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Predictive quality-aware control for scheduling of potato starch production

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Abstract

Modern technologies have enabled approaches to estimate freshness of perishable products during production and distribution. This allows supply chains to apply more advanced decision support systems in order to further reduce the loss of perishable products. In this paper we focus on the postharvest scheduling of starch potatoes. In particular we propose a quality-aware scheduling method that can be used in a decision support system for starch potato postharvest operations. Considering the quality of stored potatoes in real-time, the method determines when and how many potatoes should be harvested, sent for starch production, or stored. A centralized and a distributed control strategy are developed, with the aim of minimizing total starch loss in dynamic environments. Simulation experiments illustrate how the proposed approaches deal with disturbances, and that the total starch loss can be reduced when real-time quality information of potatoes is taken into account.

Keywords: postharvest scheduling, perishable goods, starch potatoes, model predictive control, quality-aware modeling

1. Introduction

An increasing number of perishable goods, including food, flowers, and medicine, are produced, transported, and consumed worldwide. Meanwhile,

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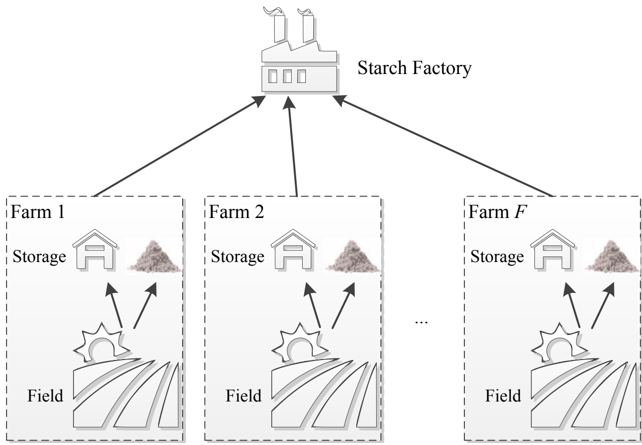


Figure 1: Movements of potatoes during a starch campaign. Growers of each farm move harvested starch potatoes to the on-farm storages and the starch factory.

there is a considerable amount of perishables going wasted before being consumed. Particularly, one third of food is lost throughout different supply chains (i.e., production, postharvest, distribution, retail, and consumption) [1]. Research has shown that the wastage could be reduced via better supply chain coordination with real-time information on the freshness of products [2, 3].

Potato starch is a widely used ingredient in food and other industrial applications. In the year 2014, 6.9 million tonnes of starch potatoes were harvested and processed for starch in Europe [4]. The harvest period of starch potatoes in Europe is between August and April, which is referred to as the starch campaign [5]. During this campaign, a starch production factory receives potatoes grown by farms in neighboring areas. The largest factory today can process about 250 ton potatoes per hour [5]. Nevertheless, not all potatoes can be processed immediately due to the large volume of harvested potatoes. As shown in Fig. 1, growers of each farm move harvested potatoes to the starch factory or store them at storages in barns or in pits. The stored potatoes awaits to be transported to the factory for processing [6].

According to Wustman and Struik [7], weight and quality loss happens over time in stored potatoes, because they have an active metabolism. The loss is 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 affect the weight and quality loss. For instance, a too low storage temperature can cause more conversion of starch into reducing sugars [7]. Therefore, managing stored potatoes in uncertain environments is important for reducing loss of quality during the starch campaign.

With the developments of information and communication technology (ICT) and automation in industry, the application of decision support systems (DSS) in supply chain management is gaining increasing attention. A DSS can help decision makers solve complex problems with data and models [8]. Particularly, in perishable goods supply chains, sensing technology and weather forecasts can provide awareness of quality information at present and in the near future. With this information, DSS can operate in a manner that freshness of products is also taken into account. In a starch potato supply chain, a DSS could help operations of growers and starch production factories, indicating variety of potatoes being grown by each field, timing, and moment of harvest or storage [9]. A supply chain managed with a DSS that would also consider potatoes' real-time and predicted quality could further reduce flow of waste, cost and have a more competitive edge in uncertain environments. The readiness of technologies is discussed in more detail in Section 2.

This paper investigates how information of potato quality could be considered in designing a DSS for better starch production scheduling during harvest campaigns. Decisions made by a processing plant and growers of potato fields are considered in a fully cooperative setting and a partially cooperative setting. To include quality information, we focus on the influence that historical and predicted temperature has on potatoes' starch content at present and in the upcoming days of storage. A quality-aware modeling method and predictive control strategies are proposed for inclusion in a DSS to optimize the total starch yield from a processing plant. Simulation experiments are carried out for assessing the potential of the developed strategy under changing environments.

The remainder of the paper is organized as follows. In Section 2 we carry out a literature review on postharvest and supply chain scheduling for fresh agricultural products. We also discuss the readiness of technologies to implement DSS in scheduling of a starch campaign. Section 3 proposes models for the components of the starch production system. The design of the predictive control strategies is proposed in Section 4. Section 5 carries out several simulation experiments and discusses the results. In Section 6 we conclude this paper and provide directions for future research.

2. Literature review

Good decision support systems can be beneficial for perishable goods supply chain players: it can reduce operation costs, and improve the effectiveness of the supply chain and freshness of the products. This section firstly reviews research of scheduling methods that can be used in DSS for postharvest handling and supply chains of fresh agricultural products. Subsequently, we focus on the models that use real-time quality information to benefit supply chain players models. Then, we discuss technological foundations for DSS with real-time quality information in potato starch production operations.

2.1. Raw agricultural products postharvest handling

Research has investigated postharvest operations of some agricultural products taking into account information on product quality. López-Milán and Plà-Aragonés [10] develop a DSS for sugarcane harvesting operations. Freshness of sugarcanes is only inexplicitly considered in their model. Ferrer et al. [11] 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. [12] develop an optimization model for apple orchards with the goal of minimizing handling costs and loss of quality. The model considers different categories of apples, which should be harvested in different time windows of the year to achieve the overall maximum quality. Caixeta-Filho [13] 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.

These models ([10, 11, 12, 13]) do not consider product quality in real-time, and thus cannot respond to disturbances in changing environment over time. As pointed out by Ahumada and Villalobos [14], planning models for perishable goods often fail to consider realistic, stochastic shelf-life features present in supply chains, and thus these models cannot respond disturbances during operations.

2.2. Implementation of real-time quality information

Emerging technologies on sensors and communication have enhanced the traceability of supply chains and can provide real-time information about goods and their status [15]. An example is shown in [16], where smart tags are used to measure light, temperature, and humidity during transportation of fresh products, and can transmit this information to examiners by radio frequency identification (RFID). Such technologies applied in supply chains could provide insights by which better decisions can be made in order to increase the effectiveness of supply chain activities [17, 2]. Some examples can be seen in the literature. Rong et al. [18] discuss a perishable good supply chain in which a network flow model is used to describe the logistic system and to determine the movements of the flows and the temperature of the facilities. In their method, goods in a flow are distinguished by using multiple nodes representing one location, according to their quality levels. Similarly, De Keizer et al. [19] use fractions of a flow to represent goods of different quality. Using a different approach, Dabbene et al. model supply chains using a hybrid flow-shop model [20]. The model considers both physical parameters (including quality of goods) and logistic parameters.

These studies ([18, 19, 20]) take quality of products into consideration and show that a perishable goods supply chain can benefit from making use of quality information. Nevertheless, their approaches limit the representations of quality features and logistics features in the same model. One one hand, in [18] and

[19], quality features are attached to logistics features, which prevents these models from considering more realistic quality models [14]. On the other hand, the approach proposed in [20] limits the logistics features to a single supply chain rather than a network with route choices.

In our earlier research [21], a preliminary quality-aware model is developed to resolve the aforementioned problems. The proposed method uses a state-space representation to capture both quality and logistics features of perishable goods in supply chains. In such models, quality features and logistics features do not depend on, but can influence each other. Next, we discuss the technical foundation for this model to be applied in a DSS for a starch potato production problem.

2.3. Toward a quality-aware DSS for potato starch production

On-line quality monitoring methods have shown promising applicability in acquiring quality information of potatoes [22]. This real-time information has previously been used for quality control in potato storage. Verdijck et al. [23] develop a model predictive control strategy to optimize the temperature settings in a potato storage.

We propose to further benefit from the real-time quality information in operational decision makings in a potato supply chain, in this case, postharvest operation in potato starch production. In our previous research [24], we made the first step to discuss the potato starch production problem. There, a model predictive control strategy is proposed, considering the current and predicted quality information of stored potatoes, enabling daily decision making on how many potatoes are sent from each farm to the starch producing plant. Here we further investigate this problem, considering some more realistic elements that can be included in a DSS, such as labor availability in harvest operations, influence of storage and environment conditions, and heterogeneity in quality of different groups of potatoes.

A quality-aware DSS is made possible by sensing and communication technology. Since in this paper the starch content is the desired produce from potatoes, we focus on the monitoring and preservation of starch content. There are two approaches by which information about starch content from potatoes can be obtained: direct measurements and indirect estimation.

Direct measurements take samples of potatoes and physically measure the starch content. These approaches are often more accurate than indirect methods, but with less efficiency. Under water weight (UWW) is the most commonly used method for determining starch content [25]. Meanwhile, a near infrared (NIR) approach is studied and it is reported to be more accurate in measuring starch content [26]. Because NIR is not destructive to the samples, it is suitable for rapid, on-line measurement [22]. This approach has great potential to be further developed into fully automatic measuring systems [27, 28]. In addition, NIR approach can also be used to estimate the harvest time for potatoes, by monitoring chemical composition in tubers [22].

Indirect methods obtain environmental information (e.g., temperature or humidity) to estimate the quality change of fresh products. Compared to direct measurements, they are less accurate but very efficient if used properly. Quality models are powerful tools to describe the way environmental factors affecting the chemical changes in fresh products. These models are widely used in estimating the quality of fresh food products [29]. For instance, kinetic models can calculate the conversion rate from starch to reducing sugar, given the temperature over time and the quality at the beginning [30].

The reviewed literature demonstrates that, on one hand, modern technology has enabled the development of DSS, which can improve supply chain operations with the consideration of products' quality information. By this information, not only can stakeholders better schedule logistics operations with more effectiveness, but also better preserve their fresh products. On the other hand, reviewed planning models do not consider real-time quality information in an effective way. Thus their capability is limited in coping with disturbances of environmental factors (e.g., temperature) and product quality. In this paper, we propose a quality-aware model [21] for the potato starch production system in more detail compared to [24]. Decisions made for both the factory 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 fully cooperative farm-factory structure and the other for partially cooperative structure. The proposed approaches could be implemented in a DSS for potato growers and starch production factories to better schedule starch potato postharvest activities.

3. Dynamics of starch potato postharvest

In this section, we describe the dynamics of potatoes in a starch campaign using a quality-aware modeling approach. This approach builds on our previous research [21], where product quality and logistics activities can be considered simultaneously. First, we discuss how quality information can be acquired in a starch potato farm. Second, we introduce the considered problem and explain assumptions made in our approach. Then, a model is build to represent potatoes' dynamics in a starch production campaign, with the consideration of both quality and logistics features of potatoes.

3.1. Obtaining quality of starch potatoes

To obtain quality information, we design a framework for monitoring potatoes and the environment they are exposed to. Potatoes on each farm could be positioned at different locations: in the field, in a pit, or in a barn. Besides, potatoes can be processed at the factory [31]. When potatoes are harvested, they are put in a pit or a barn, or directly transported to the factory. While potatoes are growing in the fields, the starch content first rises and then decreases [32]. In the literature, no model that estimates and predicts starch content in growing potatoes has been found. Therefore, the content of starch from them can be estimated by directly measuring samples from the field, which requires constant operations by growers. After potatoes have been harvested and put into storage in a pit or a barn, a kinetic model can be used to represent the relation between starch content and temperature in storage [30]. The change of quality of potatoes can be automatically estimated on-line using the temperatures measured in storages.

3.2. Problem statement and assumptions

Starch content in potatoes changes during the time of harvest and storage [32, 30]. Although factors such as mechanical damage, humidity, and microorganisms can also influence potatoes' quality [33], in this paper, we start by taking into account the effect of temperature on the decreasing rate of starch content during storage [30].

We investigate how real-time quality information can help make decisions in a starch campaign and to cope with uncertainties in changes of environmental factors and quality. We consider an area with a starch production factory and a few farms nearby, each owned by a grower. During a starch campaign, the factory takes from the growers a limited number of potatoes per day for processing. The growers harvest and gather potatoes and put them in the field or in a barn, waiting for their turn to send potatoes to the factory [31]. During storage, the changes of starch content in potatoes may follow different courses because each farm has different 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 our research. First, sensing and communication technologies are assumed ready to implement real-time estimating of potatoes' starch content. Second, we assume that in different farms, factors other than temperature have the same influence on potatoes' starch content, which allows us to use the kinetics model presented in [30] to estimate and predict starch content.

3.3. Description of system variables

In order to structure our scheduling design, we adopt a system and control perspective. The system consists of all potatoes in the considered area, which is described in this section. The control strategies contain one or more agents, which take in information of the state of the system and make decisions accordingly. The control strategies are presented in Section 4.

A quality-aware modeling approach is used to represent the system. We divide potatoes on each farms into "units". Each unit of potatoes can fill up a truckload (5 ton), and is moved as a "minimal controllable entity" [21]. The system consists of state variables of all units. Variables of each unit are twofold: the location of the unit over time as logistical state variable, and average quality of potatoes in the unit as biological state variable. The logistical variables consider a number of units that physically go through different phases in order to move from origins to destinations. The biological variables consider the quality and quality change of the units over time, as they take different positions. These variables evolve over a discrete time line, depending on decisions taken at each time step. Possible decisions are considered at two levels: a factory operation level, where units are called by the factory and moved from farms to the factory; and a farm operation level, where units are harvested and put into different types of storages. These decisions can affect the quality of the units being moved in the next time step because the environment changes as location changes. These variables and decisions are explained in the following.

3.3.1. Logistical variables

The logistical variables of the units represent the places where the units are located. We consider a set of farms $\mathcal{F} = \{1, \ldots, f, \ldots, F\}$ and a factory. Fig. 2 shows an illustration with a factory and two farms. A unit of potatoes can be in one of the several locations $\mathcal{N} = \{1, \ldots, i, \ldots, N\}$, including being in the field, being in a pit, being in a barn of different farms, and being processed in the factory.

The possible locations of *each* unit can be represented by a set of nodes. The possible movements 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 $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$. Let M_f be the number

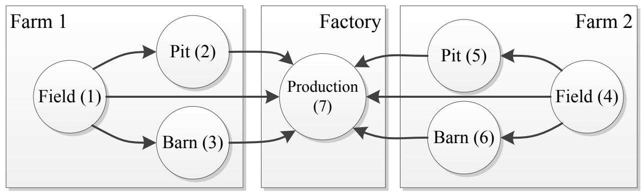


Figure 2: Possible location (nodes) and transition (arcs) of each unit from different farms.

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:

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

Units of potatoes can be moved to different locations within the farm or to the factory. The arcs between nodes represent the possible movements that each unit can take for the example of 2 farms. Actions carried out on the units may also include staying at a particular location for a time step. Binary variable $u_{fmij}(k)$ represents whether unit m from farm f is moved from i to j at time step k (when $i = j$ the 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 $k+1$. Therefore we have the following:

$$u_{fmij}(k) = \begin{cases} 1, & \text{unit } m \text{ moves from } i \text{ towards } j \text{ at the end of time step } k; \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

To give an example using Fig. 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 factory, and moves unit 1 to the factory 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 $l_{117}(2) = 1$.

The condition of a storage may affect the environment that potatoes are exposed to. For instance, potatoes maintain their starch content better if they are stored in warehouses. In other words, the quality of potatoes is influenced by the environmental factors at their location. This aspect is discussed below.

3.3.2. Biological variables

Since our goal is to find approaches for starch production with a higher starch yield, we define the quality of potatoes as their starch content. The starch content changes over time depending on the location of the unit. When potatoes are in the ground, the starch content firstly rises as tubers grow, and then decreases as starch starts to decompose [32]. After potatoes have been harvested and put into a storage, the starch content continues to decrease. After potatoes have been transported to a starch production facility and have been processed into dry starch, the deterioration process stops. We therefore consider the change of starch content in a unit of potatoes as a function of time and location. We denote the starch changing rate as $\rho_i(k)$, denoting the percentage of starch is left after a time step if the unit is stored at location i, time step k; and denote 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:

$$q_{fm}(k+1) = q_{fm}(k)\rho_{fi}(k). \tag{3}$$

In the storage, potatoes deteriorate following the so-called first-order kinetics, which can predict the remaining quality of stored potatoes. We next discuss the kinetic model and the method to estimate the quality of stored potatoes via temperature measurements.

In food engineering, kinetic models are widely used to describe temperature-related chemical reactions and quality parameters in food [29]. 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 [30]:

$$\frac{\mathrm{d}A(t)}{\mathrm{d}t} = -rA^n(t), \tag{4}$$

where $A(t)$ is the starch concentration at time t, r is the temperature-dependent rate of starch decomposing. The index n denotes the order of the reaction. In the case of starch in potatoes, $n = 1$ as the decomposing of starch follows the first-order kinetics, with $r_i(k)$ the decreasing rate of starch of storage i at time step k [30]. This reaction happens more rapidly when the temperature is lower. According to Arrhenius' law [29], this temperature dependent relation can be described as follows:

$$\ln \frac{r}{r_0} = \frac{E_a}{RT}, \tag{5}$$

where $r_0 = 8.75 \times 10^{-9}$ is a pre-exponential factor, $E_a = 34.2$kJ/mol the activation energy, $R = 8.314$J/mol$^\circ$K the gas constant, T the absolute temperature. Note that the term on the right-hand-side of (5) can also be negative in other cases when a raising of temperature increases the reaction rate. For potato starch, a higher temperature slows down the decreasing of starch. However, potatoes are more likely to sprout with higher temperatures [30].

In this paper, decisions on where to move the units are made at discrete time steps. Therefore, a discrete kinetic model is used. Let τ be an equally divided time interval between two adjacent time steps, and represent reaction rate r as function of time. We have the following discrete model:

$$A(k+1) = A(k)e^{-r(k)\tau}. \tag{6}$$

In our case, when considering the quality evolution of units at location i, we can define $\rho_i(k) = e^{-r_i(k)\tau}$, as the rate of decomposition of starch follows the first-order kinetic model. When stored, the rate of decreasing starch ρ_i can then be described as a function of temperature T_i (which also depends on location) as follows:

$$\rho_i(T_i) = \exp\left(-r_0\tau \exp(\frac{E_a}{RT_i})\right). \tag{7}$$

3.4. Dynamics and constraints of the system

Based on the variables introduced above, we can now formalize the dynamics and constraints of the units in the farm-factory system.

3.4.1. 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 logistical part and a biological part. Let $\mathbf{l}(k) = [l_{111}(k), \ldots, l_{fmi}(k), \ldots]^{\mathrm{T}}$ be the logistical 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 we 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:

$$\mathbf{l}(k+1) = \mathbf{l}(k) + \mathbf{K}\mathbf{u}(k). \tag{8}$$

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 Appendix A.

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

$$q_{fm}(k+1) = q_{fm}(k) \sum_{i \in \mathcal{N}} \rho_{fi}(k) l_{fmi}(k). \tag{9}$$

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 as follows:

$$\mathbf{q}(k+1) = \mathbf{P}(k)\mathbf{q}(k), \tag{10}$$

where

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

$$= \operatorname{diag}\left(\mathbf{d}_1^{\mathrm{T}}(k)\mathbf{l}_{11}(k), \ldots, \mathbf{d}_f^{\mathrm{T}}(k)\mathbf{l}_{fm}(k), \ldots, \mathbf{d}_F^{\mathrm{T}}(k)\mathbf{l}_{FM}(k)\right), \tag{12}$$

and

$$\mathbf{d}_f(k) = [\rho_{f1}(k), \ldots, \rho_{fi}(k), \ldots, \rho_{fN}(k)]. \tag{13}$$

Therefore, we can describe the evolution of the system, including both biological and logistics aspects, as follows:

$$\mathbf{x}(k+1) = g\left[\mathbf{x}(k), \mathbf{u}(k), \mathbf{d}(k)\right] \tag{14}$$

3.4.2. *Constraints of the system*

In the following we consider the constraints on the state variables. For mathematical modeling, constraints regarding the network topology assure that the model adequately represents the transport dynamics. There are also several physical constraints that need to be considered: the factory 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. We consider how to formulate these constraints next.

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

$$\sum_{i \in \mathcal{N}} l_{fmi}(k) = 1, \ \forall f \in \mathcal{F}, m \in \mathcal{M}, k \in \{1, 2, \dots\}. \tag{15}$$

Let $P(j)$ 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 $S(i)$ 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:

$$\sum_{i \in P(j) \cup \{j\}} u_{fmij}(k) = l_{fmj}(k), \forall f \in \mathcal{F}, m \in \mathcal{M}, j \in \mathcal{N}, k \in \{1, 2, \dots\}, \tag{16}$$

$$\sum_{j \in S(i) \cup \{i\}} u_{fmij}(k+1) = l_{fmi}(k), \forall f \in \mathcal{F}, m \in \mathcal{M}, i \in \mathcal{N}, k \in \{1, 2, \dots\}. \tag{17}$$

Storage capacity. Constraints on storage capacity represent 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. Then we have the following:

$$\sum_{m\in\mathcal{M}} l_{fmi}(k) \leq C^{\mathrm{s}}_{fi}(k),\ \forall f \in \mathcal{F}, i \in \mathcal{N}, k \in \{1, 2, \dots\}. \tag{18}$$

Labor availability. Constraints 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 factory 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:

$$\sum_{m\in\mathcal{M}} \sum_{j\in S(o)} u_{fmoj}(k) \leq C^{\mathrm{l}}_f(k), \forall f \in \mathcal{F}, k \in \{1, 2, \dots\}. \tag{19}$$

Capacity of processing facility. Constraints on processing capacity limit the amount of potatoes that can be processed by the factory at each time step. Let the factory in the network be denoted as $d \in \mathcal{N}$, and $i \in P(d)$ denotes a location i that is connected to the factory 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:

$$\sum_{m\in\mathcal{M}} \sum_{f\in\mathcal{F}} \sum_{i\in P(d)} u_{fmid}(k) \leq C^{\mathrm{p}}(k), \forall k \in \{1, 2, \dots\}. \tag{20}$$

In summary, the system dynamics of the model includes (8), (10), and (14). Constraints of the system are (15)–(20).

4. Scheduling with quality information using model predictive control

To coordinate actions among the two different parties, namely factory operators and growers, we propose two coordination strategies. 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 factory 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. 3) in a centralized way. A distributed strategy can be used in a partially cooperative

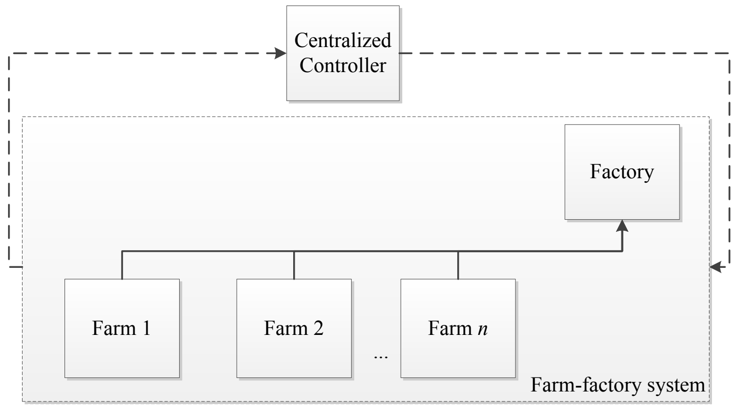


Figure 3: Centralized control architecture. Solid lines represent the flows of potatoes, and dashed lines represent the flows of information.

scenario (as shown in Fig. 4). In this setting, growers share part of the information to the processing factory and can make decisions at the farm level. The distributed strategy considers one farm controller for each farm, and one factory controller for the factory. In this distributed control architecture, the factory controller communicates with every farm controller. To assess the performance of these control strategies, a basic approach is added to the experiments. The basic 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 a model predictive control strategy, and decisions are made at each time step over a prediction horizon of K_p steps, based on predicted information and system dynamics over the same horizon. This strategy makes decisions using the latest information, with the expectation that the effectiveness of scheduling in changing environments can be enhanced.

4.1. Centralized control architecture

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. 3. The controller predicts the quality of potatoes in future days

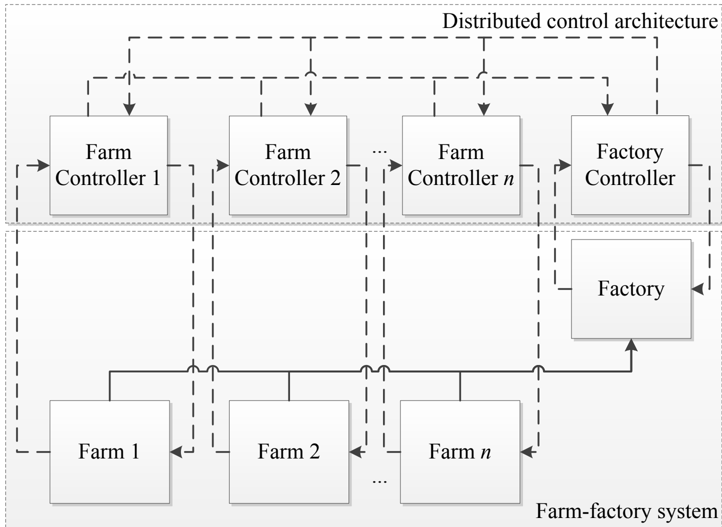


Figure 4: Distributed control architecture. Solid lines represent the flows of potatoes, and dashed lines represent the flows of information.

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 K_p. For this, it maximizes the following objective function:

$$J = \sum_{f\in\mathcal{F}} \sum_{m\in\mathcal{M}} q_{fm}(k) \prod_{\tau=k+1}^{K_\mathrm{p}} \sum_{i\in\mathcal{N}} l_{fmi}(\tau)\rho_{fi}(\tau), \tag{21}$$

subject to constraints (8), (10), (14), and (15)–(20). In this objective function, 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 are already processed, at the end of the prediction horizon. Note that the prediction horizon K_p should not exceed the scheduling horizon K_s.

The algorithm used by the centralized controller is listed in Alg. 1. This

Algorithm 1 Centralized control algorithm at time step k

1: Predict deterioration rate $\mathbf{d}(\tau)$ for the coming K_{p} time steps using kinetic model and temperature forecasts $T_{fi,\tau}(k)$ on time step k, where $\tau \in \{k, \ldots, k + K_{\mathrm{p}} - 1\}$.

2: Maximize J in (21) by solving the optimization problem with the constraints (8)–(19) to determine $\mathbf{u}(\tau)$, where $\tau \in \{k, \ldots, k + K_{\mathrm{p}} - 1\}$.

3: Implement to the system the decisions for upcoming time step $\mathbf{u}(k)$.

strategy requires the information flows unrestrictedly, 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 then make it infeasible for a centralized controller to do all the scheduling by its own. Therefore, we next consider a distributed control strategy that does not require all information in a single controller.

4.2. Distributed control strategy

In the distributed control architecture, as shown in Fig. 4, each farm and the factory is managed by a controller. A farm controller measures the situation of the farm, communicates with the factory controller and makes decisions on farm operations. The factory 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 factory. In this strategy, both types of controllers use model predictive control, with a prediction horizon of K_{p} that can be smaller than scheduling horizon K_{s}. In the following, the factory 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.

4.2.1. Factory controller

The factory controller interacts with all farm controllers at each time step. From each farm, the factory 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 ensure that it will not make demands that farms cannot fulfill. Then the factory controller maximizes the starch yield over the upcoming K_{p} time steps, by deciding on the number of units that each farm should send to the factory 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 factory at time step k. The factory controller can then make the decisions by solving the following optimization problem:

$$\max J = \sum_{f\in\mathcal{F}} \sum_{\tau=k}^{k+K_{\mathrm{p}}-1} y_f(\tau) q_f^{\mathrm{a}}(\tau), \tag{22}$$

subject to:

$$\sum_{f\in\mathcal{F}} y_f(\tau) \leq C^{\mathrm{P}}(\tau), \qquad \forall \tau \in \{k, \ldots, k+K_{\mathrm{p}}-1\}, \tag{23}$$

$$\sum_{\tau'=k}^{\tau} y_f(\tau') \leq \sum_{\tau'=k}^{\tau} C_f^{\mathrm{Q}}(\tau'), \qquad \forall f \in \mathcal{F}, \tau \in \{k, \ldots, k+K_{\mathrm{p}}-1\}, \tag{24}$$

where the objective for the factory is to maximize the estimated starch production over the horizon of K_{p} steps. For each time step within the horizon, the maximum amount of potatoes that the factory can accept from the farms in $\mathcal{F}$ is $C^{\mathrm{P}}(\tau)$, which limits the daily total demand that the factory can request from the farms as shown in (23). For each farm, the request from the factory should be no more than what the farm has, as shown in (24), 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 factory controller.

4.2.2. 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 factory controller. Based on that, the factory 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 factory at every future steps. After being informed about

Algorithm 2 Factory 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 $\tau \in \{k, \ldots, k + K_{\mathrm{p}} - 1\}$

2: Decide on $y_f(k)$ for each farm by solving the MILP problem in (22), with constraints (23) and (24), where $f \in \mathcal{F}$ and $\tau \in \{k, \ldots, k + K_{\mathrm{p}} - 1\}$

3: Deliver the call over the prediction horizon K_{p} to farm controllers

Algorithm 3 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 $K_{\mathrm{p}} - 1$ steps according to temperature forecasts from time step k, $\tau \in \{k, \ldots, k + K_{\mathrm{p}} - 1\}$.

2: Calculate number of available units $C_f^{\mathrm{Q}}(\tau)$ using (26)–(28).

3: The information regarding quality and availability of potatoes is then sent to the factory controller.

4: Stand by until the factory controller returns a call to the farm controller.

5: Compute the movements for the upcoming K_{p} steps, by solving the optimization problem with (29) the objective function, and subject to (30)–(35).

6: Implement the decisions $\mathbf{u}_f(k)$ for the upcoming time step.

the decisions, farm controllers then decide on which specific units should be moved within their own farms to fulfill the requests from the factory.

The average quality of units on farm f at time step $\tau \in \{k, \ldots, k + K_\mathrm{p} - 1\}$ is calculated by the farm controller before the information is sent to the factory controller as follows.

$$q_f^\mathrm{a}(\tau) = \begin{cases} \dfrac{\sum_{m \in \mathcal{M}} \sum_{i \in \mathcal{N}, i \neq d} q_{fm}(\tau) l_{fmi}(\tau)}{\sum_{i \in \mathcal{N}, i \neq d} l_{fmi}(\tau)}, & \displaystyle\sum_{i \in \mathcal{N}, i \neq d} l_{fmi}(\tau) \neq 0, \\ 0, & \displaystyle\sum_{i \in \mathcal{N}, i \neq d} l_{fmi}(\tau) = 0. \end{cases} \tag{25}$$

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 are already, or can be harvested ($C_f^\mathrm{H}(\tau)$). The number of available units is the smaller one of the two variables:

$$C_f^\mathrm{S}(\tau) = \sum_{m \in \mathcal{M}} \sum_{i \in \mathcal{N}} l_{fmi}(\tau) - \sum_{m \in \mathcal{M}} l_{fmd}(\tau), \tag{26}$$

$$C_f^\mathrm{H}(\tau) = \sum_{m \in \mathcal{M}} \sum_{i \in \mathcal{N}} l_{fmi}(\tau) - \sum_{m \in \mathcal{M}} \left(l_{fmo}(\tau) + l_{fmd}(\tau)\right) + C_f^\mathrm{l}(\tau), \tag{27}$$

$$C_f^\mathrm{Q}(\tau) = \min\left(C_f^\mathrm{S}(\tau), C_f^\mathrm{H}(\tau)\right). \tag{28}$$

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

$$\max J = \sum_{m \in \mathcal{M}} q_{fm}(k) \prod_{\tau = k}^{k + K_\mathrm{p} - 1} \sum_{i \in \mathcal{N}} l_{fmi}(\tau) \rho_{fi}(\tau), \tag{29}$$

subject to

$$\sum_{i \in \mathcal{N}} l_{fmi}(\tau) = 1, \forall m \in \mathcal{M}, \tau \in \{k, \ldots, k + K_{\mathrm{p}} - 1\}, \tag{30}$$

$$\sum_{i \in P(j) \cup \{j\}} u_{fmij}(\tau) = l_{fmj}(\tau), \forall m \in \mathcal{M}, j \in \mathcal{N}, \tau \in \{k, \ldots k + K_{\mathrm{p}} - 1\}, \tag{31}$$

$$\sum_{j \in S(i) \cup \{i\}} u_{fmij}(\tau + 1) = l_{fmi}(\tau), \forall m \in \mathcal{M}, i \in \mathcal{N}, \tau \in \{k, \ldots, k + K_{\mathrm{p}} - 1\}, \tag{32}$$

$$\sum_{m \in \mathcal{M}} l_{fmi}(\tau) \leq C^{s}_{fi}(\tau), \forall i \in \mathcal{N}, \tau \in \{k, \ldots, k + K_{\mathrm{p}} - 1\}, \tag{33}$$

$$\sum_{m \in \mathcal{M}} \sum_{j \in S(o)} u_{fmoj}(\tau) \leq C^{\mathrm{l}}_{f}(\tau), \forall \tau \in \{k, \ldots, k + K_{\mathrm{p}} - 1\}, \tag{34}$$

$$\sum_{m \in \mathcal{M}} \sum_{i \in P(d)} l_{fmi}(\tau) = y_f(\tau), \forall \tau \in \{k, \ldots, k + K_{\mathrm{p}} - 1\}. \tag{35}$$

Similar to the centralized strategy, the farm controllers are subject to constraints (30)–(35). Constraints (30), (31), and (32) ensure that the movements of units follow the topology of the network. Constraint (33) limits the number of units stored in locations with capacities. Constraint (34) limits the number of units harvested each time step by growers due to the availability of labor. Constraint (35) indicates that the call from the factory has to be fulfilled by each farm controller. Note that the capacity of the factory is not considered as a constraint for the farm controllers, since in the distributed control architecture, the factory controller already makes calls considering this limit. The algorithm for each farm controller in the distributed control architecture is listed in Alg. 3. The actions taken at each time step by the controllers of the factory and the farms and the interactions among them are shown in Fig. 5.

4.3. Basic approach

Apart from the two proposed control strategies, we also consider a currently used approach for comparison. In this approach, growers agree upon a basic sequence of moving potatoes within the farms and to the factory, regardless of

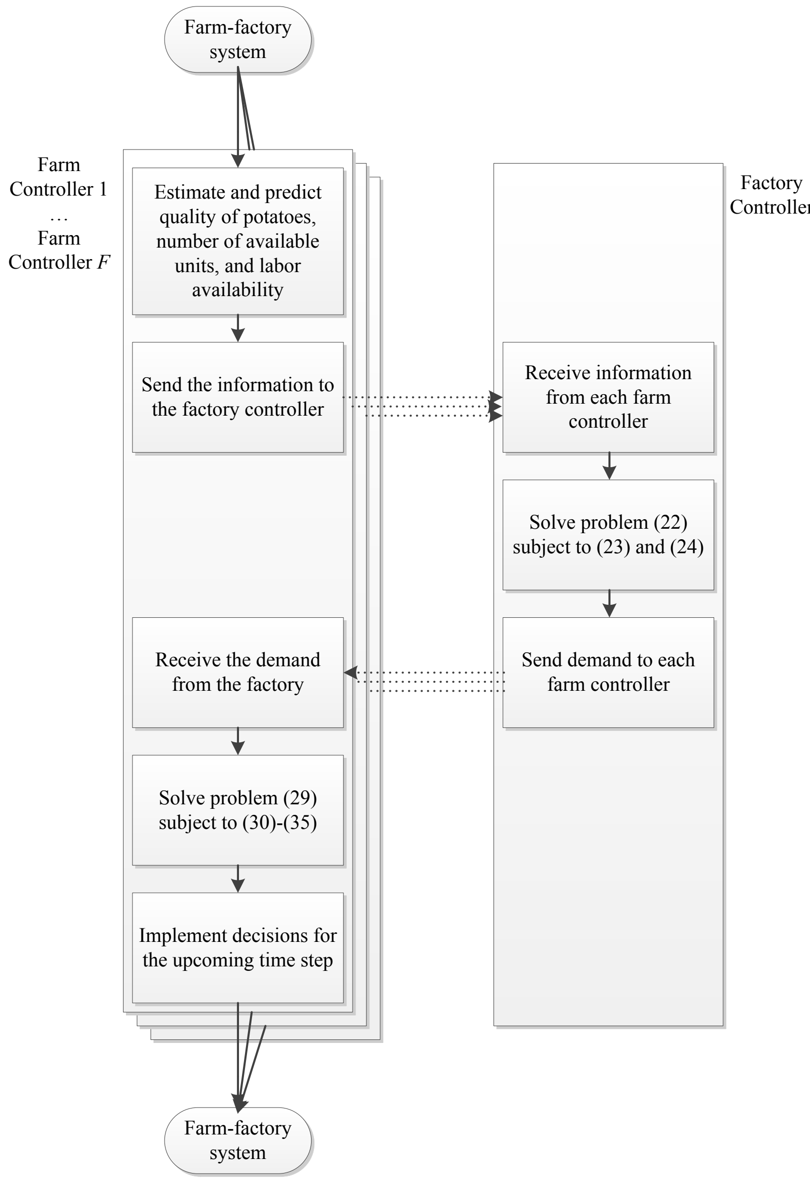


Figure 5: Actions taken by the two types of controllers in a distributed control strategy at each time step k.

Algorithm 4 Basic approach for the factory to make calls on farms at time step k

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

the upcoming weather conditions. In this paper we 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. 4. In addition, each of the farms operates to harvest potatoes as fast as possible and responds to calls from the factory.

5. Simulation experiments

In this section, we carry out simulation experiments in order to evaluate the effectiveness of the proposed scheduling methods, which are supposed to be implemented in DSS. Scenarios with different environmental conditions are considered. We also compare the performance of the strategies in different weather conditions.

The experiments are carried out on a desktop with Intel(R) Xeon(R) E5-1620 3.70GHz CPU and 32GB RAM, using Matlab 2014b. For the centralized control strategy, the controller solves the optimization problems using SCIP (v3.2.0) [34], a mixed integer non-linear programming (MINLP) solver provided by Opti toolbox (v2.21) [35]. For the distributed control strategy, the factory 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.

5.1. Simulation setup

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.

5.1.1. System parameters

Tab. 1 shows the system parameters used in the experiments. To distinguish differences in temperature and labor availability, we consider 12 hours as the time interval for decision making. Therefore, 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 factory at each time step. The factory 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 (4) and (5). When potatoes are transported to the factory, 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 we use 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

Table 1: Parameters of the system

Parameter	Value
C^{p}	1
C_f^{l}	Day: 1, Night: 0
C_f^{s}	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 %	$(q_{11}(1), \ldots, q_{21}(1), \ldots, q_{33}(1)) = (12, 13, 14, 15, 16, 17, 14, 15, 16)$
T^{Out}	$T_{k+\tau}^{\mathrm{Out}}(k) \sim N(T_{k+\tau}^{\mathrm{Out}}(k+\tau), 0.02\tau)$
T^{In}	$T^{\mathrm{Out}} + T^{\mathrm{Diff}}$, $T^{\mathrm{Diff}} \sim N(1, 0.2)$

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, we also consider a scenario with an extreme environmental condition, 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 DSS can update decisions to avoid such loss as much as possible. Unwanted weather conditions can take on many forms and can affect potatoes in different storage conditions. We consider below the experiment in which a bad weather condition occurs on time step 7. 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%:

$$\rho_{f2,7}(k) = 0.5, k \in [3, 7], f \in \mathcal{F}. \tag{36}$$

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

5.1.2. 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., $K_{\mathrm{s}} = 21$ and a prediction horizon is considered as $K_{\mathrm{p}} = 10$.

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

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

5.2. Results and discussion

We compare the performances of the three approaches, i.e., the basic, 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 and Fig. 7 show the total amount of remaining starch, including the starch left in potatoes and the starch that has already been processed by the factory. Tab.2 shows the computation time required to solve the problem and the amount of starch recovered using different approaches.

5.2.1. Quality of solutions

In the normal weather scenario, the centralized strategy had a gain of 1.64% and the distributed strategy had a gain of 1.56% compared to the basic approach. The centralized strategy had a slightly higher starch production than the distributed strategy. The performance of the basic approach was also very close to the two control strategies. In the bad weather scenario, the gap between the two control strategies became larger. While the basic approach was heavily affected by the weather condition, the centralized and distributed strategies showed 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

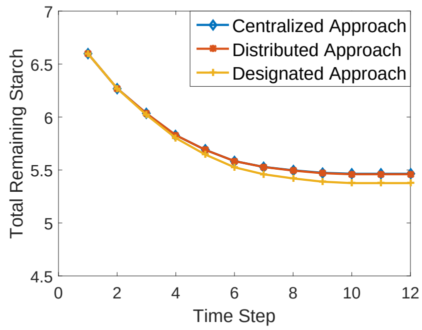


Figure 6: Normal weather scenario.

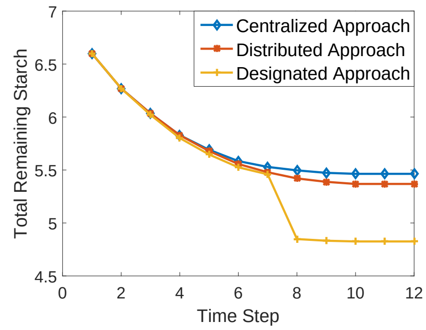


Figure 7: Bad weather scenario.

Table 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 (ton)	
		Normal weather	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

in environmental conditions than the distributed strategy, which has a gain of 11.25% compared to the basic approach.

The basic approach used a fixed scheduling plan that did 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 yielded higher starch production than the basic 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 DSS designed considering this information could support growers and factory operators to respond to possible changes of environmental disturbances and quality changes.

5.2.2. Complexity of the problem and computation time

Although the centralized strategy performs better than the distributed one in both scenarios, at each time step, the optimization problem takes the centralized strategy much longer time to compute. To solve a 3-farm problem, the centralized strategy took 1 hour 48 minutes while the distributed strategy took 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 centralized strategy. Moreover, the time for the distributed control strategy does not increase significantly if number of farm increases, which only adds more subproblems of the same size. Note that in our simulation, distributed controllers operate one after another, while in real world they can compute 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.

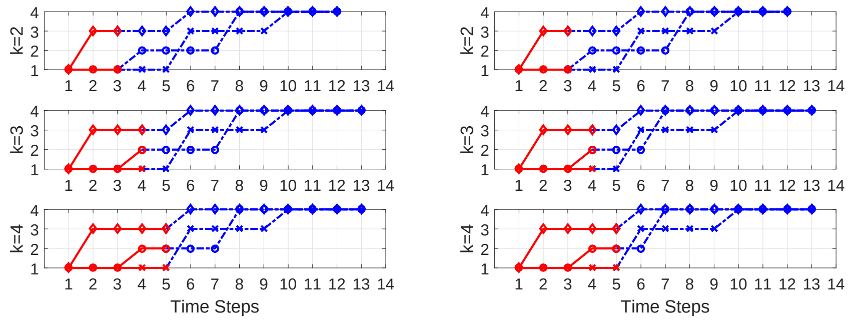
Nevertheless, if more units of potatoes are considered in each farm (which happens if we have more potatoes in one farm, or if we consider fewer potatoes as a unit), the complexity of problem does increase even in the distributed strategy, because of larger subproblems. In that case, we need to consider to look for relatively good solutions instead of exact solutions by including heuristics solving methods.

5.2.3. Impact of unwanted environmental conditions

The awareness of the potential quality change can affect decisions made by predictive controllers. From Fig. 7 we observe that the performance of the basic approach suffered from a drastic drop from time steps 7 and 8. Apparently, the basic operational procedure caused some potatoes being affected by the bad weather in this scenario. On the other hand, this fall was not seen from either in centralized or distributed control strategy. Still, controllers had to come up with alternative plans when they are aware of the weather condition in the upcoming days. We now zoom in to one of the farms and analyze the performance of the two control strategies.

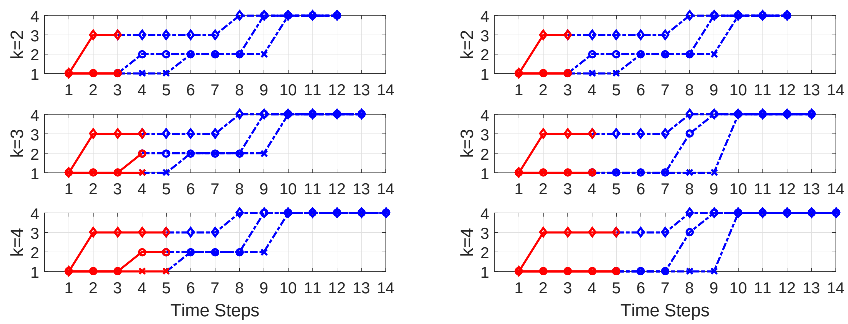
Fig. 8 and Fig. 9 show the plans and actual movements of units on farm 1 under different weather condition generated by centralized and distributed control strategies. In Fig. 8(a) and Fig. 8(b), centralized control strategy is used in normal and bad weather condition. While in Fig. 9(a) and Fig. 9(b), distributed control strategy is used in normal and bad weather condition, respectively. In each figure there are two sub-figures, for normal and 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 time steps, while the vertical axis represents locations of units (1, in the field; 2, in the pit; 3, in the barn; 4, in the factory).

In Fig. 8(a) and Fig. 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 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. 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 different control architectures in different scenarios, we can then see the effectiveness of applying model predictive



(a) Normal weather (b) Bad weather

Figure 8: Actual movements and plans produced by centralized strategy



(a) Normal weather (b) Bad weather

Figure 9: Actual movements and plans produced by distributed strategy

control strategy. When future disturbances become predictable, such as change of weather, the model predictive control strategy has the ability to deal with disturbances by updating the plan for upcoming time steps.

6. Conclusions and future research

A large amount of perishable goods are lost in different stages of supply chains due to the perishing nature and handling inefficiencies. With the help of decision support systems, better decisions can be made in scheduling of the supply chain activities, which can result in a reduction of losses of perishable goods.

This paper focus on a starch potato scheduling problem for starch production. We develop control strategies with the consideration of potatoes' real-time and predicted quality. These strategies can be included in a DSS to improve the yield of starch production and to cope with environmental uncertainties. Approaches to acquire real-time information and quality prediction models are discussed. Then, 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 methods and the proposed control strategies are tested using simulation experiments. The results illustrate that the proposed methods can have a higher starch production and a better response to disturbances compared to the current basic method. In particular, the different control strategies work well in different situations. The centralized strategy suits smaller scale, cooperative supply chains with fewer farms. The distributed strategy works well with more farms and allows more autonomy for growers in their decision making.

This paper presents the basis for the strategies that can be implemented in a DSS to enable quality-aware scheduling for potato starch campaigns. Future research should consider the potential inaccuracy of measurements and variation of potato quality, more details in postharvest operations, applications in larger scale problems with real-world experiments, and optimization techniques such as heuristics. The modeling approach and control strategies could also be used in DSS for other kinds of agricultural products, leading to more developed, quality-controlled perishables logistic systems.

Appendix A

This appendix explains how logistic decisions take effect on the states of the system. The evolution of location (8) represents how each unit moves from one location to another. The matrix $\mathbf{K}$ 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 the $\mathbf{l}(k)$ and $\mathbf{u}(k)$ into FM blocks. We have

$$\mathbf{l}(k) = [\mathbf{l}_{11}^{\mathrm{T}}(k), \ldots, \mathbf{l}_{fm}^{\mathrm{T}}(k), \ldots \mathbf{l}_{FM}^{\mathrm{T}}(k)]^{\mathrm{T}} \tag{.1}$$

$$\mathbf{u}(k) = [\mathbf{u}_{11}^{\mathrm{T}}(k), \ldots, \mathbf{u}_{fm}^{\mathrm{T}}(k), \ldots \mathbf{u}_{FM}^{\mathrm{T}}(k)]^{\mathrm{T}}, \tag{.2}$$

where $\mathbf{l}_{fm}(k)$ and $\mathbf{u}_{fm}(k)$ have the length of N and E, respectively. Apply this to (8), we get the following:

$$\begin{bmatrix} \mathbf{l}_{11}(k+1) \\ \vdots \\ \mathbf{l}_{fm}(k+1) \\ \vdots \\ \mathbf{l}_{FM}(k+1) \end{bmatrix} = \begin{bmatrix} \mathbf{l}_{11}(k) \\ \vdots \\ \mathbf{l}_{fm}(k) \\ \vdots \\ \mathbf{l}_{FM}(k) \end{bmatrix} + \mathbf{K} \begin{bmatrix} \mathbf{u}_{11}(k) \\ \vdots \\ \mathbf{u}_{fm}(k) \\ \vdots \\ \mathbf{u}_{FM}(k) \end{bmatrix} \tag{.3}$$

Therefore, matrix $\mathbf{K}$ can also be divided into blocks:

$$\mathbf{K} = \mathrm{diag}(\mathbf{K}_{11}, \ldots, \mathbf{K}_{fm}, \ldots, \mathbf{K}_{FM}). \tag{.4}$$

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 $\mathbf{u}_{fm}(k)$:

$$\mathbf{l}_{fm}(k+1) = \mathbf{l}_{fm}(k) + \mathbf{K}_{fm}\mathbf{u}_{fm}(k). \tag{.5}$$

where $\mathbf{K}_{fm}$ is an $N \times E$ matrix determined by graph $\mathcal{G}$. Since we have the constraints (15) – (17), 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. We then separate $\mathbf{K}_{fm}$ into two parts:

$$\mathbf{l}_{fm}(k+1) = \mathbf{K}_{fm}^{+}\mathbf{u}_{fm}(k), \tag{.6}$$

$$\mathbf{l}_{fm}(k) = \mathbf{K}_{fm}^{-}\mathbf{u}_{fm}(k); \tag{.7}$$

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:

$$TP_{ij} = \begin{cases} 1, & (i,j) \in \mathcal{E}; \\ 0, & \text{otherwise.} \end{cases} \tag{.8}$$

Algorithm 5 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 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

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. 5 and Alg. 6.

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