# Chapter 6
# Quality-Aware Predictive Scheduling of Raw Perishable Material Transports

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**Abstract** This paper proposes a new mathematical model for predictive scheduling of perishable material transports with the aim of reducing losses of perishable goods. The model is particularly designed for allocation of potatoes from several farms to a nearby starch mill, which produces starch from a limited amount of potatoes each day. Scheduling should determine how much amount of potatoes be sent from which farm to the mill on each day. It is known that the quality of potatoes decreases over time and as a result less starch is produced. A model predictive control approach is proposed to maximize the production of starch. Simulation experiments indicate that predictive scheduling can yield higher starch production compared to non-predictive approaches.

**Keywords** Transport scheduling · Predictive control · Perishable products · Kinetics modeling

## 6.1 Introduction

Potatoes are one of the important sources of high quality starch, suitable for most industrial and food engineering (Grommers and van der Krogt 2009). It is reported that 6.9 million tonnes of potatoes are processed for starch in the year of 2014 in Europe (Starch Europe 2016). However, potatoes cannot be stored for a long time as the starch concentration drops and starch producing campaign is short in each year, lasting only a few months. Due to the high water content, the transport of starch potatoes is preferably limited from the field to nearby starch mills (DG Agriculture and Rural Development 2010).

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The extraction of starch from potatoes is an important step in starch supply chains. Usually a starch mill 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 mill 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. However, limited research has been done on how to schedule the transport between farms and starch mills more effectively.

For other products, earlier research has been carried out. Grape harvesting scheduling is investigated for decision-making on which vineyards should be harvested (Ferrer et al. 2008). A model is developed to schedule harvesting time for grapes considering operation costs as well as quality of the grapes. Similarly, an orange harvesting scheduling problem (Caixeta-Filho 2006) also considers the quality of the products when deciding harvesting moments. In both of the studies, changes in quality are described using historical data. Studies are also carried out for sugarcane supply scheduling on mill sugar production (Gal et al. 2008; López-Milán and Plà-Aragonés 2015). The first study takes into account variability of sugarcane quality between areas. Historical data is used to identify regions based on different quality of yields. The second study investigates sugarcane processing supply considering an index of ripeness for deciding on harvesting moments, which affect the quality of sugar in products. The definition of this quality index is however, not explained explicitly.

Historical data can be useful in the scheduling of production processes. However, it does not thoroughly reflect real-time quality. The objective of this research is to show how real-time quality can impact the decisions for allocation and processing of raw perishable material. In this paper we consider a case in which a starch mill locates amongst several potato farms. Potatoes from the farms are sent to the mill and from which starch is extracted. Starch degrades as potatoes are stored in chambers. Therefore, the mill has to run all the time to maximize the production of starch. The key feature of the approach we propose is that it considers real-time quality of perishable goods instead of historical data to assist decision-making in fresh product logistics scheduling. This paper illustrates that with the information of "quality," fewer losses can be achieved and producers can benefit more from effective scheduling.

We adopt a system and control perspective to solve the scheduling problem. As illustrated in Fig. 6.1, there are two parts of the model. The system part is our representation of the real world, consisting of the amount and quality of potatoes in each chamber of each farm. The controller part takes measurements from the system and makes decisions on when and which farm shall be called to send potatoes to the mill. This perspective enables us to demonstrate the performance of controllers with different scheduling strategies.

The remainder of this paper is organized as follows. Section 6.2 describes the perishable material system and its dynamics. Section 6.3 discusses different strategies for controller design. Section 6.4 focuses on a case study, its results, and discussions. Section 6.5 concludes this paper and provides directions for future research.

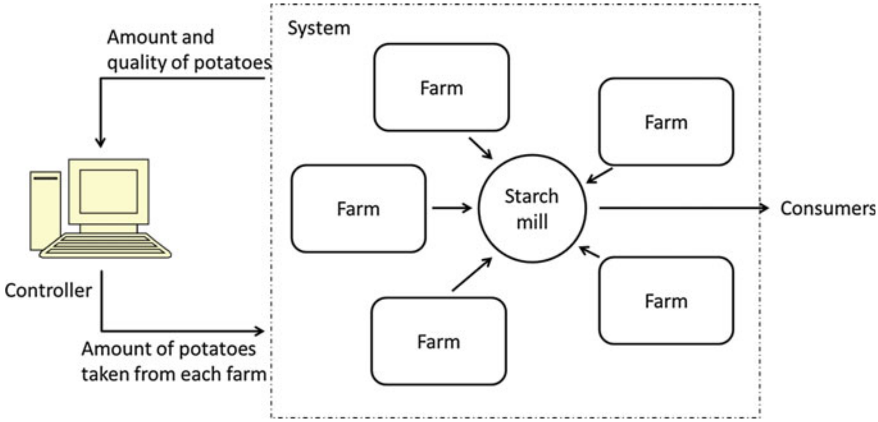


**Fig. 6.1** System and control perspective

## 6.2 System Design for Perishable Material Distribution

This section describes the details of the system, consisting of assumptions, farm and quality dynamics and constraints.

### 6.2.1 *Assumptions*

In this study a few assumptions are made

- the farmers and transport of potatoes are assumed to be contracted; cost for potatoes and transport are therefore not considered explicitly in this study;
- the quality of potatoes decreases monotonically, and can be accurately measured and predicted; the transport process does not affect quality of potatoes;
- quality measurements, decision-making, transport, arrival, and processing of potatoes happen during the same day.

### 6.2.2 *System Dynamics*

#### 6.2.2.1 Farm Dynamics

The system consists of a set of farms $\mathscr{F} = \{1, \dots, i, \dots, F\}$ with $S_i$ chambers $\mathscr{S}_i = \{1, \dots, j, \dots, S_i\}$ on each farm, and a starch mill as components of the system. Each day 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

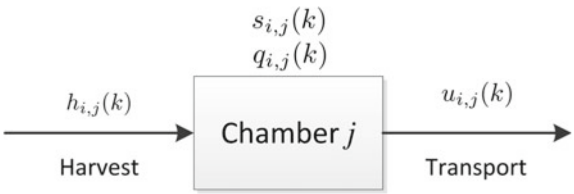


**Fig. 6.2** A chamber


**Fig. 6.3** The mill

mill, where $k \in \mathscr{T} = \{1, \dots, k, \dots, T\}$. 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. 6.2. Each day during the campaign potatoes from different chambers are transported to the mill, and $P(k)$ is the total starch production on that day, as shown in Fig. 6.3. Therefore we have

$$s_{i,j}(k+1) = s_{i,j}(k) - u_{i,j}(k) + h_{i,j}(k), i \in \mathscr{F}, j \in \mathscr{S}_i, k \in \mathscr{T} \tag{6.1}$$

$$P(k) = \sum_{i \in \mathscr{F}, j \in \mathscr{S}_i} u_{i,j}(k) q_{i,j}(k). \tag{6.2}$$

#### 6.2.2.2 Quality Dynamics

In food engineering, kinetic models are widely used to describe food quality (Van Boekel 2008). The following equation represents the evolution of the quality $q(t)$:

$$\frac{\mathrm{d}q(t)}{\mathrm{d}t} = -rq^n(t), \tag{6.3}$$

where variable $n$ is determined by the type of reaction, and the coefficient $r$ is determined by Arrhenius' law, which describes the temperature dependence of chemical reactions (Van Boekel 2008). The starch concentration of stored potatoes decreases over time. According to an experimental study (Nourian et al. 2003), the degradation of the starch concentration follows a first-order kinetic model, with $n = 1$ and $r$ ranging from 0.02074 to 0.04735 in different storage temperatures. With $q_0$ the initial quality when harvested, the remaining quality at continuous time $t$ can then be denoted as

$$q(t) = q_0 \exp(-rt). \tag{6.4}$$

In this study, we use the discrete kinetic model as decisions are made at discrete time steps. Let $\tau$ 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 $R(k) = \exp(-r(k)\tau)$, we then have

$$\begin{aligned} q(k+1) &= q_0 \exp(-r(k+1)\tau) = q(k)\exp(-r(k)\tau) \\ &= q(k)R(k). \end{aligned} \tag{6.5}$$

#### 6.2.2.3 System State-Space Representation

To formulate a compact state-space representation of the system dynamics, let vector $\mathbf{x}(k)$ denote the state of the system, consisting of the amount of potatoes and the quality of potatoes in all farms and chambers. In this research, the states of the system are assumed measurable, so $\mathbf{y}(k) = \mathbf{x}(k)$. Decision variables are collected in vector $\mathbf{u}(k)$, denoting the amount of potatoes to be transported from each chamber to the mill 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 disturbances of the system $\mathbf{d}(k)$. The element of matrix $\mathbf{H}$ (with the size of $F * T$) on row $i$, column $k$ is 1 if there is harvesting for farm $i$, day $k$; and 0 otherwise. The state-space form of this system is

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A}(k)\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{C}\mathbf{d}(k) \\ &= \begin{bmatrix} \mathbf{I} & 0 \\ 0 & \mathbf{R}(k) \end{bmatrix} \begin{bmatrix} \mathbf{s}(k) \\ \mathbf{q}(k) \end{bmatrix} + \begin{bmatrix} -\mathbf{I} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{u}(k) \\ 0 \end{bmatrix} + \begin{bmatrix} \mathbf{I} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{h}(k) \\ 0 \end{bmatrix} \end{aligned} \tag{6.6}$$

$$\mathbf{y}(k) = \mathbf{x}(k) \tag{6.7}$$

where

$$\mathbf{A}(k) = \begin{bmatrix} \mathbf{I} & 0 \\ 0 & \mathbf{R}(k) \end{bmatrix} \tag{6.8}$$

$$\mathbf{R}(k) = \begin{bmatrix} R_{1,1}(k) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & R_{F,S}(k) \end{bmatrix} \tag{6.9}$$

$$\mathbf{x}(k) = [\mathbf{s}^{\mathrm{T}}(k), \mathbf{q}^{\mathrm{T}}(k)]^{\mathrm{T}} \tag{6.10}$$

$$\mathbf{s}(k) = [s_{1,1}(k), s_{1,2}(k), \dots, s_{i,j}(k), \dots, s_{F,S}(k)]^{\mathrm{T}} \tag{6.11}$$

$$\mathbf{q}(k) = [q_{1,1}(k), q_{1,2}(k), \dots, s_{i,j}(k), \dots, s_{F,S}(k)]^{\mathrm{T}} \tag{6.12}$$

$$\mathbf{u}(k) = [u_{1,1}(k), u_{1,2}(k), \dots, u_{i,j}(k), \dots, u_{F,S}(k)]^{\mathrm{T}} \tag{6.13}$$

$$\mathbf{h}(k) = [h_{1,1}(k), h_{1,2}(k), \dots, h_{i,j}(k), \dots, h_{F,S}(k)]^{\mathrm{T}} \tag{6.14}$$

$$\mathbf{d}(k) = \mathbf{h}(k) \tag{6.15}$$

### *6.2.3 Constraints*

There are a number of constraints among the system variables that need to be satisfied. First, the amount of potatoes $u_{i,j}(k)$ transported is nonnegative and no more than potatoes in the chamber. Second, the mill limits the daily processing capacity. Therefore we have

$$0 \leq u_{i,j}(k) \leq s_{i,j}(k), \tag{6.16}$$

$$\sum_{i \in \mathscr{F}} \sum_{j \in \mathscr{S}_i} u_{i,j}(k) \leq c(k). \tag{6.17}$$

## 6.3 Controller Design

The controller takes measurements of the system and makes decisions on what actions to take to control the system, which, in this paper, is when and from which farm potatoes shall be transported to the mill for processing (as illustrated in Fig. 6.1). We consider three different control strategies

- $C_1$: Quality-unaware controller: scheduling without any knowledge of quality;
- $C_2$: Quality-aware controller: with information of quality of the day;
- $C_3$: Predictive quality-aware controller: considering quality over a prediction horizon.

The difference between these strategies is the amount of information regarding quality of the goods the controller uses. Because the degradation rate of quality can easily be affected and thus differs from place to place, it is expected that controllers that use the knowledge of quality can yield better performance.

### *6.3.1 Quality-Unaware Controller*

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 1.

**Algorithm 1** Quality-unaware controller $C_1$

```
1: u_{i,j}(k) ← 0 for each i ∈ 𝓕 and j ∈ 𝓢_i
2: repeat
3:     Randomly pick a farm i ∈ 𝓕
4:     Take away potatoes most recently harvested, u_{i,j}(k) ← u_{i,j}(k) + s_{i,j}(k)
5: until s_{i,j}(k) ≥ c(k) − u_{i,j(k)} (the daily capacity reached)
```

**Algorithm 2** Quality-aware controller $C_2$

1: Take measurements $\mathbf{q}(k)$ for all the stored potatoes
2: Solve the optimization problem (6.18)–(6.22) to get values for $\mathbf{u}(k)$, that maximize the starch production of the day

### *6.3.2 Quality-Aware Controller*

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 as shown in Algorithm 2. This controller maximizes the daily production of starch by solving the following optimization problem:

$$\max_{\mathbf{u}(k)} J(\mathbf{x}(k), \mathbf{u}(k), \mathbf{d}(k)) = \sum_{i \in \mathscr{F}} \sum_{j \in \mathscr{S}_i} q_{i,j}(k) u_{i,j}(k) \tag{6.18}$$

subject to

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{C}\mathbf{d}(k) \tag{6.19}$$

$$\mathbf{y}(k) = \mathbf{x}(k) \tag{6.20}$$

$$0 \leq u_{i,j}(k) \leq s_{i,j}(k) \tag{6.21}$$

$$\sum_{i \in \mathscr{F}} \sum_{j \in \mathscr{S}_i} u_{i,j}(k) \leq c(k) \tag{6.22}$$

### *6.3.3 Predictive Quality-Aware Controller*

A predictive quality-aware controller considers predicted quality over a prediction horizon. Therefore the optimal decision for these days can be made at the beginning of each day to maximize the total production. The controller is designed in a model predictive control fashion (Camacho and Bordons 2013; Rawlings and Mayne 2013): only the decisions for the first day are implemented and rest discarded. New optimization is carried out at the next day. These iterations go on until the end of the experiment. The optimization problem solved by the controller is then[1]

$$\max_{\tilde{\mathbf{u}}(k)} J(\tilde{\mathbf{u}}(k), \tilde{\mathbf{u}}(k), \tilde{\mathbf{d}}(k)) = \sum_{l=0}^{N_\mathrm{p}-1} \sum_{i \in \mathscr{F}} \sum_{j \in \mathscr{S}_i} q_{i,j}(k+l) u_{i,j}(k+l) \tag{6.23}$$

[1]Because the simulation is finite, on the last several days (from the day $T - N_\mathrm{p} + 2$ to day $T$), the prediction horizon based on current date exceeds the length of the simulation, resulting in errors. To solve this, the controller reduces the prediction horizon if it exceeds the length of the simulation.

**Algorithm 3** Predictive quality-aware controller $C_3$

1: Take measurements and predictions for all the stored potatoes within the prediction horizon $l$
2: Solve the problem (6.23)–(6.27) to find the optimal solutions for $\tilde{\mathbf{u}}(k)$
3: Implement the decision $\mathbf{u}(k)$

subject to

$$\mathbf{x}(k+l+1) = \mathbf{A}\mathbf{x}(k+l) + \mathbf{B}\mathbf{u}(k+l) + \mathbf{C}\mathbf{d}(k+l) \tag{6.24}$$

$$\mathbf{y}(k+l) = \mathbf{x}(k+l) \tag{6.25}$$

$$0 \leq u_{i,j}(k+l) \leq s_{i,j}(k+l) \tag{6.26}$$

$$\sum_{i\in\mathscr{F}} \sum_{j\in\mathscr{S}_i} u_{i,j}(k+l) \leq c(k+l) \tag{6.27}$$

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 3.

## 6.4 Experiments

In this section, the potential of the three different control strategies is illustrated on scenarios randomly generated to simulate the variability of potato quality and the changing rate of it. Potatoes stored in one farm are assumed to have the same deterioration rate, which may be affected by local temperature and other conditions in the chambers. To simulate the impact from the variability of external conditions, we generate the deterioration rate from normal distributions. Results of the quality-aware controller and predictive quality-aware controller with different prediction horizons are compared to the quality-unaware controller to prove the improvements of considering quality information in scheduling.

### *6.4.1 Simulation Setup*

Each simulation considers one scenario, in which all three strategies are implemented. We consider 10 simulations altogether. In each simulation, different strategies are performed. In order to set up different scenarios, some of the variables are nondeterministic, following some distributions. Other variables remain deterministic.

*Deterministic variables* The sets of farms and chambers, the length of the simulation in days, initial amount of potato storage, amounts and dates of harvesting on each farm remain the same. Variable $s_{i,1}(1)$ represents the initial storage of farm $i$, which is placed in the first chamber of each farm. Potatoes of new harvest are placed in other empty chambers for simplification. We consider three times of harvest for each farm. Together with the original storage the number of chambers $S_i$ for each farm $i$ is therefore 4. The maximum daily capacity $c(k)$ is assumed constant. Moreover, we let

$$
\begin{aligned}
F &= 5,\\
T &= 60,\\
s_{1,1}(1) &= 4400, s_{2,1}(1) = 4300, s_{3,1}(1) = 4400, s_{4,1}(1) = 4500, s_{5,1}(1) = 4200,\\
h_{i,j}(k) &= 400\mathbf{H}(i,k), i \in \mathscr{F}, k \in \mathscr{T}\\
c(k) &= 800, k \in \mathscr{T}.
\end{aligned}
$$

*Nondeterministic variables* Qualities of potatoes differ from farm to farm. The deteriorating rate of the potatoes is influenced by time and temperature. In each scenario these variables are randomly set from certain distributions. On the first day of the experiment, the qualities of potatoes already in first chambers of each farm $q_{i,1}$ follow normal distributions with $E_i$ and $d_i$ as the expectations and standard deviations. In the other chambers, the qualities are 0 until newly harvested potatoes come in. The kinetics variables also follow normal distributions with $\mu_i$ and $\bar{\sigma}_i$ as their expectations and standard deviations. The kinetics variables after the first day of simulation follow normal distributions with the kinetics value of the previous day as the expectation, and $\sigma_i$ as the variables. So the deterioration rate of potatoes in one chamber does not change largely in a short period of time. The quality of potatoes harvested on farm $i$ and stored in chamber $j$ have the quality $q_{i,j}$ on that day, and starts deteriorating afterwards. We then have

$$
\begin{aligned}
q_{i,j} &\sim N(E_{i,j}, d_{i,j}),\\
r_{i,j}(1) &\sim N(\mu_{i,j}, \bar{\sigma}_{i,j}),\\
r_{i,j}(k+1) &\sim N(r_{i,j}(k), \sigma_{i,j}).
\end{aligned}
$$

We consider the length of simulation 60 days for the length of starch production campaign is around 2 months. The simulations consider controller $C_1$, $C_2$, and $C_3$ with prediction horizons varying from 2 to 60 days, so that we can compare the performance of controllers with different amount of quality information. An example of the quality deterioration on one farm is shown in Fig. 6.4. The harvesting of this farm happens on day 3, 13, and 23.

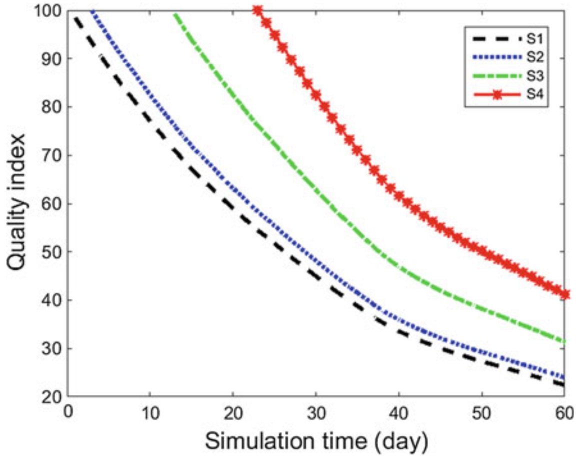


**Fig. 6.4** An example of the deterioration of the quality in different chambers of one farm

**Table 6.1** Performance of different controllers

| Controller | $C_1$ | $C_2$ | $C_3$ 5-day | $C_3$ 10-day | $C_3$ 30-day | $C_3$ 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 |

## 6.4.2 Results

In this paper, we take the average of starch production of 10 scenarios. We normalize the results so that they are shown in percentages. Table 6.1 compares the performance of the different controllers regarding the mean and standard deviation of the results. Controller $C_1$ yields 100 % production, while $C_2$ has an increase of production by 9.9 %. The predictive controller with 5 day's prediction produces 11.6 % more starch compared with $C_1$. With quality prediction of 60 days, the controller has the highest production by an increase up to 14.9 % compare with $C_1$.

Figure 6.5 shows that as the prediction horizon increases, the controller yields higher production. The horizontal axis is different prediction horizons used by the controller, and the vertical axis is the relative production of starch compared to controller $C_1$. Note that the first and second point in the figure represent controller $C_1$ and $C_2$. We can immediately see the impact that information of quality brings. Besides, the predictive controller is able to obtain higher production from information of future quality. Moreover, the performance of the controller is better when using longer prediction horizons. When the prediction horizon covers the length of the campaign, the scheduling is optimal.

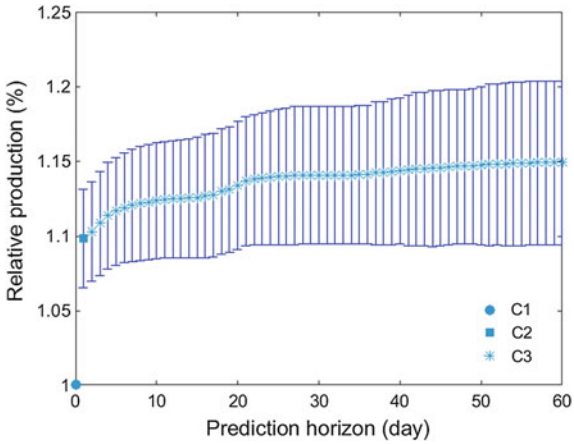


**Fig. 6.5** Profit gained compared to quality-unaware controller

## 6.5 Conclusions and Future Research

This paper investigates the impact of accurate quality information on starch production control. We consider a transport scheduling problem with perishable items. A predictive scheduling approach is developed for raw material distribution considering the perishing nature. A model is established to describe the system of several potato farms and a starch mill. Quality decreasing is described using kinetic models and is assumed to be accurately predicted over a certain amount of days. The objective is to maximize starch production. The predictive, quality-aware scheduling strategy is performed using a model predictive control approach. The performance of the controller is compared with the performance of a quality-unaware controller and a nonpredictive, quality-aware controller. It is illustrated that the information of current as well as predicted quality can be used to improve decision-making with the model predictive control method.

Further research will include uncertainties and accuracy of quality information. Different commodities as well as other stages of supply chains will be investigated. Our detailed vision for the future research can be found in previous publication (Lin et al. 2015).

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