8.1: Supply chain features of the three case studies

		Chapter 5: Banana logistics	Chapter 6: Potato postharvest	Chapter 7: Cut rose
Supply Chain Features	Quality Dynamics	Green-life model/Linear ripeness model	First-order kinetics	Time-temperature model
	Quality Requirements	Hard	Soft	Hard
	Logistic Dynamics	Pull	Push	Pull
	Bundling			✓
	Players share the same interest	✓	✓	
	Fast Moving			✓
	Operation on Ripening	✓		
Modeling and Control Approaches	Quality-aware modeling	✓	✓	✓
	Model predictive control		✓	✓
	Control Architecture	Centralized	Centralized/Hierarchical	Distributed
	Decisions directly affect quality	✓		
	Rotating Unit Method			✓

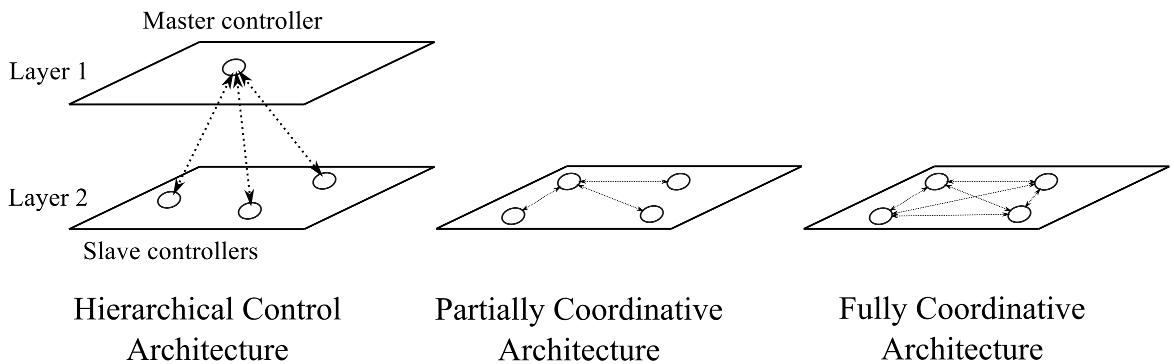


Figure 8.1: Three different distributed control architectures that can be used in different perishable goods logistics.

8.1.2 Main research question

The main question addressed in this thesis is: *Given real-time information of quality and logistics, in what ways can perishable goods supply chain players improve logistic operations and reduce loss?*

After addressing the key questions, the main research question can now be answered. Perishable goods take various forms, with different perishing nature. Therefore, no universal models can be used to describe quality changes or logistic processes of every type commodity. Supply chain dynamics also vary due to the type of commodities considered, the way products should be handled, the relationship among players in the considered supply chain, and the requirements of customers. To make use of real-time information with a particular commodity in logistic process, the first step is to understand what information is available via sensor and communication technologies. This includes estimating changes of quality and situation of logistic processes. Secondly, quality prediction models are necessary. This allows logistic planners to gain physiological insight from the acquired information. The third step is to make use of the real-time information obtained in the first two steps. Focusing on the third step, this thesis applies the methodology of general framework: the quality-aware modeling method combines logistic aspects and quality aspects; the model predictive control strategy keeps the planning up-to-date with supply chain dynamics and the perishing nature of the considered commodity. The three different case studies show that the general framework is applied differently and yet effectively in representing and optimizing the logistic activities with different supply chain and quality features.

8.1.3 Contributions

The main contributions if this research are:

- A general, methodological framework by which logistic operations in perishable goods supply chains can be flexibly modeled and controlled with the consideration of reducing loss of product quality.
- Mathematical models for three case studies on different commodities in supply chains with various dynamics, and different control strategies to fit different supply chain features (shown in Table 8.1).
- Different distributed control architectures (shown in Fig. 8.1, the first two sub-figure) with their effectiveness illustrated using simulation studies in application.

We have some applications to which the proposed approaches can be applied. Our main contributions with respect to these applications are:

- The proposed framework is a ready-to-use tool in developing quality-aware logistic systems in perishable goods supply chains.
- Logistics companies in role of transporter, forwarder, importer, or exporter can use the methods developed in this thesis to estimate the added value of certain technologies before they invest to apply them.
- New quality-driven business modes can be developed with the support of the proposed framework, such as the cut rose subscription discussed in Chapter 7.

8.2 Future research

With respect to the proposed methodological framework and its applications addressed in this thesis, challenging issues that require future research are:

- *Computational efficiency.*

  A common challenge is that the required computational efforts grow rapidly when optimization problems get larger. To a certain extend, exact solutions become no longer available within reasonable time. Heuristics can be used in order to find a near optimal solution given limited time and computational power.

- *Level of detail.*

  The methodological framework proposed in this thesis considers logistic planning in a perishables supply chain from a system and control perspective. This thesis addresses the planning problems at an operational level, providing a pathway for future research and application towards intelligent, fully automated perishables transport systems. In order to do so, details at an equipment/infrastructure level are to be considered. This will create connections from perishable goods logistics to precision agriculture, autonomous vehicle, intelligent infrastructure, and Industry 4.0.

- *Mixture of multiple commodities.*

  This thesis considers for each case study homogeneous commodity. Future research should explore the dynamics in a supply chain with various commodities. For instance, in a cut flower supply chain, a florist receives flowers of all kinds, and bundles them into bouquets with different styles. The complexity in this case will largely increase due to the various quality features and requirements of flowers.

- *Fully coordinated distributed control architecture.*

  As shown in Fig 8.1, in comparison with the first two control architectures, a fully coordinated architecture can also be developed. This control architecture suits supply chains in which multiple players that do not share the same interest but need to closely coordinate evenly.

- *Inaccuracy in measurements and stochasticity in prediction.*

  This thesis considers only deterministic scenarios. More often information from measurements and predictions is of a stochastic nature. Techniques should be developed to make use of such information.

In addition to these topics, more general, fundamental future research directions are:

- *More comprehensive quality models.*

  It is clear that the accuracy of quality models affects the effectiveness of the proposed control strategies. Therefore, more comprehensive quality models considering factors such as humidity and atmosphere may further enhance the accuracy of quality estimation and prediction, resulting in even better planning of logistic operations.

- *Cheaper and more accurate sensors.*

  Companies always compare cost and benefit before applying a certain policy. Therefore, development of cheaper and more accurate sensors can lower the cost and raise the benefit, and thus companies are more willing to equip their logistic processes with such technologies.

- *Customer-supplier relationship and e-commerce.*

  With more end consumers using e-commerce with expectation of fast delivery and good quality, demand-supply dynamics become more rapid and disruptive. Therefore, understanding better customer-supplier relationship can help e-commerce businesses be better supported by traceable and controlled logistic systems.

- *Standardized protocol and platform for implementation in a farm-to-consumer supply chain*

  A standardized protocol can bring more potential in supply chain optimization among supply chain players via more transparent information sharing and better coordinated decision making. A healthy protocol ensures that every participant in supply chains can benefit evenly. Thus supply chain players have an increased willingness to collaborate. A platform for implementation should provide more detailed technological support for the protocol to be implemented. The platform guarantees that the protocol and the proposed approach function in the intended way even in environments where practical problems such as missing of communication may occur.

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Glossary

Conventions

The following conventions are used in this thesis for notation and symbols:

- A lower case character typeset in boldface, e.g., $\mathbf{x}$, represents a column vector.
- A capital case character typeset in boldface, e.g., $\mathbf{A}$, represents a matrix.
- A capital case character typeset in calligraphics , e.g., $\mathcal{M}$ represents a set.
- A subscript case character represents a particular element in a set e.g., l_i represents the i-th element from set $\mathbf{l}$.
- A superscript T e.g., x^{T} represents that a transpose is taking place.
- A hat $\hat{\mathbf{u}}$ represents the optimal values of $\mathbf{u}$.

List of symbols and notations

Below follows a list of the most frequently used symbols and notations in this thesis.

k	actual discrete time step
τ	time step in a prediction horizon
m	the m-th unit
i, j	the i-th or the j-th node
N_{p}	length of prediction horizon
N_{s}	length of simulation horizon
$\mathbf{x}$	system states
$\mathbf{y}$	system outputs
$\mathbf{u}$	system inputs
$\mathbf{d}$	system disturbances
$\mathbf{l}$	logistic states
$\mathbf{q}$	quality states
$\Delta\mathbf{q}$	quality changes
$\mathcal{G}$	set that contains all graphical elements
$\mathcal{N}$	set that contains all nodes in a graph
$\mathcal{E}$	set that contains all edges in a graph

$\mathcal{M}$	set that contains all units in a system
$\mathcal{P}(i)$	set that contains all nodes that are predecessors of node i excluding i
$\mathcal{S}(i)$	set that contains all nodes that are successors of node i excluding i
$l_{mi}(k)$	binary variable representing unit m is at state i at time step k
$u_{mij}(k)$	binary variable representing unit m goes from state i at time step k to state j
$q_m(k)$	the value or states of quality of unit m at time step k
$\Delta q_m(k)$	the change of value of quality of unit m at time step k

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Samenvatting

In dit proefschrift worden hulpmiddelen geformuleerd voor beslissingsondersteunende systemen voor de logistiek van bederfelijke goederen. Het proefschrift bevat ook een methode waarmee bedrijven een schatting kunnen maken van wat het gebruik van het voorgestelde logistieke systeem kan opleveren.

Bederfelijke producten worden overal op de wereld geproduceerd, vervoerd en gebruikt. Door de transportketens voor deze producten kunnen we beschikken over veilige, verse en betaalbare producten. Maar naar schatting gaat een derde van de agrarische producten, die bedoeld zijn voor menselijke consumptie, verloren; wat neerkomt op 1.3 miljard ton per jaar. Dit betekent ook dat een derde deel van de gebruikte grondstoffen en een derde deel van de CO_2-emissie ten gevolge van de productie en het transport van deze producten worden verspild. Het verlies van de verse producten treedt op in de gehele keten, veelal door de bederfelijke aard van de producten en door inefficienties en verstoringen in de keten. Bijvoorbeeld: opstoppingen in de keten en overbevoorrading van een distributiepunt kunnen verlies tot gevolg hebben. Storingen, zoals niet goed werkende koeling, kunnen bijdragen aan verlies in de keten.

Recente technologische ontwikkelingen geven nieuwe inzichten voor het beheer van de transportketen, waardoor het verlies kan worden verminderd. Met sensoren en communicatietechnologie kunnen planners beschikken over real-time informatie over de producten, zoals locatie en versheid. De onderzoekvraag in de proefschrift is *daarom hoe kunnen de spelers in logistieke toevoerketens voor bederfelijke producten door gebruik van real-time informatie de besturing en afstemming van de logistieke processen verbeteren, om verlies van goederen te beperken*?

Met klassieke wiskundige methoden kunnen niet genoeg details worden verwerkt voor de beschrijving van bederfelijke producten in de logistieke keten. Daarom wordt in dit proefschrift een algemeen framework voorgesteld waarin logistieke operaties worden beschreven en bestuurd volgens methoden uit de syteem- en regeltechniek. Het algemene framework bestaat uit een modelleringsdeel, waarin rekening wordt gehouden met de kwaliteit van de producten, en een modelgebaseerde voorspellende regelstrategie. De goederen in de keten worden gemodelleerd als een systeem met productkwaliteit en logisteke kenmerken als variabelen. Het regelmodel bemeet het systeem en stuurt het zodanig dat de verspilling kan worden geminimaliseerd.

In dit proefschrift is de voorgestelde methode gebruikt in case studies van de logistieke keten van drie verschillende artikelen: bananen, industrie-aardappelen en rozen. De drie producten verschillen in hun eigenschappen, gevoeligheid voor bederf en teruggang van kwaliteit. Daardoor is een keten die geschikt is voor het ene artikel mogelijk niet geschikt

zijn voor andere. De logistieke kenmerken van de drie ketens zijn daardoor verschilled. De beschrijvingen van de drie systemen verschillen en ook de regelstructuren zijn mogelijk verschillend. Uit resultaten van de drie case studies blijkt dat met het algemene framework de effectiviteit van de planning van de logistieke keten kan worden verbeterd en verlies kan worden verminderd. De grootte van de verbeteringen geeft aan hoeveel kan worden verdiend door gebruik te maken van informatie over de goederen in de keten.

Summary

This thesis provides tools for decision support systems for perishable goods logistics. It also provides an approach for enterprises to estimate the benefit of adopting the proposed logistic systems.

Perishable products are produced, transported, and consumed all over the world. Thanks to perishable goods supply chains, we can enjoy safe, fresh, and affordable products. Nevertheless, it is estimated that one third of the agricultural products produced globally for human consumption end up wasted, which amounts to 1.3 billion tonnes per year. This also means that one third of the resources and greenhouse gas emissions for producing and transporting these products are in vein. The wastage of these fresh products happens throughout the supply chains, which are often caused by the perishing nature and inefficiencies of supply chain planning. For instance, congestions at a certain location or over supply at a retailer may result in spoilage. Disruptions such as malfunctioning of cooling equipment can also contribute to wastage in supply chains.

Recent technological developments provide new insights into supply chain management, allowing further waste reduction. With sensors and communication technologies, information of products such as location and freshness can be made known to supply chain planners in real-time. Thus the research question of this thesis is *given real-time information of perishable goods logistics, in what ways can perishable goods supply chain players better control and coordinate logistic processes to reduce loss of perishable products*?

Traditional mathematical methods cannot capture enough details when describing perishable goods in their supply chains. Therefore, this thesis proposes a general framework in a system and control fashion to describe and control logistic operations. This general framework consists of a quality-aware modeling method and a model predictive control strategy. The quality-aware modeling method considers the perishable goods in the supply chain as a system, with quality and logistic features. The model predictive control strategy observes the system and steers the system in a manner that the wastage can be minimized.

In this thesis, the proposed method is used in case studies of supply chains with three different commodities, namely bananas, starch potatoes, and cut roses. In each case study, because each commodity is unique in its physiological nature, it perishes in a unique way. Therefore, the supply chain takes care of the commodity in a way that may not suit other commodities. As a result, the logistic features of the supply chains are also different from each other. This requires the systems to be described differently, and control architectures can also vary. Results from the case studies show that the general framework can improve the effectiveness of supply chain logistic planning, and to reduce wastage. The improvements are quantified to illustrate the benefit of making full use of the information on perish-

able goods in supply chains.

Curriculum vitae

Xiao Lin was born on November 21, 1989 in Wuhan, China. He finished his high school in 2008 at Wuchang Shuiguohu (Fruit Lake) High School, Wuhan, China. After this, Xiao Lin began his undergraduate studies in electrical engineering in Wuhan University of Science and Engineering (which has later been named as Wuhan Textile University). After receiving his bachelor's degree in 2012, he started his study for Master of Science in transportation engineering at the Intelligent Transportation Systems Research Center, Wuhan University of Technology, Wuhan, China.

Upon acquiring his master's degree in 2014, Xiao Lin decided to continue with his study in transportation engineering. Sponsored by the China Scholarship Council, Xiao Lin started his PhD research in September, 2014 at the Department of Maritime Technology and Transport, Delft University of Technology. In his PhD project, he focused on real-time coordinations in logistics for perishable agricultural products. His research interests include operations research, model predictive control, and their application in logistic systems.

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