Chapter 12
Uncertainty Analysis of Weather Controlled Systems

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Abstract The indoor climate of many storage facilities for agricultural produce is controlled by mixing ambient air with the air flow through the store room. Hence, the indoor climate is affected by the ambient weather conditions. Given hourly fluctuating energy tariffs, weather forecasts over some days are required to effectively anticipate. Hence, typically a real-time optimal control strategy results. As weather forecasts are uncertain, predicted model outputs and related costs of the control strategy become uncertain. Usually, a medium-range weather forecast for a period of some days consists of an ensemble of forecasts. Hence, the uncertainty in the weather forecast is known a priori. In addition to this, in past-performance studies where weather forecasts and observed weather variables are given, an a posteriori evaluation of the forecast errors can be made as well. The objective of this study is to evaluate the uncertainty in the costs related to weather forecast errors and uncertainty, given the control inputs. In a simulation case-study with real weather forecasts and observed weather, it appeared that only slight cost increases can be expected due to errors and uncertainties in weather forecasts if the optimal control problem is calculated every 6–12 h in a receding horizon context.

12.1 Introduction

Indoor climate in greenhouses, office buildings and storage facilities for agricultural produce are generally affected by outdoor weather conditions [2, 9, 13], for instance by heat transfer through the boundaries, solar radiation and ventilation with outdoor air. In addition to this, the indoor climate is also affected by the respiration and evapotranspiration of living creatures and biological material, or by active heating or cooling. Typically, in practice, indoor temperatures and relative humidities are

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controlled by feedback controllers with P or PI structure (see [14] for an overview) using direct measurements of temperature and relative humidity. In this study, we focus on indoor climate control that uses ambient air in the air flow through the (store) room. Hence, optimal control strategies that are able to anticipate on future changes of the weather conditions or on hourly-daily changes in energy tariffs allow, in principle, a better cost-effective performance. Clearly, in such control strategies weather forecasts become important and uncertainties in weather forecasts then lead to uncertain predictions of the indoor climate. Moreover, the cost function related to any kind of optimal control becomes subject to uncertainties and errors in the weather forecasts. The sensitivity of the model outputs and the related costs therefore needs to be investigated. In what follows, we restrict ourselves to a so-called receding horizon optimal control (RHOC) strategy in discrete-time. The basic idea behind RHOC is that a finite-time optimization problem over the horizon H, with or without inequality constraints, is solved, i.e.

$$u(k, k+H) = \arg\min \phi(x(k+H)) + \sum_{\kappa=k}^{k+H} \mathcal{L}(x(\kappa), u(\kappa), d(\kappa)) \qquad (12.1)$$

$$s.t. \quad x(k+1) = f(x(k), u(k), d(k)), \quad g(x(k), u(k)) \leq 0$$
$$x_0 = x(k)$$

Subsequently, only the first $l < H$ inputs are implemented and at $k + l$, given an update of x_0, the optimization problem is solved again, but now on the time interval $[k + l, k + l + H]$. For both air conditioned buildings [7] and potato storage facilities [8, 10] it was shown that a good weather forecast reduces the cost function almost as much as a perfect weather forecast. In these studies short term weather forecasts (1–2 days ahead) were used. However, because of the slow dynamics of products in storage facilities, knowledge of medium-range predictions of the indoor climate may be profitable. Hence, this study focuses on the effect of errors and uncertainties in medium-range (up to 10 days ahead) weather forecasts on the indoor climate predictions, in real-time, and associated product temperature and costs.

Nowadays, the medium-range weather forecast [11] consists of an ensemble of 50 different weather forecasts. All 50 ensemble members have an equal probability of occurring. Hence, the uncertainty, or variation, in the weather forecasts is known a priori. This knowledge can then be used to evaluate a calculated optimal control solution by calculating the differences in costs related to each of the ensemble members. Next to this, with observed weather given, in a post-performance analysis the optimal control solution can also be evaluated a posteriori.

The objective of the study is to evaluate the effect of errors and uncertainties in the weather forecasts on the costs of the calculated optimal control problem of a (potato) bulk storage facility.

This chapter is structured as follows: first a brief description of the bulk storage model and the cost function is given. Next, some information about the weather forecasts is provided. Then, open loop and closed loop evaluations using weather forecasts and observations are given in subsequent sections. Finally, the results are discussed and conclusions are drawn.

12.2 Preliminaries

12.2.1 Bulk Storage Model

Models that describes the dynamics of the product in a bulk storage facility can be found in, e.g. [6, 8, 9, 15–19]. The model developed in [9] was simplified to make it suitable for use in an RHOC algorithm [10]. A brief description of this discrete-time dynamic model is presented in this subsection. The model is given by

$$\begin{aligned} x_T(k+1) &= x_T(k) + p_1 + [d_1(k) - x_T(k)] \\ &\quad \Big(p_3 + p_2 p_5 u_1(k)[p_7 + (1-p_7)u_2(k)]\Big) \qquad (12.2) \\ x_{CO_2}(k+1) &= x_{CO_2}(k) + p_1 p_4 + [d_2(k) - x_{CO_2}(k)] \\ &\quad \Big(p_2 u_1(k)[p_7 + (1-p_7)u_2(k)] + p_6\Big) \qquad (12.3) \end{aligned}$$

where x_T represents the product temperature, x_{CO_2} the CO_2 concentration in the bulk, $d_1 = T_{wb,ext}$ the ambient wet bulb temperature, d_2 the ambient CO_2 concentration, $u_1 = u_{mix}$ the fraction of ambient air in the air flow, $u_2 = u_{vent}$ the fraction of maximum possible internal ventilation, and p a vector containing physical and design parameters. Hence, the control input is defined by: $u = [u_1, u_2]^T$. The sample time used for this model is 1 h.

The temperature of the bulk can be measured and thus (12.2) is regularly updated. The CO_2-concentration, however, is difficult to measure in practice. The store room is, therefore, basically controlled on the product temperature. In the model-based RHOC strategy, the CO_2-concentration is calculated using (12.3) without any measurement correction. The CO_2-concentration is taken into account via constraints to avoid too high concentrations that lead to damage of the product. This approach suffices, because of the fast dynamics of the CO_2-concentration, when the room is ventilated. That is, during ventilation the CO_2-concentration quickly reaches the known external CO_2-concentration, so that large modeling errors are avoided. Consequently, right after a period of ventilation, $x_{CO_2}(k)$ is equal to $d_2(k)$.

12.2.2 Weather Forecasts

The medium-range weather forecasts have been provided by Weathernews Benelux. These forecasts contain hourly forecasts of weather variables up to 10 days ahead. The ensemble weather forecasts used in this paper consist of 50 ensemble members with equal chance of occurring. In what follows, the ensemble mean is used as the nominal weather forecast.

New weather forecasts and actual weather observations become available every 24 and 6 h, respectively. It has been shown in [3] that short-term weather forecasts (up to 36 h ahead) can be improved by using more frequent, local observations in combination with Kalman filtering techniques. A similar method is used here to correct the medium-range weather forecasts every 6 h.

12.2.3 Cost Function

To give some physical insight into the control objectives of the potato storage facility, the elements of the cost function are mentioned below. How the weighting factors in the cost function are chosen is beyond the scope of this paper. In our application, the following control objectives are to be fulfilled:

- The temperature of the bulk must be kept as close as possible to a pre-specified reference temperature T_{ref} (i.e. minimize $||x_T(k) - T_{ref}||$).
- The temperature must always be kept above a specified minimum temperature T_{min} (i.e. inequality constraint: $x_T(k) > T_{min}$)
- The temperature may not decrease faster than a specified limit T_Δ within 24 h (i.e. inequality constraint: $x_T(k-24) - x_T(k) < T_\Delta$).
- The weight loss of the product due to evaporation must be as small as possible (i.e. minimize $\sum_{k=0}^{H} f_1(x_T(k), u(k), d(k))$ with H the prediction horizon.
- The CO_2-concentration must always be kept below a specified maximum $CO_{2,max}$ (i.e. inequality constraint: $x_{CO_2} < CO_{2,max}$)
- The energy costs related to ventilation must be as small as possible (i.e. minimize $\sum_{k=0}^{H} f_2(u_2(k))$).

12.2.4 Receding Horizon Optimal Control

Given the model (12.2)–(12.3) with corresponding initial states, a weather forecast containing $d_1(k)$ for $k = 1, \ldots, H$ and assuming $d_2(k) = 0.0314$ to be constant, control trajectories of u_1 (fraction of ambient air in the air flow) and u_2 (fraction of maximum possible internal ventilation) can be calculated such that a cost function on the time interval $[0, H]$ is minimized according to:

$$\min_u J = \min_u \phi(x(H)) + \sum_{k=0}^{H} \mathcal{L}(x(k), u(k), E[d(k)]) \qquad (12.4)$$

where the expected value (denoted by $E[\cdot]$) is taken because the weather forecast is a stochastic variable. In our application of bulk storage in a store room there are no final costs at the end of the prediction horizon, i.e. $\phi(x(H)) = 0$. From the preceding subsection we notice that $\mathcal{L}(\cdot)$ contains a weighted combination of $||x_T(k) - T_{ref}||$, $f_1(\cdot)$ and $f_2(\cdot)$. If this open-loop control problem is solved repeatedly every l hours (with $l < H$) given the updated (or measured) states and weather forecasts the control loop is closed. As mentioned before, this type of control strategy is called receding horizon optimal control (RHOC).

In the following, the RHOC solution with the nominal weather forecast is taken as the reference point for the uncertainty evaluation. For the evaluation a period from 13 April to 2 June 2005 (almost 51 days) had be chosen. The medium-range weather forecasts have been obtained for location “De Bilt, The Netherlands”. The forecast horizon of the weather forecast also determines the maximum horizon of the RHOC strategy ($H = 217$ h). In fact, one would expect a maximum horizon of $(10 \times 24 + 1)$ h. However, the medium-range forecasts are released with a delay of 1 day and thus $H = 241 - 24 = 217$ h. During the evaluation period every 6 h a new optimal control trajectory was calculated (i.e. $l = 6$) with an updated weather forecast, according to the procedure suggested in [3]. For each optimal control run the initial conditions of the states were set to the corresponding measured values. In an RHOC framework the calculated optimal inputs for the pre-specified control interval (l) of 6 h are implemented and recalculated when after 6 h new information becomes available. Consequently, in our application the optimal control input trajectories are calculated over an interval of 217 h and updated every 6 h. In total 203 optimal control trajectories, given the nominal weather forecasts, are calculated (four times a day, almost 51 days). An example of a calculated control trajectory with the accompanying predicted state and cost evolution is presented in Fig. 12.1. The reference temperature (T_{ref}) in this case was 7°C. Notice that the calculated open loop optimal control inputs are in antiphase with the external wet bulb temperature. As expected, the product temperature (T_p) follows the ventilation pattern. Notice, furthermore, that with increasing temperature differences between the product temperature and the external wet bulb temperature also the costs increase accordingly.

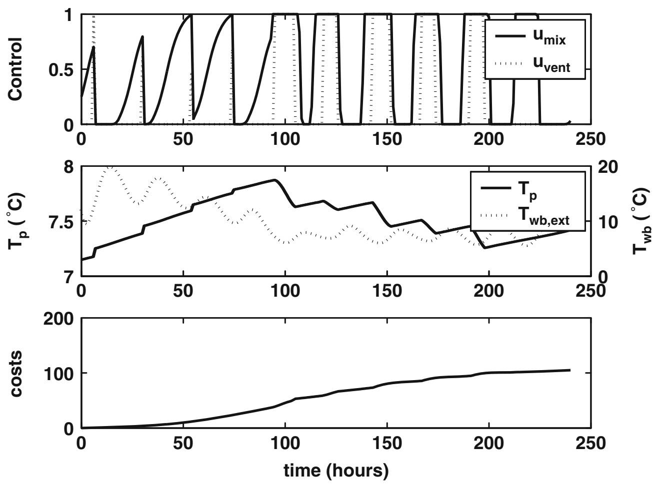

Fig. 12.1 Optimal control output starting from 1 May 2005. The sub-figures show respectively: calculated optimal controls; predicted product temperature and external wet bulb temperature; predicted cumulative costs

12.3 Weather Forecast Uncertainty and Error Analysis

In this section, we investigate several possibilities to evaluate the weather forecasts errors and uncertainties on the costs. First, the change in costs is investigated when observations of the weather are used instead of the nominal forecast. Hence, this analysis, based on 203 control trajectories with associated costs, evaluates the effect of errors in the weather forecasts on the costs. Second, the effect of individual ensemble members on the costs is investigated. Thus, this type of analysis evaluates the maximum effect of variation in the ensemble on the absolute costs.

12.3.1 Open Loop Evaluation

Let us start by evaluating the effect on the absolute costs when observed instead of nominal forecasted weather data is used. Recall that the prediction horizon is 217 h, which defines the maximum length of the evaluation. However, in what follows the summation variable r is introduced to account for intermediate changes in the costs. If now the model with fixed optimal control trajectories is ran again but with observed weather (d_1 and d_2) instead of nominal forecasted weather data, a change in costs is observed. In Fig. 12.2, 203 differences between calculated (using forecasts) and realized (using observations) running costs, as a function of the summation variable r, are presented. Herein, the running costs are defined by:

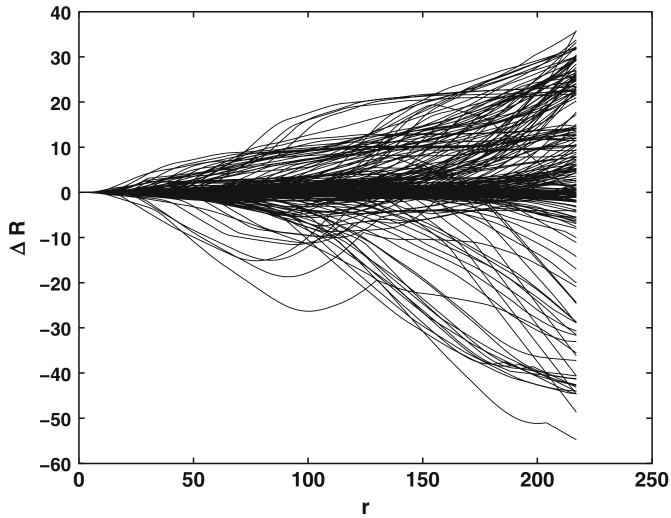

Fig. 12.2 Difference in calculated absolute costs and realized costs for each of the 203 optimal control runs

$$R(r) = \sum_{k=0}^{r} \mathcal{L}\left(x(k), u(k), d(k)\right) \quad \text{for } r = 1, \ldots, H \tag{12.5}$$

For what follows, we define $J \triangleq R(H)$.

From Fig. 12.2, it can be seen that the total cost difference, as expected, can be both positive and negative. This implies that, given the optimal control trajectory based on forecasts, the realized weather can reduce the total costs more than was expected from the forecasted weather. However, it does not mean that, if the observed weather was used in the RHOC calculations (which is only possible afterwards), the calculated optimal control trajectory generates minimal costs. Furthermore, histograms derived from Fig. 12.2 for different r show that the mode is around $\Delta R = 0$, and that the frequency distributions are rather skewed with a "thin" tail for ΔR negative.

Since the total absolute costs J change for every optimal control run, because of changing initial states and changing weather forecasts after each 6 h, the relative change in the costs, i.e. $\Delta R^{rel} = \frac{R_{obs}-R_{fct}}{J_{obs}}$, is calculated as well and presented in Fig. 12.3. In addition to the absolute or relative differences, we noticed that the absolute costs R can change dramatically (not shown here) over the evaluation period from 13 April to 2 June, because the outdoor temperature significantly increases. Especially, the cost criterion term $||x_{k,T} - T_{ref}||$ then increases. Relatively to the costs at the beginning or the end of the prediction horizon H, however, the change in costs does not seem to change that dramatically.

Using the observed weather to calculate the costs is a useful a posteriori tool, since it evaluates the positive and negative costs when controlling a system under expected disturbances. Nevertheless, it should be emphasized that the conclusions

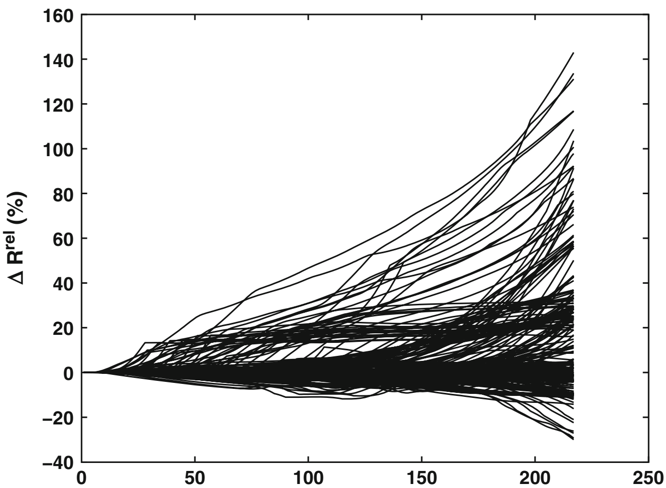

Fig. 12.3 Difference in calculated relative costs and realized costs, for $r = 1, \ldots, H$, for each of the 203 optimal control runs

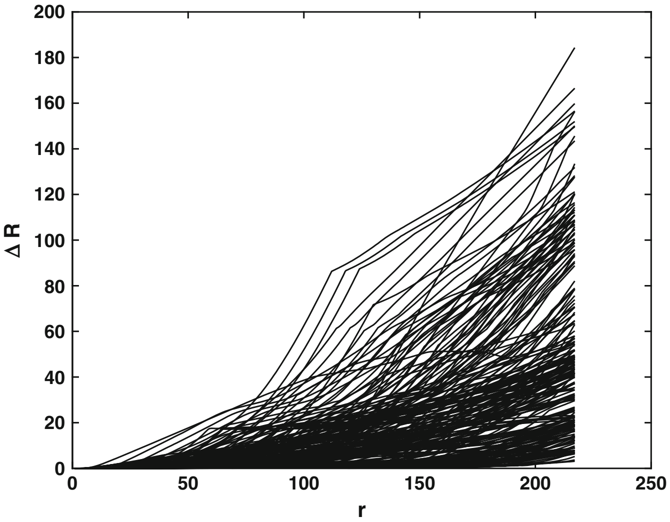

Fig. 12.4 Difference in calculated absolute costs and maximum costs based on the ensemble related to each of the 203 optimal control runs

certainly depend on the weather data and thus the type of weather. For a full analysis of the posterior behavior, other periods over a couple of years should have been evaluated, as well. However, such analysis was out of the scope of this study. To evaluate the uncertainty of the costs a priori, however, other information about the uncertainty of the weather forecast is needed. As mentioned before, the uncertainty of the weather forecast is embedded within the ensemble (see Sect. 12.2.2). By calculating the costs related to each of the ensemble members the worst case scenario can be evaluated, i.e. the ensemble member for which the costs are highest of all for $r = H$. In Fig. 12.4 the worst-case cost differences are presented, again as a function of r with $r = 1, \ldots, H$. Since only the worst case differences, related to the largest difference at $r = H = 217$, are presented, only 203 out of 50×203 runs are shown. It can be seen here that the worst-case scenarios always lead to increased costs, as expected, and these costs are considerably larger than the realized costs (Fig. 12.2). The question remains what the effect of a receding horizon control strategy on the uncertainty in costs is. This question will be answered in the next subsection.

12.3.2 Closed Loop Evaluation

In the specific RHOC implementation every 6 h, when actual weather data and updated forecasts become available, the optimal control trajectories are recalculated from (12.4) and implemented. Hence, only the control inputs for the first 6 h are

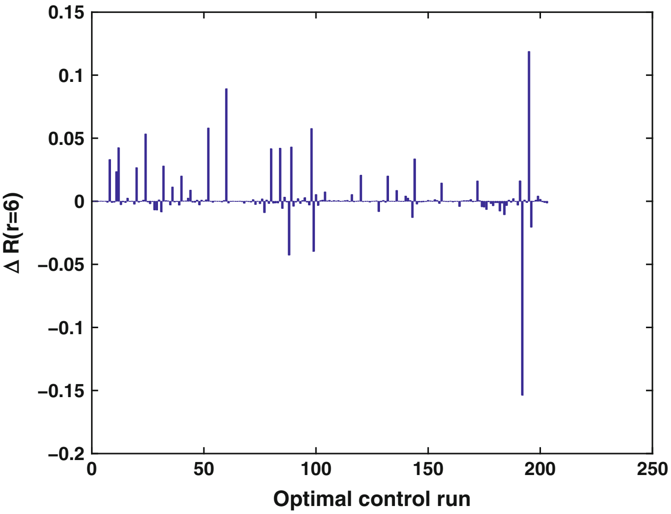

Fig. 12.5 Difference in calculated costs and realized costs after 6 h for each of the 203 optimal control runs

effectively used in the control strategy. This also implies that the uncertainties and errors in the cost function after 6 h needs to be evaluated. In Fig. 12.5 the differences between calculated costs, after 6 h because of the updates and using nominal weather, and actual costs based on observed weather are presented for each of the 203 control runs. Hence, this allows an a posteriori evaluation of the forecast errors. The small differences in costs after 6 h can be clearly seen from this figure. Notice that the small magnitude of the differences could also have been seen from Fig. 12.4. If all the costs shown in Fig. 12.5 are summed the additional costs due to errors in the nominal weather forecasts are known for the given period from 13 April to 2 June 2005.

From the a priori known weather forecast uncertainties, which can be directly obtained from the ensemble predictions, the worst-case scenario can be calculated as before. It appeared that the differences in calculated costs and maximum costs after 6 h (not shown here) based on the ensemble related to each of the 203 optimal control runs are very small, $\Delta R(r = 6) < 0.2$. However, the question remains how ΔR will evolve when the control horizon ℓ is chosen larger. In Table 12.1 the maximum (relative) deviation in the cost function, obtained from the weather forecast ensemble, is given for different control intervals (l).

Hence, for this case study it can be concluded that applying feedback every 6 h will reduce the uncertainty in the calculated costs, due to weather forecast errors and uncertainty, tremendously. It can also be seen from Table 12.1 that the difference in costs up to 24 h remains relatively small. In other words, in case of a communication failure between the optimization algorithm and the control computer of less than, e.g. 1 day no manual intervenience is required. However, it should be realized that these statements are only valid for our specific application in the pre-specified

Table 12.1 Additional costs of the realized costs and the worst-case scenarios for weather forecast uncertainty

ℓ	$\Sigma(\Delta J)/J$ (%)
6	0.37
12	1.15
18	2.05
24	3.17
48	8.0
72	14.2

evaluation period. Nevertheless, as can be seen from Figs. 12.2–12.4, the weather forecasts do not show much variation in the first 12 h. This phenomenon has been observed for other periods, as well. Thus, for $l \leq 12$, we conclude that in general the effect of the weather forecast uncertainty on the costs, as defined in (12.4), is marginal. Hence, under the assumption that CO_2 is never limiting, a control horizon of $l = 12$ instead of 6 would suffice in practice. Clearly, the weather forecast ensemble can be used for an a priori uncertainty evaluation on the costs. But we would be more flexible if we could anticipate on the forecast uncertainty. This idea will be further exploited in the next section.

12.4 Discussion

If in open loop the calculated costs based on the weather forecast and the *actual* costs, given observed weather and realized controls, are compared, it is evident that the costs can both increase and decrease. Not only the total costs are of importance but also the relative costs. During a long warm period the calculated costs will increase significantly. The absolute increase or decrease due to uncertain weather forecasts can then be quite large whereas the relative change may be reasonable. The opposite may also occur, i.e. large relative change versus a low absolute change.

Prior knowledge about the uncertainty of the forthcoming weather is very useful to study uncertainties in the near-future costs. From Figs. 12.2 and 12.4 it can be seen that, for this specific case, the (expected) cost increase is in general much larger for the a priori forecast uncertainty than for the a posteriori forecast error. Similar conclusions can be drawn in the closed loop case, see Fig. 12.5. From these figures it can be seen that the ensemble, indeed, is a useful tool to evaluate the uncertainty of the cost function a priori.

Recall that in optimal control theory a cost function, like (12.4), is minimized by adjusting the control inputs u, see, e.g. [12]. In case of the storage facility, genuine optimal control trajectories could be calculated if the (near) future weather would be exactly known in advance. However, future weather forecasts are never exactly known. A common approach, as we introduced in the previous subsections, is to define a cost function on the basis of the nominal disturbance trajectory (d^0, i.e. the nominal weather forecast), solve the optimization problem and evaluate the uncertainties in the costs. Alternatively, an approach based on implicit formulation of uncertainties in the cost function could have been chosen, such that an effective uncertainty reduction can be obtained. A classical example of this approach is minimum variance control [1].

For instance, in the case of our storage facility, minimum variance control would lead to $u = 0$, that is no ventilation of the store room, because the uncertainty in the product temperature is directly related to the weather forecast. Clearly, the product temperature uncertainty increases during ventilation. Hence, minimum variance control is not an option in our case. Thus, future work should focus on appropriate extensions of the cost function (12.4), for instance in line with [5] or [4].

12.5 Concluding Remarks

In post-harvest storage of agricultural produce, optimal control strategies can be used to anticipate on future weather conditions. In the simulation case-study with real weather forecasts and observed weather it appeared that there are only slight cost increases due to uncertainty and errors in weather forecasts if the optimal control problem is calculated every 6 h within a RHOC framework. In our application, even an increase of the control horizon to 24 h leads to a maximum increase of less then 5%.

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