Model-based product quality control : applied to climate controlled processing of agro-material

Model-based

Product Quality Control

applied to climate controlled processing of agro-material

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Verdijck, Gerardus J.C.

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prof.dr.dipl.-ing. H.A. Preisig
en
prof.dr.ir. G. van Straten

Contents

Summary

Operations handling agro-material are more and more confronted with the overall objectives of increased productivity and product quality. Climate controlled operations, such as storage and container transport, constitute an important class of operations involving agro-material. Currently used controllers in these operations focus on maintaining (fixed) climate settings. However, realising the overall objectives asks for a more integral approach directly including product quality and its variation. Therefore, the objective in this research was to develop a model-based product quality control methodology for the class of climate controlled operations that process agro-material.

The most striking communality in the process behaviour of climate controlled operations is the fact that the interaction between product and its influencing environment may be seen as a concentric series of process domains in which the product is in the center. This results in a functional separation of the process into domains. A special feature of the class of climate controlled operations considered in this research is that the characteristic time scales increase as one moves to the center and that the time scale separation coincides with the functional operation. This is illustrated by considering the involved state variables on their corresponding time scale. The primary sub-state with slow dynamics of e.g. reactive mass concentrations inside the product. The direct environment sub-state with intermediate dynamics of e.g. product and air temperatures. The indirect environment sub-state with fast dynamics of e.g. air temperatures in air-supply channels. Then these observations are cast into a mathematical model of such processes based on a first-principle approach. This basic model consists of three parts. These are the behaviour of the product with its quality on the slow time scale, and its direct and indirect environments respectively on the intermediate and fast time scales.

Modelling product behaviour with its quality attributes involves both nominal dynamic behaviour and its variation. Nominal behaviour of the quality determining variables is modelled using a limited number of basic reactions. To deal with the variation the presented model structure is extended with a three step lumped model

using discretised intervals. Models for the direct and indirect environments may be deduced from the well-known conservation laws.
The resulting modelling concept is linked with measurements and output relations. Based on both the modelling and measurement concept the control structure is designed by mirroring the model hierarchy directly, resulting in a hierarchical control structure. The significance of the explicit inclusion of product behaviour is that the control is much more geared to the demands of the product.
On the intermediate time scale the controller belongs to the class of Model Predictive Controllers. The novel controller fits in the methodology that is based on a time scale separation and the property of controlling the slowly reacting product with a fast-reacting environment. The controller enables the control of product quality by means of the product responses respiration and fermentation. It directly drives the quality and response of the product to the desired setpoint. To achieve an energy efficient operation the presented controller is closely linked with the (existing) local controllers that act on the fast time-scale where energy savings can be achieved allowing (controlled) high-frequent climate fluctuations.
On the highest control level of the hierarchical control structure, corresponding with the slowest time-scale, an economic-based optimisation procedure is introduced. The result is a trade-off between operational cost and product quality. The characteristic variation in products and product quality is included in the procedure using the new lumped model.
The developed control methodology is implemented and tested in full-scale industrial operations on storing large quantities of potatoes and in both small-scale and full-scale CA-container transport of apples. Herewith the applicability and possibilities of the methodology are shown. As these operations cover a broad range of post-harvest processing operations the use of this methodology will enable the maximum use of knowledge about process and product (quality) to design controllers that are safe, energy efficient, reduce quality variation and maximise product quality to meet the overall objectives of increased productivity and product quality.

Chapter 1

Introduction

1.1 Motivation for this research

Process industries in general and more specifically the food and pharmaceutical industries face a continuous drive to improve their operations. This drive is enforced by global competition, (environmental) regulation and consumer demands (e.g. Mittal (1997)). A contribution to the improvement of the operations can be achieved by implementing an improved control strategy in the process aiming at increased productivity and flexibility in operations (Trystram and Courtois (1994)) and decrease of product loss, increase of product quality and its regularity. Also more cost efficient operation is an important motivation for the implementation of a new control strategy.
Currently, in process operations one usually measures the different process variables, such as temperature, humidity, pressure and flows, quite frequently. This allows for tight control of these process variables. The setpoints are determined off-line in advance and are usually constant, or, at best, manually adjusted as conditions change out of the normal. In contrast, quality variables, which are the key indictors for the performance of the overall process, are measured off-line, if measured at all, but are usually rather slow. Thus their use in control applications introduces time delays and periods where the process is not operating on specifications (Chen et al. (1998)). However, improvement of process operations with respect to product quality requirements can only be achieved by combining knowledge about both the product and the process, as e.g. for drying operation is concluded by Kerkhof (2000). This motivates the development of a control methodology that can be used to determine the most appropriate control strategy for a specific process operation.
Although its results may be used to improve process operations in other industries, this thesis focuses on food processing and then especially on the class of climate controlled operations.

1.2 Climate controlled operations

Climate controlled operations involving agro-material, such as storage, transport and drying, represent an important class of operations in the food industry. Although it is broadly accepted that physical phenomena occur at different time scales it is often not clear how to incorporate these time scales in the control strategy (Stephanopoulos and Ng (2000)). Considering the different time scales, climate controlled operations involving agro-material can be described with sets of state variables as a sequence of interacting sub-processes. This will be explained and motivated in more detail in this thesis. The discussion builds a system theoretical concept, in particular the state space representation of system behaviour in the time domain. The following classification of state variables can be made:

- primary sub-state, x_p, with slow dynamics of e.g. reactive mass concentrations inside the product,
- direct environment sub-state, x_d, with intermediate dynamics of e.g. product and air temperatures,
- indirect environment sub-state, x_i, with fast dynamics of e.g. air temperatures in air-supply channels.

Together these sub-states describe the process operation and may, in general, be written as

$$\begin{aligned}\dot{x}_p &= f_p(x_p, x_d), \\ \dot{x}_d &= f_d(x_p, x_d, x_i), \\ \dot{x}_i &= f_i(x_d, x_i, u, d).\end{aligned} \tag{1.1}$$

Besides the presence of different time scales climate controlled operations are characterised by the property of controlling the slowly-reacting product with a fast-reacting environment. This environment affects the dynamics of the product through its state, which, in turn, is affected again by the outer environment. This concentric view of climate controlled operations is largely generic and results naturally in a hierarchical model of such operations.

1.3 Problem definition

Ideally, a process operation is optimised using an economic objective function directly resulting in the appropriate control actions, u,

$$\min_u J = -P(Q(t_f))M(t_f) + \int_{t_0}^{t_f} L(x, u, d, \tau)d\tau, \tag{1.2}$$

with P the price of the product that depends on the end-quality $Q(t_f)$ that, in turn, directly depends on the primary sub-state, x_p. $M(t_f)$ represents the end-mass of the product that depends on the mass components in the direct environment sub-state, x_d. The integral represents the cost that are made to meet the targets of the process operation. This objective function is subject to the differential state equations in Equation (1.1) and to the algebraic relations

$$\begin{aligned}Q &= f_q(z), \\ M &= f_m(x_d), \\ z &= f_z(y),\end{aligned}$$

$$
\begin{aligned}
y &= f_y(x), \\
x &= [x_p \; x_d \; x_i]^T,
\end{aligned}
$$

where z represents the reconstructed process outputs from the available measurements represented by y.

1.4 Solving the defined problem

The formulated control problem could be solved with a large multivariable controller for the whole process operations. This would not be an acceptable solution, because:

- on-line optimisation involves a large computation time,
- disturbances (d) are not known beforehand,
- closed-loop optimisation to deal with uncertainties requires feedback on all relevant quality attributes.

An alternative solution will be proposed in this thesis. It uses the characteristics of the climate controlled operations considered in this thesis and a hierarchical control structure will be proposed. The general objective function in Equation (1.2) will be translated into targets for the controllers on the appropriate time scales.

1.5 Applications

The proposed control methodology in this thesis with its control structure and control components is implemented and tested in industrial applications. The applications are briefly introduced.

Potato storage

Storage is an important part of the production cycle in the food industry. Although harvesting is season-bound, the food industry demands year-round supply of potatoes. During the storage period product quality declines. In potato storage, product quality is defined as the sugar content that is expressed in the so-called frying colour index. High sugar contents result in excessive undesired browning. The sugar content is affected by the storage conditions. Economic pressure forces the industry to improve process control to increase the added value of processing/storing potatoes.
• Product specialists look at this storage operations from a physiological point of view. They consider the reactions inside the product that are responsible for the production of sugar during the storage operations. This requires understanding of all

reaction mechanisms that play a role in the (difficult) reaction scheme.
• Control and climate specialists focus on airflow distributions, energy usage, insulation and narrow temperature control.

Container transport of apples

Climate controlled container transport of agro-material is a common way to get products at the desired location. During transport the product quality changes due to time and transport conditions like temperature, relative humidity and concentrations of oxygen, carbon dioxide and ethylene. These quality changes could e.g. lead to fruits that are too soft and eventually to product loss.
• Concerning the product, transport operations require adaptation of all (internal) physiological mechanisms to the new climate. This leads to a retardation of the senescence of the fruit that ends with the arrival at the destination, but adverse storage conditions may also lead to damage and product loss.
• Considering the climate, of interest are: airflow distributions, design of packaging, control of the climate unit and stowage space conditions.

1.6 Objectives of this research

The objective in this research is to develop a model-based product quality control methodology for a class of climate controlled operations that process agro-material. The use of this methodology will enable the maximum use of knowledge about process and product (quality) to design controllers that are safe, energy efficient, constrain quality variation and maximise product quality to meet the overall objectives of increased productivity and product quality.
Another objective of this research is to close the gap that exists between control theory and implementation of modern control technology in industrial applications. Furthermore, this thesis wants to contribute to the improvement of understanding and exchange of knowledge between the product specialists and the control and climate specialists. Only by combining knowledge from both fields an improvement may be achieved for the operations considered in this thesis.

1.7 Outline thesis

This thesis is divided in three parts. Part one with Chapter 2 gives an overview of all relevant thoughts and concepts for this thesis.
Part two, with Chapters 3 and 4, studies the models required for the design of the controllers. In particular the models concerning the primary state variables are

studied in detail. The result is a model and control structure for the class of climate controlled operations that through the explicit inclusion of product behaviour is much more geared to the demands of the product.

Part three, with Chapters 5 and 6, considers the new control components that together with the current (local) controllers comprise the presented control structure. This involves a Model Predictive Controller on the intermediate time scale that is closely linked with the (existing) local controllers on the fast time scale. On the slow time scale an economic objective function will be optimised which may include product variation.

The work in parts two and three with Chapters 3-6 is implemented in both small-scale and full-scale industrial applications on potato storage and CA-container transport of apples. These applications show the benefits that are achieved with the presented control methodology with respect to both product quality and economically efficient processing. [1]

In Chapter 7 this thesis ends with the major findings and suggested directions for future research.

[1] Chapters 3-6 are the result of full papers published or submitted to different scientific journals. Where appropriate this is mentioned at the beginning of a chapter. This may result in a slightly different notation between the chapters. Therefore, notations are included at the end of every chapter.

Part I

Theoretical Framework

Chapter 2

Modelling and Control Concepts

2.1 Introduction

The objective in this thesis is to develop a model-based product quality control methodology for a class of climate controlled operations that process agro-material. The desired control performance puts demands on the model (complexity and accuracy) and on the process (control) design. Indeed, the confidence one has in the ability of the model to describe the system is often limiting the performance, as this confidence is directly carried into the controller through the design procedure. When developing a control concept that covers a broad range of post-harvest processing operations one must exploit the similarities, that are the common parts, of the operations. The similarities are to be sought through process analysis resulting in a representative generic model structure. The use of this model structure will enable the maximum use of knowledge about process and product (quality) to design controllers that are safe, energy efficient, reduce quality variation and maximise product quality. This chapter presents the modelling and control concepts, whilst the remaining chapters of this thesis discuss specific topics in more detail. Section 2.2 discusses the most striking communality in the process behaviour, namely the fact that the interaction between product and its influencing environment may be seen as a concentric series of process domains in which the product is in the center. This leads to a functional separation of the process into domains. A special feature of the class of climate controlled operations considered in this research is the fact that the characteristic time scales increase as one moves to the center and that the time scale separation coincides with the functional operation. These observations are cast into a mathematical model based on a first-principle approach in Section 2.3. The resulting modelling concept is linked with measurements and output relations in Section 2.4. Based on both the modelling and measurement concept Section 2.5 is devoted to the design of the control structure by mirroring the model hierarchy directly, resulting in a hierarchical control structure. The individual controllers are designed separately. Both the modelling and control concepts, together forming the control methodology for the class of operations of interest, are summarised in Section 2.6.

2.2 Process Analysis

Prior to any modelling an analysis of the process is made for the main features of the process operations. The analysis consists of four main steps. First, the processing operation is analysed for a structure from a spatial or physical orientation (section 2.2.1). Second, properties of the process operations of interest are stated (section 2.2.2). Third, the structure is extended with reaction kinetics (2.2.3). Finally, state variables are defined and possible model reductions are discussed (2.2.4).

2.2.1 Generic process structure

In any processing operation involving agro-material, the product is encapsulated in an immediate environment. This environment affects the dynamics of the product through its state, which, in turn, is affected again by the outer environment. This concentric view of post-harvest processing operations is largely generic and results naturally in a hierarchical model of such operations. The central idea in this thesis claims that the processes aimed at in this research consist of sequentially linked sub-processes and a decomposition along the same line is beneficial for control purposes. Starting with the product the perception of product quality by the market and consumer is often in terms of quality attributes, Q, such as colour, shape, taste and smell/odour. These attributes are related to and determined by quantitative product properties in terms of concentrations or pseudo (lumped) concentrations. These concentrations are subject to biological and/or chemical reactions directly affecting product quality. The rates of these reactions depend on product and climate variables, such as temperature and moisture content of the product, and humidity and pH of the direct surrounding environment. These variables do not directly affect product quality. The direct climate variables are also connected with indirect climate variables that are not in direct contact with the product.
The separation of the process operation (shown in Figure 2.1) into different domains is motivated by the observation of the relative time scales in which the relevant (sub)-processes take place and which will be the main subject of next section.
The overall domain of the process is thus split into different sections, namely

- Product domain P.
- Direct (climate) domain D that is directly in contact with the product (air within the bulk, packaging, boundary layer etc.).
- Indirect (climate) domain I that is not directly in contact with the product (air channels, air rooms etc.).
- Control domain C that manipulates the process.
- Universe U representing the exterior of the process operation with disturbances affecting the indirect environment.

Each domain represents physically a part of the space occupied by the process operation.
The structure of the process operation is strictly hierarchical whereby the product is in the center, encapsulated by the direct environment. The indirect (climate) domain forms yet another outer shell. The manipulative input to the process operation is

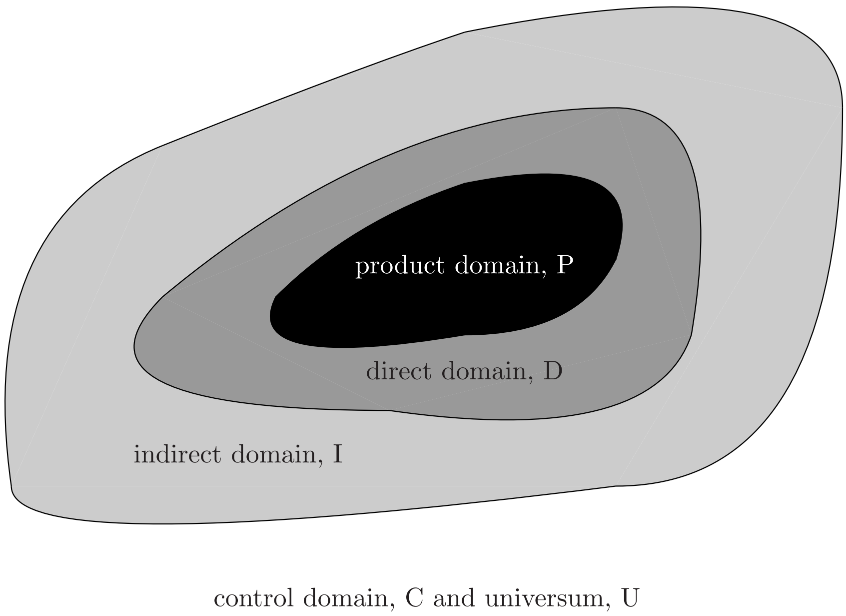


Figure 2.1: *Topology of the sub-domain in processing agro-material*

sequentially linked together with the manipulation of the product, which is the target, with the environments in between. This is illustrated in Figure 2.2. Each of these

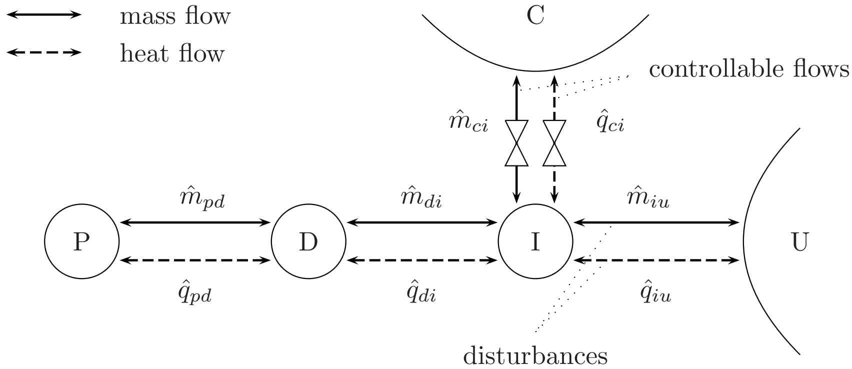


Figure 2.2: *Sequential order of the process domains*

domains can be modelled as a physical system, which is characterised by a state, which drives the interactions between the individual parts. The exchange is in the form of extensive quantities, namely mass, heat and work. The exchange of momentum does

usually not come into play as the velocities are very fast. Consequently, the pressure dynamics are modelled as events and the pressure changes occur instantaneously over the entire process operation. Pressure differences, though, are the driving force for convective mass flow.
The flows shown in Figure 2.2 can be defined as follows:

Mass flow is the flow of mass components between two domains

Heat flow is the flow of heat between two domains (that is not related to mass flow between two domains)

Because of this definition heat flows do not affect mass concentrations, but mass flows do affect temperatures. This is illustrated with the following equations for the enthalpy of the direct (D) domain, H_d. The enthalpy balance is formulated as follows

$$\dot{H}_d = \hat{q}_{pd} - \hat{q}_{di} + \hat{H}_{pd} - \hat{H}_{di}, \tag{2.1}$$

where $\hat{q}$ represents the effect of heat flow and $\hat{H}$ of mass flow on the enthalpy. In Equation (2.1) it is assumed that potential and kinetic energy terms may be neglected. Furthermore, it is assumed that pressure is constant, and that volume work, mixing enthalpy and external forces are not affecting the process. By assuming the specific heat, c_p, constant, the differential equation for the temperature of the direct environment, T_d, can be written as

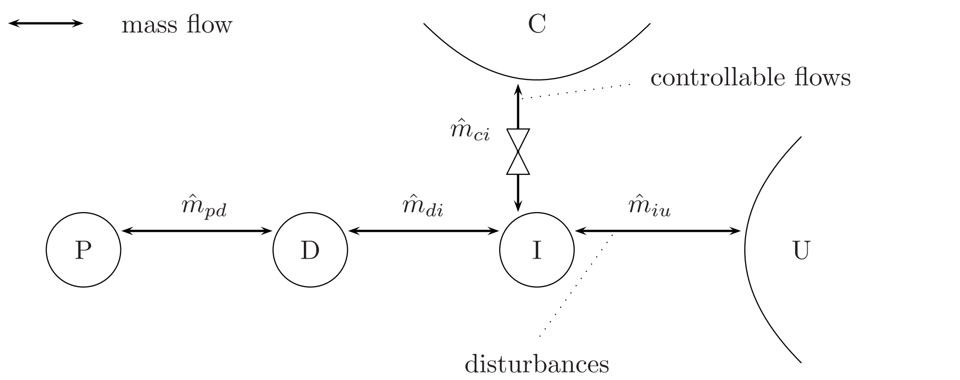
$$\begin{aligned} \rho c_p\, V \frac{dT_d}{dt} \;&=\; h_{pd}\; A_{pd}\; (T_p - T_d) \;-\; h_{di}\; A_{di}\; (T_d - T_i) \;+ \\ &\quad c_p\; \hat{m}_{pd}(T_p - T_d) \;-\; c_p\; \hat{m}_{di}(T_d - T_i). \end{aligned} \tag{2.2}$$

One should note that in case $\hat{m}_{pd}$ or $\hat{m}_{di}$ are outgoing flows, they do not affect temperature of the sub-domain.
The product and direct domains can not be controlled directly, while the indirect domain is directly controllable and measurable. As the direct domain is often not directly accessible to observation its state variables have to be reconstructed using the model equations. Through the sequential nature of the process operations the same holds for the product domain. These problems will be discussed in one of the following sections.

2.2.2 Properties of the domain interactions

Earlier, separate process domains and their sequential order were defined. Considering the heat and volume capacities of these domains, the capacity of the product (P) domain will be much larger than the capacities of the direct (D) and indirect (I) domains. Regarding the interactions between the separate domains six observations can be made for the class of process operations that is considered in this thesis. These observations and their consequences will be discussed hereafter.

First observation: it is noted that in the operation of interest the desired changes in the state variables (setpoints or reference trajectories) are limited in order to prevent product stress/damage. This means that changes in the input flows (both controllable and disturbance) $\dot{\hat{q}}_{ci}$, $\dot{\hat{q}}_{iu}$, $\dot{\hat{m}}_{ci}$ and $\dot{\hat{m}}_{iu}$ in Figure 2.2 are constrained as not to negatively affect the product and its quality. In Chapters 4 and 5 this will lead to weighing the change of the control inputs (Δu^2) on the intermediate control level. In case of large changes it is assumed that these, immediately, lead to a new equilibrium. E.g. this occurs in on-off control of air ventilation and circulation. This means that the dynamics resulting from the conservation law for momentum are not considered explicitly.
Second observation: external disturbances only slowly affect the process states due to e.g. insulation, meaning $\hat{q}_{iu}$ and $\hat{m}_{iu}$ are small as compared to the involved capacities. In some operations this would not be a valid assumption, e.g. in the case of greenhouse climate control with respect to solar radiation and a different approach should be used. Here we assume that no disturbance is present in Equation (2.2) which disturbs the thermal behaviour of the direct environment.
Third observation: the mass flow, $\hat{m}_{di}$, between the direct (D) and indirect (I) domains can be considered relatively large compared to the total volume meaning that the mass concentrations of the direct and indirect environment can be considered equal. In Figure 2.3 the mass flow network is shown and its simplification when applying this assumption.
Fourth observation: the heat flow $\hat{q}_{di}$ between direct (D) and indirect (I) domains is negligible as compared to the convective exchange of energy caused by the mass flow $\hat{m}_{di}$. In Equations (2.1) and (2.2) the fourth term on the r.h.s. ($h_{di}\ A_{di}\ (T_d - T_i)$) may be neglected.
Fifth observation: the heat flow, $\hat{q}_{pd}$, between product (P) and direct (D) domains is often relatively large as compared to the capacity of the direct (D) domain and in relation to the enthalpy associated with the mass flow, $\hat{m}_{pd}$, between product (P) and direct (D) domains.
Sixth observation: The effect of the heat flow between product (P) and direct (D) domains, $\hat{q}_{pd}$, is larger than the effect of the enthalpy associated with the mass flow $\hat{m}_{di}$ between direct (D) and indirect (I) domain.
Using the fourth and fifth observations and assuming that evaporation heat and heat associated with reactions inside the product only (directly) affect the product (P)



For third observation :

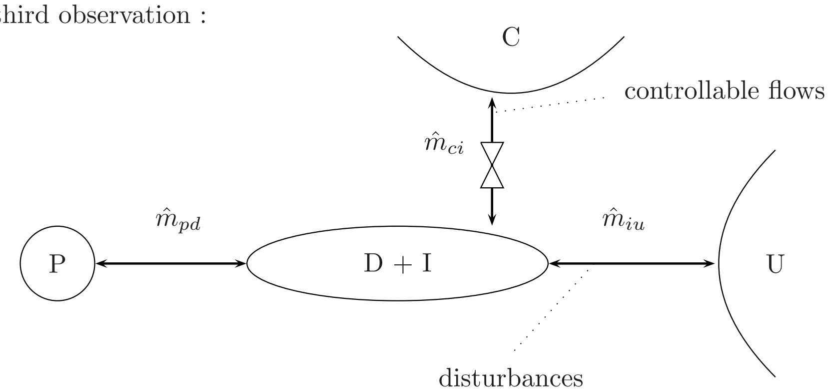


Figure 2.3: *Mass flows between different domains*

domain, Equation (2.2) can be written as

$$\begin{aligned} \frac{dT_d}{dt} &= \frac{\hat{m}_{di}}{\rho\ V}(T_i - T_d) + \frac{h_{pd}\ A_{pd}}{\rho\ c_p\ V}\ (T_p - T_d), \qquad (2.3) \\ \frac{dT_d}{dt} &= c_1(T_i - T_d) + c_2(T_p - T_d), \end{aligned}$$

where c_1 and c_2 can be considered as time constants associated with the mass flow between the indirect (I) and direct (D) domains and the heat flow between product (P) and direct (D) domain, respectively. Looking at this equation three different situations can occur with respect to the energy flows:

i. $c_1 \gg c_2$,

ii. $c_1 \approx c_2$,

iii. $c_1 \ll c_2$.

These three situations are illustrated in Figure 2.4 using the observations and the order of magnitude for the capacities of the different domains.

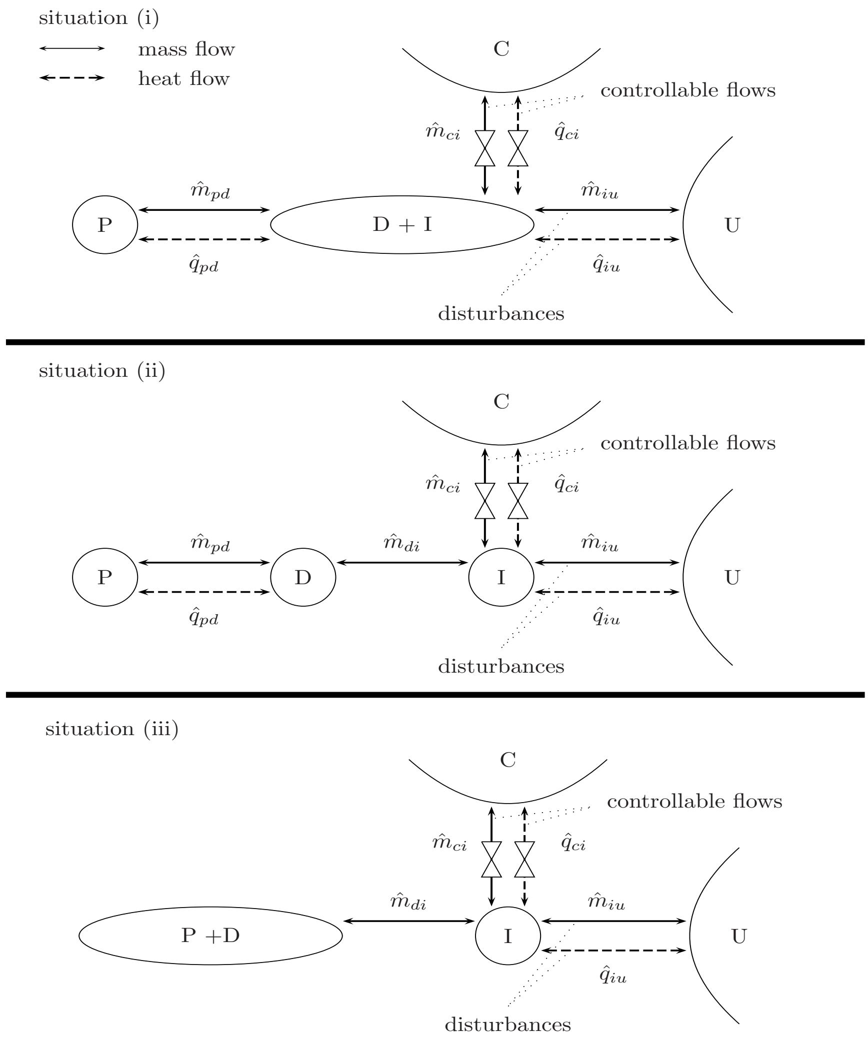


Figure 2.4: *Energy and mass flows for three different situations*

• Situation (i) is valid for operations that show a low heat exchange between the product and its direct environment. An example is transport or storage of closely packed products.

• Situation (ii) is valid for operations with a low heat exchange between the separate

domains. An example of such operations is the bulk storage of mangoes that have a relatively large heat capacity and natural heat production, and often a relatively low air flow through the packaging and the pallets.
• Situation (iii) is valid for operations with a relatively high heat exchange between product and its (direct) environment. This is true for most transport and storage operations with products, e.g. potato storage.
From these three situations the third case is most common for the climate controlled operations considered in this thesis. The second situation can be easily extended from the third case by considering product temperature as a separate state variable in the product (P) domain. In the remaining of this thesis it is assumed that the third situation, thus $c_1 \ll c_2$, can be applied with respect to the energy flows, unless stated otherwise.

2.2.3 Reaction kinetics

Processing agro-material involves dealing with the reaction mechanisms that occur during the operation inside the product. Generally, it is safe to assume that no relevant reactions occur outside the product domain. The reactions taking place inside the product affect some of the mass concentrations and may produce heat. A separation of product mass components is made into reactive (m_r) and non-reactive (m_n) components. The reactive components are involved in the reactions inside the product domain. As these reactions are taking place at a relatively slow rate a separate reactive product (P_r) domain is defined. The mass concentrations in this domain will be mainly responsible for the quality and quality change of the products in the process operation meaning that product quality is a function of some mass concentrations.
In Figure 2.5 the four domains and their connections with respect to the energy flows are illustrated. Also, using the observations from the previous section the situation with $c_1 << c_2$ (situation iii in Figure 2.4) is shown.

2.2.4 Definition of state variables

On the basis of the previous analysis now for the different domains corresponding state variables can be formulated. With respect to the reactive product domain (P_r) this involves the reactive mass components, m_r, while for the non-reactive product domain (P_n) the state variables are the non-reactive mass components m_n and product temperature T_p. For the direct (D) and indirect (I) domains the state variables are mass concentrations m_d and temperature T_d, and mass concentrations m_i and temperature T_i respectively. For the control domain (C) the input variables are temperature T_c, mass concentrations m_c and for the universum (U) the input variables are temperature T_u and mass concentrations m_u.

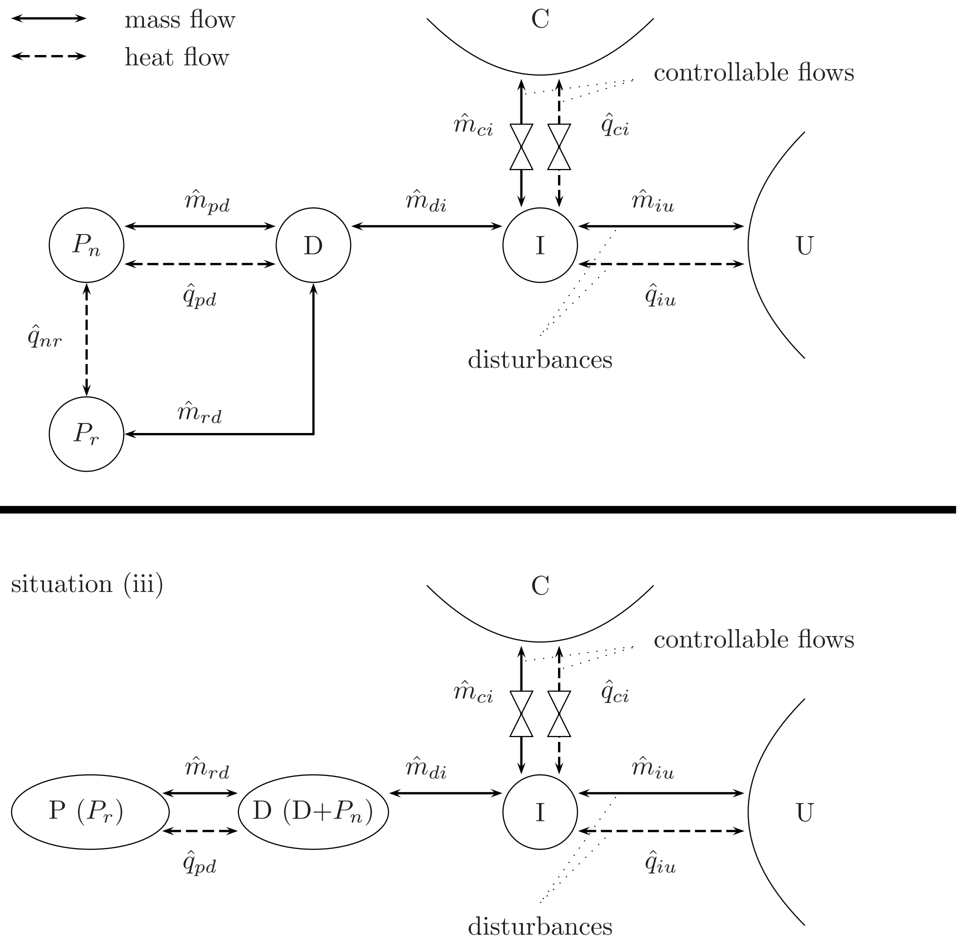


Figure 2.5: *Energy and mass flows with reaction kinetics*

Using the observations for the interactions between the different domains from Subsection 2.2.2 which are:

1. changes in input flows $\dot{\hat{q}}_{ci}$, $\dot{\hat{q}}_{iu}$, $\dot{\hat{m}}_{ci}$ and $\dot{\hat{m}}_{iu}$ are limited or can be considered infinitely fast,

2. disturbance flows $\hat{q}_{iu}$ and $\hat{m}_{iu}$ are small,

3. the mass flow $\hat{m}_{di}$ between the direct and indirect domains can be considered relatively large,

4. the heat flow $\hat{q}_{di}$ between direct and indirect domains is negligible,
5. the heat flow $\hat{q}_{pd}$ between product and direct domains is often relatively large and
6. the effect of the heat flow $\hat{q}_{pd}$ is larger than the heat effect associated with the mass flow $\hat{m}_{di}$.

Together with the fact that the capacity of the product (P) domain is much larger than those of the other domains, the following model reductions can be made:

- following from observations (4) and (5), given observations (1) and (2), product temperature T_p is in rapid equilibrium with the direct surrounding temperature T_d (situation (iii) in Figures 2.4 and 2.5) and
- following from observation (3), given observations (1) and (2), the mass concentrations in the direct domains m_d are equal to the concentrations in the indirect domain m_i (Figure 2.3).

The process state, in the class of processes discussed here, can be separated into three principal sub-states based on a time-scale decomposition. Assigning the remaining state variables to their corresponding time scales the following classification can be made for the operations discussed in this thesis:

- Primary sub-state (x_p) with slow dynamics consists of reactive mass concentrations m_r.
- Direct environment sub-state (x_d) with medium dynamics consists of product temperature T_p (equal to T_d) and non-reactive mass concentrations m_n.
- Indirect environment sub-state (x_i) with fast dynamics consists of (indirect) temperature T_i and (direct) mass concentrations m_d (equal to m_i).

In Chapter 4 several industrial cases will be discussed in which this classification of state variables is clearly visible and will be used in the development process of the product quality controllers.

2.3 Modelling concept

In this thesis modelling efforts will focus on the product and its quality attributes as this is the main objective of the research. First the modelling approach will be presented (Subsection 2.3.1), followed by the modelling concepts of the different sub-states of the process (Subsections 2.3.2 and 2.3.3). The equations are summarised in Subsection 2.3.4.

2.3.1 Modelling approach

The modelling approach followed in this thesis consists of four steps:

1. Split the process into relevant sub-domains with separate state variables.
2. Identify the connections or interactions of transferred quantities.
3. Assume lumped systems and model the sub-processes in extensive variables using the balance equations (mass and energy) and reaction equations.
4. Establish the model equations in intensive variables (concentrations and temperatures).

The first two steps are discussed in the previous section. Some assumptions will be made before establishing the model equations. The main assumption is that the individual domains of the process operation can be modelled using a lumped approach. In the next subsections more details will be discussed about the modelling in the different sub-domains.

2.3.2 Modelling product quality

It can be shown that in the product model the influence of primary states, x_p, can be separated from the environment state variables in x_d. This can be written as

$$\dot{x}_p = K(x_d)r(x_p), \tag{2.4}$$

and will be discussed in Chapter 3. The separation enables the study of time scales and the effect of non-linearities. Results of this study will be used in the optimisation on the slowest time scale (Chapter 6).

Modelling product variation

Most often in practice variation or spread in product quality is dealt with using so-called quality classes. Measurement data is available in terms of these discretised quality classes. As the model structure for quality variation has a control purpose the use of a complicated continuous distribution model for the quality variation is not a feasible possibility. As an alternative, a three-step approximation procedure is proposed that is discussed in more detail in Chapter 3:

- Discretise the main quality variable into separate intervals, called classes.
- Model the transfer between the classes.
- Express the variation as an extension to the nominal model structure.

The state variables of the product are separated into a main primary state variable, x_p^m, such as e.g. the sugar content of potatoes or firmness of apples and mangos, and assisting state variables, such as e.g. enzyme concentrations. The main primary state variable is discretised in different classes, as illustrated in Figure 2.6.

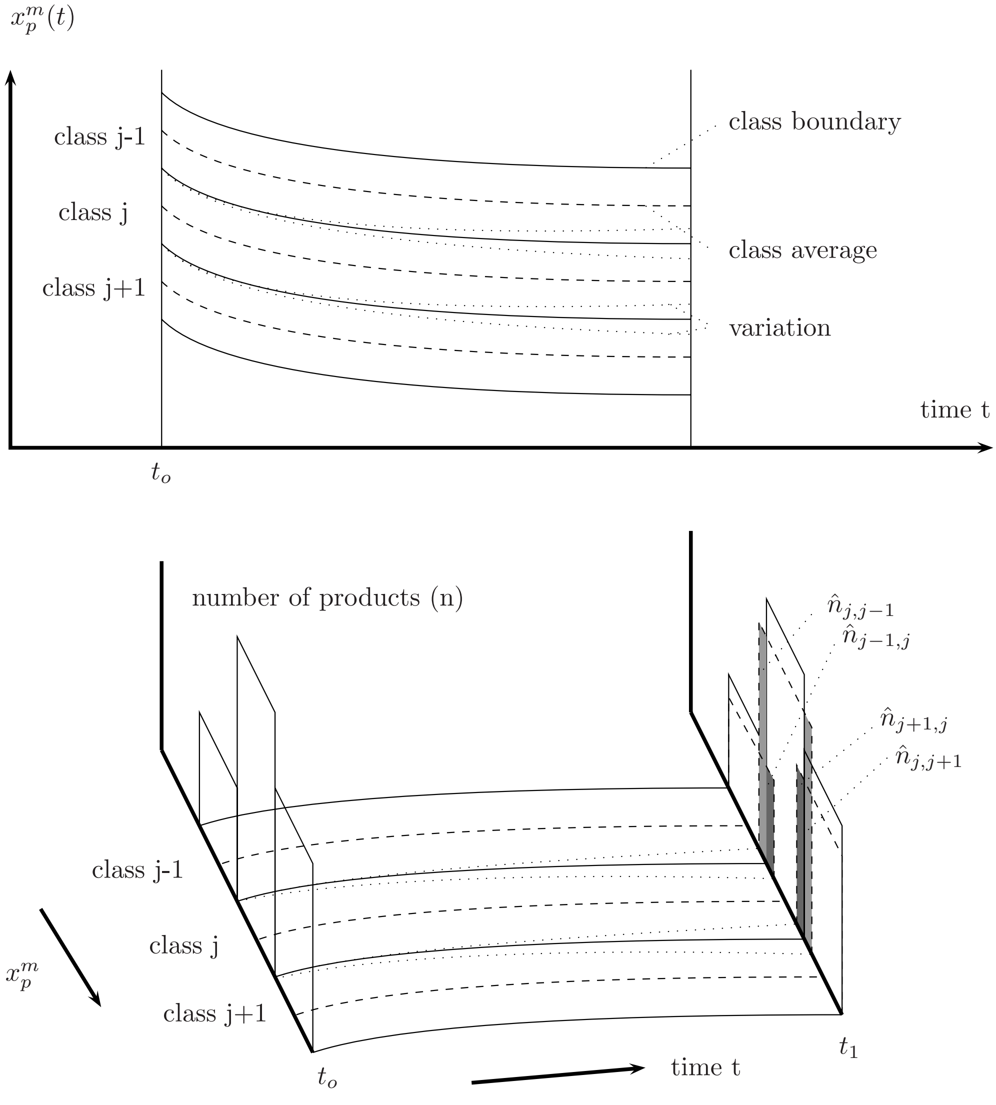


Figure 2.6: *Class behaviour*

Nominal or average behaviour of this main primary state variable determines the time-evolution of the classes and class boundaries. The benefit of these (nominal) changing class boundaries is that transfer between classes only occurs if variation in

the assisting state variables affects the product behaviour. In that case a product does not show nominal behaviour and may transfer.
The number of products in a class can be described with

$$\dot{n}_j = -\hat{n}_{j,j+1} + \hat{n}_{j+1,j} - \hat{n}_{j,j-1} + \hat{n}_{j-1,j}, \tag{2.5}$$

where e.g. $\hat{n}_{j,j+1}$ represents the transfer from class j to class $j+1$. Transfer between classes occurs if the difference in value of the assisting state variable between this product and a nominal or average product is large enough. Otherwise the effect of variation in the assisting state variable on the main primary state variable is too small to cause transfer.
With the extensions to the nominal model structure, variation in the main product state caused by initial variation in the main and assisting state variables can be described. This extended model will be used to control quality variations. More details are discussed in Chapter 3 for modelling and in Chapter 6 for control.

2.3.3 Modelling product environments

A first principle based modelling approach is followed that starts by defining a network of domains (capacities) and connections, as is done in the previous sections. The conservation laws for the extensive variables mass, energy and sometimes momentum are formulated for each subprocess. The conservation laws result in differential equations for the extensive variables mass, energy and momentum for each subprocess that may depend on the control inputs in u

$$\begin{aligned} \textit{direct environment } (D): \quad \dot{x}_d^f &= f_d(x_p^f, x_d^f, x_i^f), \\ \textit{indirect environment } (I): \quad \dot{x}_i^f &= f_i(x_d^f, x_i^f, u, d). \end{aligned}$$

The model equations in extensive variables can be reformulated in terms of intensive variables, such as temperature and concentration. Such a transformation occurs in rewriting the equations for mass in terms of concentrations and in the change from energy to temperature. Generally, in these transformations several assumptions on pressure, volume and temperature dependency will be made that must be validated in the specific process of interest. The transformation results in the differential equations for the intensive variables as e.g. shown before in Equations (2.1) and (2.2) for T_d

$$\dot{x} = f(x, u),$$

with

$$x = \begin{bmatrix} x_d \\ x_i \end{bmatrix},$$

where x_d represents the direct environment state variables, and x_i the indirect environment state variables.

2.3.4 Model structure

The model structure that is proposed in this research can be written as

$$\begin{aligned}
\dot{x}_p &= K(x_d)r(x_p), \\
\dot{x}_d &= f_d(x_p, x_d, x_i), \\
\dot{x}_i &= f_i(x_d, x_i, u, d), \\
y &= f_m(x_p, x_d, x_i),
\end{aligned}$$

where u represents the controllable inputs, d the disturbances, and y the outputs. As it is, the plant input, that can be manipulated only, is sequentially linked together with the primary state variables, which are the target, with the environments in between.

An example of this classification according to the presented model structure can be seen in potato storage where the sugar content is the main product quality state variable. The temperatures of the potatoes and the air directly surrounding the product are direct environment state variables. The temperatures of the air in the air channel and air room are indirect environment state variables.

2.4 Measurement concept

To analyse process performance process outputs must be available, either from estimation or by measurement. A problem, typically occurring in processing agro-material, are the differences in information density, i.e., not all sub-states are sampled with the same frequency and accuracy. Although in this thesis the focus will be on modelling and control, both aspects, output relations and information density, will be briefly discussed in this section and in Chapter 4.

2.4.1 Output relations

Using a commonly used modern systems representation the following inputs and outputs can be defined:

- $\overline{u}$, control inputs to controllers on the different (time scale) levels and plant, $\overline{u} = [y_d^{ref}\ y_i^{ref}\ u]$,
- d, external disturbance inputs (measurable or non-measurable),
- z, reconstructed outputs, reconstructed from the direct measurements including an identity observer that carries (direct) measurements through the reconstruction filter, with $z = [z_p\ z_d\ z_i]$, and

- y, direct measurements from the plant (sufficiently frequent and automatic) with $y = [y_p \; y_d \; y_i]$.

The measurements, y, are related to the state variables with the so-called measurement equation

$$y = f_m(x).$$

The outputs, z, must be reconstructed from the available measurements (or are carried through directly)

$$z = f_z(y, \overline{u}).$$

In addition to the outputs, intended for the direct control of product quality, Q, in the class of operations of interest in this research, product quality can be defined as a function of the outputs (reconstructed and measured state of product)

$$Q = f_q(z).$$

In Figure 2.7 the measurement concept is shown with in F the reconstruction of the outputs, z, (or carrying through directly the measurements) on the corresponding time scale.

2.4.2 Information density

The time scales on which information becomes available (sampling rates) is important for the control structure that is most suitable for the operations of interest. Looking at the different process outputs, one can easily see that there will be large differences between the sampling intervals of the different sub-states. In general, the indirect environment sub-state, x_i will be sampled on a scale of seconds or minutes. The direct environment sub-state consists of state variables that are either measured directly or estimated using a reconstruction filter. The sampling frequency is typically in the order of hours or days. The primary state variables are sampled, either by measurement or reconstruction, on a weekly or even monthly basis. The (hierarchical) control structure should be able to deal with these different sampling rates or densities of information. At least, the sampling rates should be reflected in the control structure as will be presented in the next section.

2.5 Control concept

In this section first the entire control problem is formulated. After this formulation the control problem is considered in the three characteristic time scales that are defined earlier in Section 2.2.

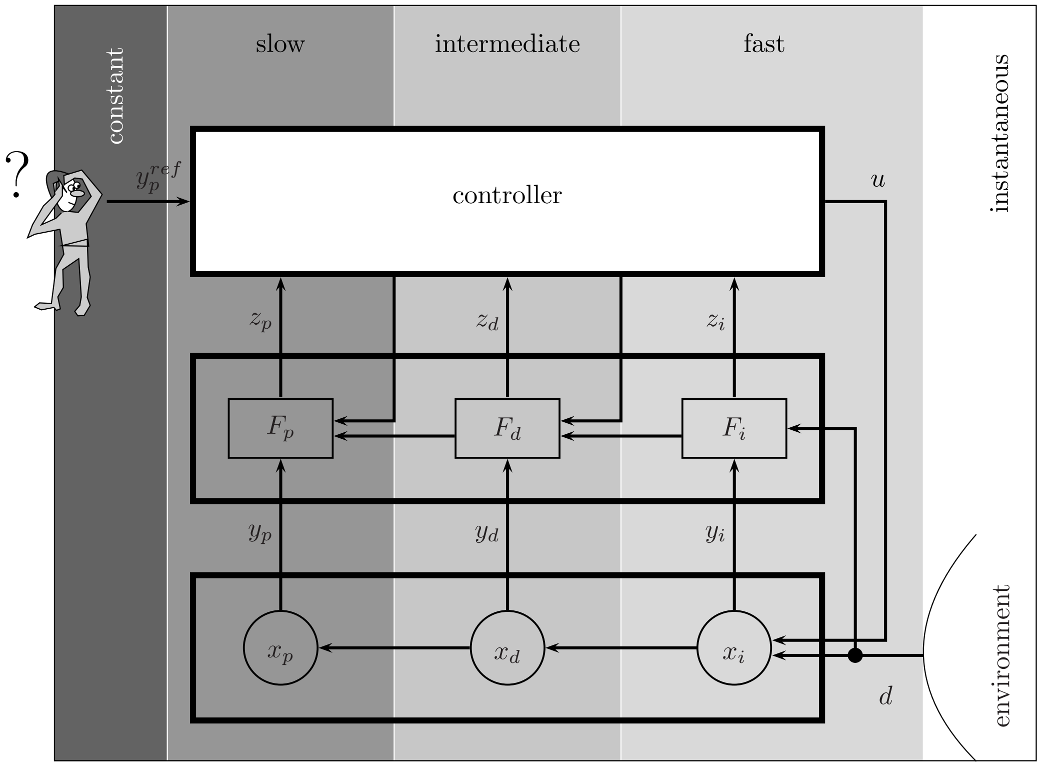


Figure 2.7: *Measurement concept*

2.5.1 Control problem formulation

Earlier in this chapter it was shown that the process operation can be described as a sequence of interacting sub-systems. The complete state space model can be written as

$$\begin{aligned}
\dot{x}_p &= Kr, && \textit{product dynamics} \\
\dot{x}_d &= f_d(x_p, x_d, x_i), && \textit{dynamics of direct environment} \\
\dot{x}_i &= f_i(x_d, x_i, u, d), && \textit{dynamics of indirect environment}
\end{aligned}$$

with the algebraic relations

$$\begin{aligned}
r &= r(x_p), && \textit{reactions} \\
K &= K(x_d), && \\
Q &= f_q(z), && \textit{quality} \\
z &= f_z(y, \overline{u}), && \textit{state reconstruction} \\
y &= f_y(x), && \textit{measurement} \\
x &= [x_p\ x_d\ x_i]^T. && \textit{state}
\end{aligned}$$

Ideally the set of equations is optimised using an economic objective function directly resulting in the appropriate control actions, u,

$$\min_u J \quad = \quad -P(Q(t_f))M(t_f) + \int_{t_0}^{t_f} L(x, u, d, \tau)d\tau, \tag{2.6}$$

with P the price of the product that depends on the end-quality $Q(t_f)$, $M(t_f)$ the end-mass of the product depending on the mass concentrations in the direct environment. The integral represents the cost that are made to meet the desired objectives. However, motivations for a separation of the control problem are:

- on-line optimisation involves a large computation time,
- disturbances, $d = [d_m \ d_u]^T$ either measured or not measured, are not known beforehand,
- closed-loop optimisation dealing with uncertainties requires feedback on all relevant quality attributes.

From a time scale analysis it is concluded that three separable time scales can be recognised in the processing of agro-material. On each time scale a separate control problem can be formulated. On the slow time scale an economic optimisation problem will be formulated, on the intermediate time scale a quadratic objective function will be formulated which is used to correct the desired settings and on the fast time scale local controllers try to reach and maintain the calculated setpoints, in other words to reject disturbances. It is plausible that "loss" of control performance due to separation of the control problem is limited. In Figure 2.8 the control structure is illustrated with the different control components, C. Details of the separate control components will be discussed in next subsections.

2.5.2 Slow time scale

The slow time scale controller or trajectory generator optimises the long-term overall economical objective of the process using e.g. the weather averages over several years. In Figure 2.9 the control structure for the slow time scale is shown. The slow time scale controller calculates the desired trajectories of the primary and direct environment states. The economic objective function can be written as

$$\min_{y_d^{ref}} J = -P(Q(t_f)) \ M(t_f) + \int_{t_0}^{t_f} L(x_d, d, t)dt, \tag{2.7}$$

where P is the price of the product that depends on the end-quality $Q(t_f)$, $M(t_f)$ is the end-mass of the product and the integral represents the cost that are made to achieve the desired primary and direct and/or indirect environment state variables,

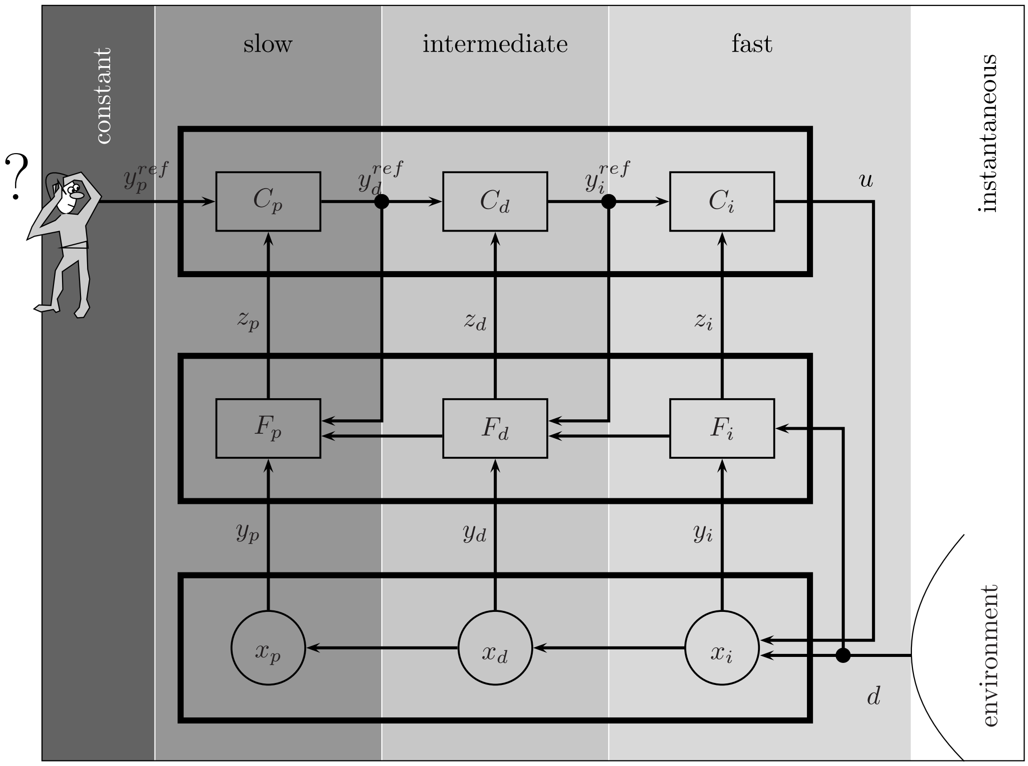


Figure 2.8: *Control Structure with control components on different time scales*

$x = [x_p \; x_d \; x_i]^T$, subject to measured and unmeasured disturbances, $d = [d_m \; d_u]^T$. This objective function optimises financial yield and product quality against weight loss and cost of the operation. The objective function in Equation (2.7) is subject to:

$$\begin{aligned} \dot{x}_p &= f_p(x_p, x_d), \\ y_d &= y_d^{ref}, \end{aligned} \tag{2.8}$$

where the differential equations describe the dynamics of the primary state variables and the dynamics of the direct environment are considered to be instantaneous at the slowest time scale. Algebraic equations describe the relations for the derived quantities Quality, Q, and total product mass, M:

$$\begin{aligned} Q &= f_q(x_p), \\ M &= f_m(x_d). \end{aligned}$$

The measured and unmeasured disturbances d_m and d_u respectively, often represent outside temperature. For this disturbance only averaged values, $d_m = \overline{d}_m(t)$ and

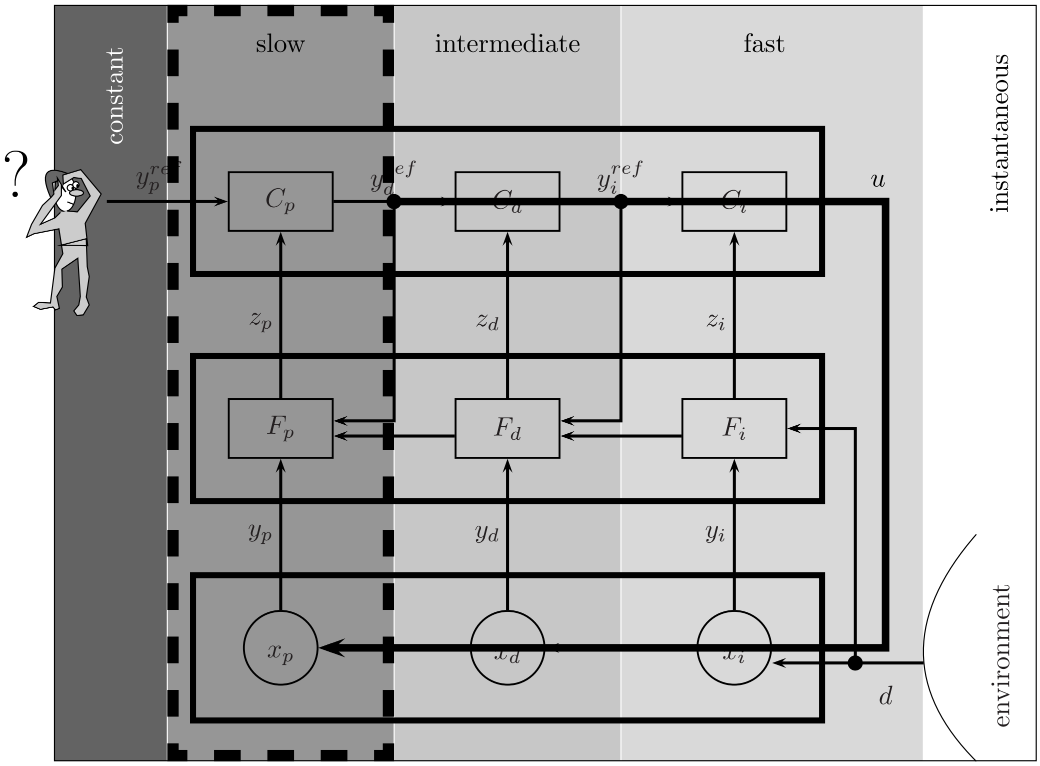


Figure 2.9: *Control Structure with control on slow time scale (its action directly affecting the plant input)*

$d_u = \overline{d}_u(t)$, are available for future processing time.
The cost L is a function of the input u, which is acting at the fast time-scale of the process directly manipulating the indirect environment state variable, x_i, which in turn affects the direct environment, x_d. Costs associated with these control actions, u, are e.g. energy consumption from fans and cooling equipment. It is assumed that on the slow time scale the indirect state variables, x_i, are equal to the direct state variables, x_d. Thus, for the evaluation of the cost function on the slow time scale an estimate of the control actions on the fast time scale must be made that depends on the output, y_d^{ref}, of the slow time scale controller. For a transport or storage operation this does require knowledge about the average heat produced by the product and the average heat exchanged with the surroundings. Together with the equipment characteristics this knowledge can be used to relate the fast time scale control actions (u) to operation costs (L). This will be illustrated in Chapter 6.
Inputs are information on the final process time, t_f, desired quality, y_p^{ref}, energy

supply and prices, and initial conditions of the primary state variables. In the solution, lower level controllers and dynamics are assumed ideal, the direct and indirect environment sub-state are assumed infinitely fast, $y_d = y_d^{ref}$ and $y_i = y_i^{ref}$. Outputs of the long-term optimisation are realisable desired trajectories, y_d^{ref}, for the intermediate controller. Realisable setpoints and reference trajectories are, to a certain degree, guaranteed by incorporation of practical constraints in the slow time scale controller.

Non-linearities in the product model

The product model, represented in the primary state variables, are written as

$$\begin{aligned} \dot{x}_p &= Kr, \\ r &= r(x_p), \\ K &= K(x_d). \end{aligned} \tag{2.9}$$

Nonlinearities are present in the system matrix K and depend on environment state variables, x_d. This type of nonlinearities may be linearised around the reference trajectory of x_d. Another type of nonlinearities involves the reaction vector r as it depends on the primary state variables, x_p. This typically involves product terms of the state variables as a result of reaction mechanisms involving two or more limiting reaction components. On the slow time scale these nonlinearities will have to be included in the optimisation.

Control of product variation

Variation in climate controlled processes with agro-material is due to:

- variation in product behaviour,
- variation in climate conditions, both in indirect and direct environment.

Variation in product behaviour is caused by differences in initial conditions or by different dynamical behaviour due to variation in model parameters. Variation in the environment sub-states are due to disturbances from outside (non-optimal insulation) and physical process limitations (e.g. inhomogeneous air flows). In Chapter 3 variation in the primary sub-state and the transfers between different classes will be discussed in more detail and in Chapter 6 an example on control of product variation will be discussed.

2.5.3 Intermediate time scale

In Figure 2.10 the control structure for the intermediate time scale is shown. Inputs

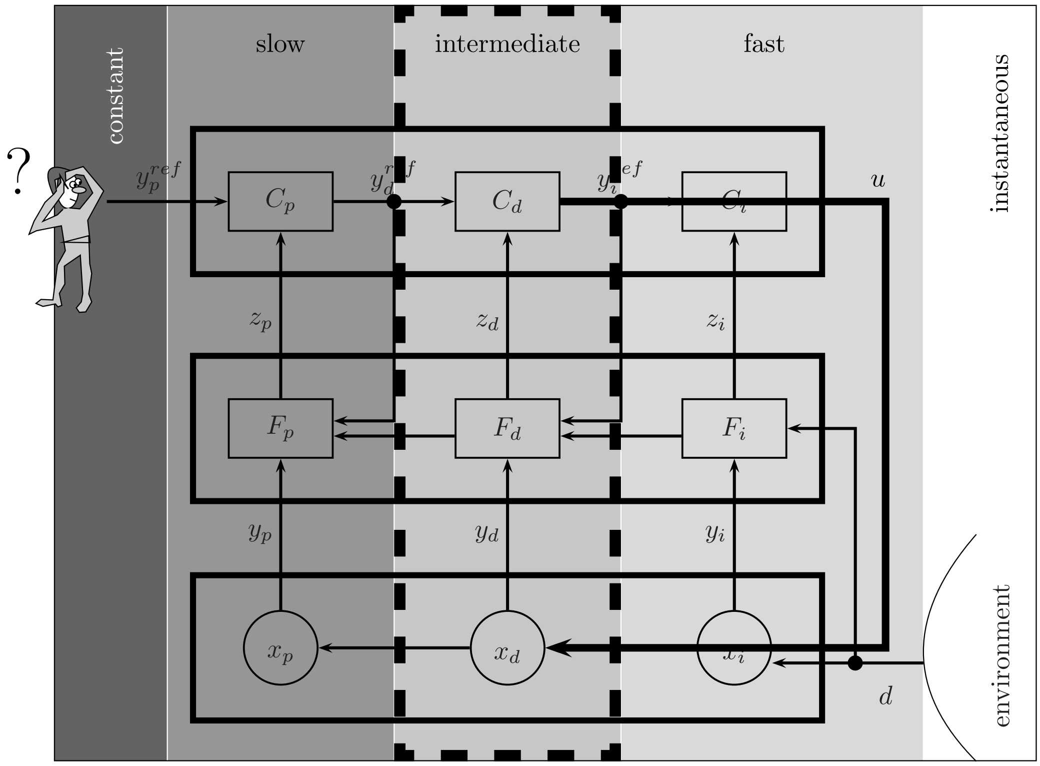


Figure 2.10: *Control Structure with control on intermediate time scale (its action directly affecting the plant input)*

for the intermediate controller are reference trajectories from the slow time scale optimisation, and actual state values from measurement information or from the state estimation. Outputs are setpoints for the indirect environment state variables, y_i^{ref}, used by the lower-level control components.

The objective of the controllers on the intermediate time scale is to reach and maintain the process at the desired trajectories with minimum cost. Undesired disturbances must be rejected. The controller must optimise between achieving the setpoint and cost. This leads to an objective function that can be written as

$$\min_{y_i^{ref}} J \quad = \int_t^{t+H} ((y_d - y_d^{ref})^T W_y (y_d - y_d^{ref}) + (\Delta y_i^{ref})^T W_u \Delta y_i^{ref}) dt, \qquad (2.10)$$

where W are the weighing factors that relate differences between actual and desired behaviour to each other and to changes in the control actions. The time horizon of this controller is denoted with H. The objective function is subject to the following set of equations

$$\begin{array}{rcll} \dot{x}_d & = & f_d(x_p, x_d, x_i), & \textit{dynamics of direct environment} \\ 0 & = & f_i(x_d, x_i, u, d), & \textit{event dynamics of indirect environment} \\ y_i & = & y_i^{ref} \quad \forall t, & \end{array}$$

assuming the indirect environment, x_i follows its setpoint immediately when considered on the intermediate time scale. There will be constraints on the state variables x_d and the outputs of the controller y_i^{ref},

$$x_{min} \leq x_d \leq x_{max}, \quad y_{min}^{ref} \leq y_i^{ref} \leq y_{max}^{ref}, \quad |\Delta y_i^{ref}| \leq \Delta y_{max}^{ref}. \tag{2.11}$$

Equation (2.10) is a quadratic objective with constraints which enables the formulation of a control problem in standard notation. The intermediate controller is a Model Predictive Controller (MPC), which is a discrete-time equivalent of Equation (2.10) with piecewise constant controls.

Non-linearities in the environments

Nonlinearities are present in almost every model parameter as these parameters depend on the actual climate conditions, such as temperature and oxygen concentration. The parameters may be linearised around the reference trajectories for the environment state variables.

A special situation arises when, besides climate conditions like temperature and O_2, also airflow is controlled. This leads to a nonlinear system model. The control model that will be used in the predictive controller is deduced from this nonlinear system model by linearisation. In the linearisation also second-order terms will be included. This results in a control nonaffine problem. Such a control nonaffine problem is a typical control problem for the climate controlled operations. In Chapter 5 an approach to deal with this control problem is discussed in more detail.

2.5.4 Fast time scale

In Figure 2.11 the control structure for the fast time scale is shown. The local controllers are often existing and currently used PID and on-off type of controllers. Leaving these controllers in place as local controllers, constitutes an advantage for acceptance of the hierarchical control structure in practice. Inputs are setpoints from the supervisory controllers. Outputs are control actions that act upon the process. The local controller continuously tries to accomplish the target settings for the indirect environment state variables, y_i^{ref}, from the intermediate time scale. The local controller performs local control actions, such as usage of ventilation with external or internal air for cooling purposes and/or by switching the ventilation units on or off.

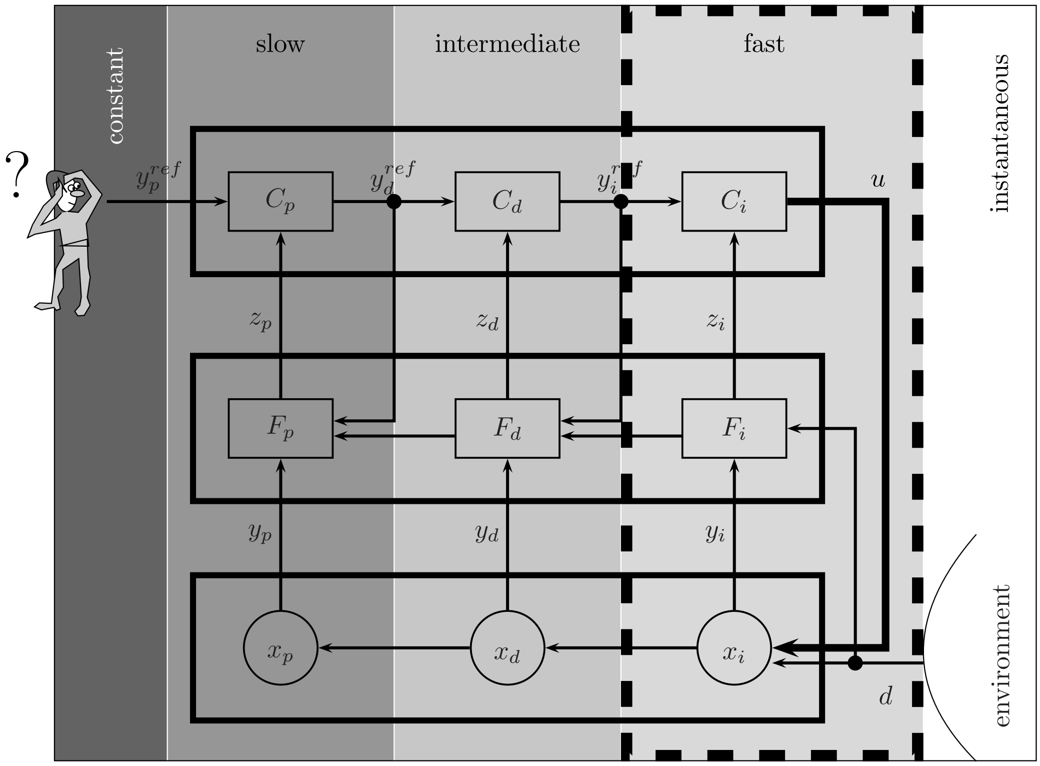


Figure 2.11: *Control Structure with control on fast time scale*

The local controllers on the fast time scale are locally optimised to achieve energy savings, as will be discussed in Chapter 5. These energy savings may result from nonlinear product behaviour and from the characteristics of the conditioning equipment. For linear product behaviour heat production and heat removal does not change with fluctuating conditions. However, as most product behaviour is nonlinear energy savings may result from allowing high-frequency fluctuations. Furthermore, most equipment operates most energy efficient when operating at full power. Instead of continuous heat removal, cycling or switching procedures can be used. Of course, this results in fluctuating conditions in the indirect environment. However, as these conditions fluctuate with a frequency that is relatively high and the product is too slow to follow these changes, it does not influence product quality. This can be understood by the fact that product behaviour is considered on the slowest time scale. Solving for the primary sub-state results in

$$x_p(t_f) = x_p(t_0) + \int_{t_0}^{t_f} K(x_d) r(x_p) dt. \tag{2.12}$$

So, every pattern of $x_d(t)$ which yields the same integral in Equation (2.12) yields the same change in x_p over the total time and hence the same economic value in the objective function on the slow time scale. On the intermediate time scale, any pattern of $x_i(t)$ which yields the same x_d over time ($\int f_d \, dt$) leads to the same quality result seen for the product on the slow time scale. This allows for local optimisation on the fast time scale. Results applying this approach in an industrial environment will be shown in Chapter 5.

2.6 Overall system approach

In Figure 2.8 the overall control concept is shown in which the three basic concepts for modelling, measurement and control, are combined into the overall control methodology.
The basic assumptions made in the methodology as presented in this chapter are:

- Product dynamics are significantly slower as compared to its two environment domains (Section 2.2.1).
- A sequential relationship can be obtained between the defined domains (Section 2.2.1).
- For the class of climate controlled operations simplifications can be made that result from observing the main features of the operations discussed in this thesis (Section 2.2.2).

In the remaining chapters of this thesis the different components of the overall system concept will be discussed in more detail. The focus will mainly be on the modelling and control concept as these concepts are most generic in their use for the operations that are of interest for this thesis.

Notation

ρ	density $[kg\ m^{-3}]$
A	surface area $[m^2]$
C	control domain
D	direct domain
H	enthalpy $[J]$
I	indirect domain
J	objective function
K	matrix with yield-coefficients
L	cost function
M	product mass $[kg]$
P	product domain
Q	product quality
T	temperature $[^{\circ}C]$
U	universe
V	volume $[m^3]$
W	weighing functions
c_p	specific heat $[J\ kg^{-1}\ ^{\circ}C^{-1}]$
d	disturbance
h	heat exchange coefficient $[J\ m^{-2}\ ^{\circ}C^{-1}]$
$\hat{m}$	mass flow $[kg\ s^{-1}]$
$\hat{q}$	heat flow $[J\ s^{-1}]$
r	reaction components
t	time $[s]$
u	control variables
x	state variables
y	measurements
z	(reconstructed) outputs
Subscripts:	
0	initial
c	control
d	direct environment
f	final
i	indirect environment
j	class number
m	measured disturbance
min	minimum value
max	maximum value
p	primary
u	unmeasured disturbance
Superscripts:	
f	extensive
ref	reference trajectory

Part II

Model and Control Structure

Chapter 3

A Model Structure for Product Quality

abstract

In this chapter a model structure is presented that captures product behaviour with respect to quality properties. Modelling product quality properties involves nominal (bulk) dynamic behaviour and the variation of these properties. Nominal behaviour is modelled using a limited number of basic reactions. To deal with the variation the presented model structure is extended with a three step approximation procedure using discretised intervals. The model structure is suitable for control purposes and will contribute to closing the gap between product specialists and the system and control community. The applicability of the model structure and the possibility to describe quality properties is shown with existing models from the literature that show a good fit with the described model structure and by an industrial case study on potato storage.

G.J.C. Verdijck, J.J.M. Sillekens, H.A. Preisig

A Model Structure for Product Quality in Processing Agro-material for Process Control Purposes, Journal of Food Engineering, 51(2):151-161,2001.

3.1 Introduction

In the food industries, interest in advanced model-based process control is increasing. Increasing consumer demands in terms of product quality, increasing environmental regulations and international competition require process operations to operate closer to their limits. At present, quality of agro-products is not directly controlled in the respective processing units. It is common to operate agro-material processing plants at setpoints for quantities such as air temperature and humidity using local controllers to reach and maintain these setpoints as close as possible. These setpoints, generally, are the result of a set of experiments and adjusted by experience yielding a sub-optimal solution, which intrinsically includes compromises.

Although it is believed that model-based controllers may have equal advantages in the food industry as they have in the (petro-)chemical process industry, as illustrated in Sanchez and Rodellar (1996), Garcia et al. (1989), Camacho and Bordons (1995) and Lee (1993), they are hardly ever employed. This motivates research into using these control techniques in processing agro-material. However, higher process performance demands correspondingly better process models that describe the relevant process dynamics in the respective time scales. In particular, the behaviour of product and all desired quality measures must be included. The model must be capable of accurately describing the product properties in different operations like storage, drying and transport. The models should be sufficiently generic to assure a minimal uniformity in the control of these different operations.

In this chapter a model structure is presented that describes the dynamic behaviour of a range of product quality properties that is relevant for operations that process agro-material. This should not only include the nominal (bulk) behaviour, but also the particularities involved in the processing of agro-material such as product quality definition, irreversibility of biochemical reactions, and natural variation of size, properties and quality. The model structure should be sufficiently generic to enable the direct use of product models in a process controller. This model shall be used in a generic model-based controller that is dedicated to the product and product quality. Sufficiently generic models will shorten development time of the controllers in processing of specific agro-material.

In Section 3.2 the relation between product quality and the process is discussed. The model structure is presented in Section 3.3. The applicability of the model is supported by a literature review on modelling of product quality aspects. In Section 3.4 constraints and the variation in processing agro-material are discussed and this leads to an extended model structure. This model structure is applied to an industrial case in Section 3.5. This chapter concludes with a discussion on further research on both modelling and control of processing agro-material.

3.2 Product quality

The quality of food products is subjective, almost by definition, and as such difficult to quantify. However, if quality is to be controlled, it must be defined. According to Porretta (1994) an objective definition of food quality largely depends on the area of interest. It can be determined by organoleptic attributes, chemical composition, physical properties, level of microbiological and toxicological contaminants, the shelf life and/or packaging and labelling. User's preferences and socio-psychological factors such as the users attitude towards the product may, however, not be disregarded (Sloof et al. (1996)) as the consumers perception of *quality* may depend on the actual market situation. Figure 3.1 illustrates the different actors in product quality in processing agro-material. The market and consumer perception of product quality is

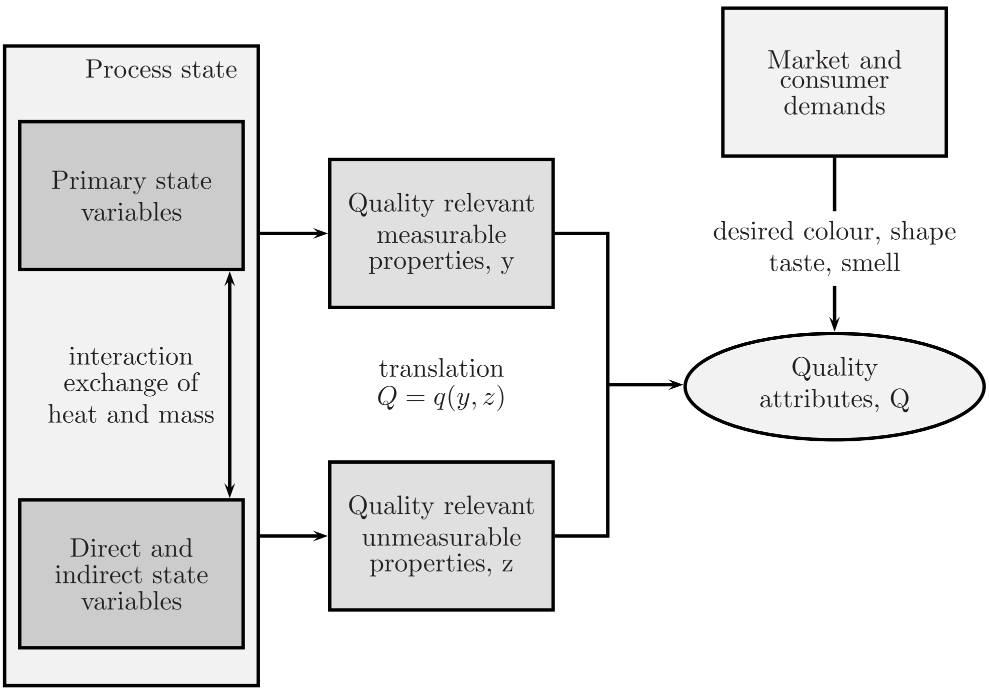


Figure 3.1: *Factors of product quality*

often in terms of quality attributes, Q, such as colour, shape, taste and smell/odour. These attributes are related to and determined by quantitative product properties in terms of concentrations or pseudo concentrations. This is an important assumption in modelling the quality attributes in processing agro-material. These concentrations are the quality-determining state variables referred to as the primary states, x_p, as will be illustrated in subsection 3.3.3. They are subject to biological and/or chemical reactions directly affecting product quality. The rates of these reactions depend on secondary state variables, x_s, such as product temperature, moisture content and pH that do not directly affect product quality. These conditions will not be considered in detail in this chapter. The process outputs are either measurable, y, or unmeasurable, z. The quality, Q, is defined by these process outputs through

$$Q = q(y, z), \tag{3.1}$$

where the unmeasured outputs, the vector z in Figure 3.1, must be reconstructed from the available measurements. The measured outputs are described by a measurement equation. This leads to

$$\begin{aligned} y &= f_m(x_p, x_s), \\ z &= f_r(y), \\ x_p &= \begin{bmatrix} x_p^m \\ x_p^a \end{bmatrix}. \end{aligned} \tag{3.2}$$

where the primary sub-state, x_p, consist of state variables representing the product quality attributes, x_p^m, that directly determine the quality attributes as outputs in either y, or z, and the assisting state variables, x_p^a, representing e.g. an enzymatic concentration, that is not directly quantified as quality. In the examples that are given from literature the state variables are classified into main and assisting states to illustrate the importance of the different states for product quality.

3.3 Modelling the primary state

To include the quality related primary state variables directly in the process controller a model structure is necessary that captures the dynamics of the relevant state variables. In Subsection 3.3.1, a nominal model structure is presented. In Subsection 3.3.2, frequently occurring reactions will be described. The application of this model structure is illustrated in Subsection 3.3.3, where several examples from literature are presented.

3.3.1 A nominal model structure

A product is considered to be a discrete, individual part that may interact with its environment. An agricultural product can be considered as a bioreactor where (biochemical) reactions may take place, such as enzymatic reactions, degradation and respiration. These reactions are quite complex. However, most reaction mechanisms can be simplified to a limited number of basic reactions. It is understood that

this is a gross simplification of reality, however, due to limited knowledge about the mechanisms in quantitative terms and the fact that the model is to be used for control purposes, such a simplification is motivated.
It is assumed that the reactions inside the product and the relation between quality states and attributes can be described with the following model structure,

$$\begin{aligned} Q &= q(y,z), \\ y &= f_m(x_p,x_s), \\ z &= f_r(y), \\ \dot{x}_p &= K(x_s)\; r(x_p), \end{aligned} \tag{3.3}$$

where Q represents the quality attributes that are considered as system output and where the process model is separated in reaction rates and reaction components. Reaction rates, k, are the components in the matrix K and are a function of the environment of the primary sub-state, x_s, such as temperature, pH and concentration, and represent the influence of these processing conditions, x_s, on the rate of the reactions. These coefficients may be subject to constraints that will be discussed in Section 3.4. The dynamics of the primary state variables also depend on the reaction components in the vector r that directly take part in the reactions and are a function of the primary state variables. This separation of dependency of primary and secondary state variables on the dynamics of the primary state variables is of interest to control as these components are associated with different non-linearities and time scales. That such a separation is possible will be illustrated by the examples in Section 3.3.3.

3.3.2 Reactions in agro-material

In this chapter the complex behaviour of biochemical transformation is lumped into three fundamental reactions, namely an enzymatic reaction, a degradation reaction, and a respiration reaction. The lumping into three reactions only is a gross simplification of reality, which, however, is for control sufficiently capturing the product behaviour. In particular modelling assumptions are made about reactions that occur in a smaller time scale. They are assumed to occur instantaneous, thus reach a pseudo steady state at all time and all conditions. Similarly for the very slow processes. In the modelled time scale they do not change and are assumed constant.

Enzymatic reaction
Enzymatic reactions are used to describe the transformation of biochemical components into a set of products. The enzyme plays thereby the role of a catalyst which is not consumed but is essential in enabling the reactions. The enzyme itself

is formed by a separate mechanism. For the consumption of a component of interest, called $Main$, forming a set of products, $Prod_1$, and the formation of enzyme, Enz, with another set of non-limiting products, $Prod_2$, write the two summarized reactions

$$\begin{aligned} Main + Enz &\stackrel{k_1}{\rightarrow} Prod_1 + Enz, \\ Enz + Prod_2 &\stackrel{k_2}{\rightarrow} 2Enz. \end{aligned}$$

The concentration of $Main$ is the primary state variable, x_p^m, and the concentration of the enzyme the assisting state variable, x_p^a, which are used to define the kinetics of these processes. The following dynamical model for the concentrations can be derived for a non-constant enzymatic reaction

$$\begin{bmatrix} \dot{x}_p^m \\ \dot{x}_p^a \end{bmatrix} = \begin{bmatrix} k_1 & 0 \\ 0 & k_2 \end{bmatrix} \begin{bmatrix} x_p^m x_p^a \\ x_p^a \end{bmatrix}, \tag{3.4}$$

the reaction being of second-order and the enzyme formation of first-order. An example for such a reaction is given in the following section.

Degradation reaction

Biochemical transformations that consume the generic component $Main$, and is transformed into products without the use of an enzyme is called a degradation reaction (or with plenty of enzyme so that it is not limiting the reaction)

$$Main \stackrel{k_{degr.}}{\rightarrow} Prod.$$

The associated kinetics are

$$\dot{x}_p^m = -k_{degr.}\, x_p^m, \tag{3.5}$$

which is a first-order reaction. Thermal degradation and firmness of products (e.g. tomatoes) can be modelled with this type of reaction. Biochemical transformations that produce the generic component, $Main$, can be modelled with Equation (3.5), but without the minus sign.

Respiration reaction

This type of reactions is known to be complex. Though, for control purposes they may be simplified by assuming the enzyme dynamics to be fast thus rectifying a pseudo steady state assumption for the enzyme. This reduces the respiration to a degradation reaction. Important is the interaction with the secondary state variables O_2 and CO_2 concentration. The respiration in agro-material can be described with

$$C_6H_{12}O_6 + 6O_2 \rightarrow 6H_2O + 6CO_2,$$

where sugars ($C_6H_{12}O_6$) are transformed into H_2O and CO_2. This reaction is important in, for instance, potato storage where the sugar content is the main quality attribute. The effect of the secondary states is captured in the reaction rates. Details on respiration can be found in Peppelenbos (1996) where the respiration reaction is reduced to a zero-order reaction. More details on the respiration reaction can be found in Hertog et al. (1998b) in which they describe their model of respiration for apple, chicory and tomato. This model considers the effect of oxygen, carbon dioxide and temperature on the respiration rate.

3.3.3 Physical modelling examples

In this section several (physical) models from literature describing product quality attributes are discussed. It is shown that these models can be rewritten into the model structure as proposed in Subsection 3.3.1. Also, some black-box models may fit into this model structure, but these lack the physical motivation and will not be illustrated here. In most examples that will be given, the reaction rates depend on temperature, while other dependencies are neglected.

Example i: Enzymatic reactions of colour in cucumber handling
Schouten et al. (1997) consider colour as the main quality attribute for cucumbers. Cucumber colour changes with time from green to yellow. The quality attribute colour is related to the concentration, c_{Gr}, of a green colour component (Gr) that acts as the main primary state variable, x_p^m. A conceptual enzyme (Enz) concentration, c_{Enz}, that can be seen as a lumped concentration of enzyme activity, is responsible for the disappearance of the green colour component. The enzyme concentration increases in time and acts as an assisting state, x_p^a. The process is described with the following enzymatic reactions that form a second-order autocatalytic model

$$Gr + Enz \quad \xrightarrow{k} \quad 2Enz.$$

This reaction differs from the enzymatic reaction as discussed in Section 3.3.2. However, the same model structure may be used as the reaction in this example is the sum of the two reactions in Section 3.3.2. The differential equations for the concentrations of the components in this example can be written as

$$\begin{aligned} \dot{x}_p &= K\ r, \\ x_p &= \begin{bmatrix} c_{Gr} \\ c_{Enz} \end{bmatrix}, \quad r = \begin{bmatrix} c_{Gr}c_{Enz} \end{bmatrix}, \quad K = \begin{bmatrix} -k(T) \\ k(T) \end{bmatrix}, \end{aligned} \tag{3.6}$$

and this fits in the nominal structure in Equation (3.3). The temperature dependence of the reaction rates in K can be described with an Arrhenius-type equation.

Example ii: Quality in heat treatments
In the food industry the main objective of heat treatments as blanching, pasteurisation and sterilisation is to decrease the enzymatic, bacterial and spore activity. This

activity is often modelled with a first order degradation reaction of an enzymatic, bacterial or spore concentration, c_D,

$$D \quad \xrightarrow{k} \quad D_{degr.}.$$

The reaction rate may depend on e.g. concentration, temperature and pH. From this reaction a differential equation for the primary state variables can be deduced, as is done e.g. in Mussa and Ramaswamy (1997) for the pasteurisation of milk and in Chan et al. (1996) for papayas. This results in

$$\begin{aligned} \dot{x}_p &= K\ r, \qquad (3.7) \\ x_p &= c_D, r = x_p, \quad K = k(T). \end{aligned}$$

Similarly, the concentrations of $\beta - carotene$ in the drying of carrots in Pan et al. (1998) and ascorbic acid in Kajiyama et al. (1998) can be described with Equation (3.7).

In processes that operate at higher temperature all enzymes will be degraded and the primary state variables change due to non-enzymatic reactions. At these temperatures colour changes in processing agro-material are the result of various reactions including Maillard condensation of hexoses and amino components, phenol polymerisation and pigment destruction as stated in Lozano and Ibarz (1997) for the heating of fruit pulp. They modelled the Maillard reaction with zero-order kinetics and the destruction of natural fruit pigments with first-order kinetics. Franzen et al. (1990) model the Maillard reaction also with a zero-order model for describing the drying of skim milk. The models mentioned here fit in the presented model structure.

In literature several models exist which describe non-enzymatic behaviour of the quality attributes firmness and texture in food during thermal operation. Rizvi and Tong (1997) state that most published studies indicate that the primary state variables follow a first-order kinetic model. Another example is the hardness or firmness of cooked beef in Califano et al. (1997) that is modelled similar to Equation (3.7).

Bacterial concentrations are often responsible for the quality of products, e.g. in the transport of strawberries. In this example the concentration of the mould Botrytis is the main quality attribute. The mould concentration is modelled in Hertog et al. (1998a) with a second order degradation reaction.

Example iii: Respiration and enzymatic reactions in potato storage and carrot firmness

In potato storage the quality attribute is defined as the frying colour. The quality attribute frying colour is translated into the quality property sugar content, c_S, of the product. In this example the changing of the sugar (S) can be described by three reactions, as stated in Hertog et al. (1997), representing cold-induced sweetening (the hypothetical enzyme En_{cold}), senescent sweetening (the enzyme En_{sene}) and respiration, where the starch concentration is considered infinite. Furthermore, the two enzyme concentrations change in time. The reactions that are important for quality in potato storage can be written as

$$
\begin{aligned}
S + O_2 &\overset{k_1}{\rightarrow} H_2O + CO_2, \\
Starch + En_{cold} &\overset{k_2}{\rightarrow} S + En_{cold}, \\
Starch + En_{sene} &\overset{k_3}{\rightarrow} S + En_{sene}, \\
En_{cold} &\overset{k_4}{\rightarrow} En_{cold_{non-active}}, \\
En_{sene} &\overset{k_5}{\rightarrow} En_{sene_{non-active}}.
\end{aligned}
$$

The first reaction represents the respiration, and the second and third reactions are enzymatic reactions representing cold-induced and senescent sweetening. Senescent sweetening is an irreversible reaction. This can be included in the model by constraining the reaction rate k_3 to positive values. The fourth and fifth reaction are reactions describing the changing of the assisting enzyme concentrations. From the reactions the following model can be derived

$$
\begin{aligned}
\dot{x}_p &= K\ r, \\
x_p &= \begin{bmatrix} c_S \\ c_{En_{cold}} \\ c_{En_{sene}} \end{bmatrix}, \quad r = x_p, K = \begin{bmatrix} k_1(T) & k_2(T) & k_3(T) \\ 0 & k_4(T) & 0 \\ 0 & 0 & k_5(T) \end{bmatrix},
\end{aligned} \tag{3.8}
$$

where $k_i(T)$ are the reaction rates that are assumed to be only temperature dependent following an Arrhenius-type equation. The model can be extended to describe c_{O_2} and c_{CO_2} dependencies (of reaction rates) and concentrations.

Product firmness is an important product quality attribute as it is related to permeability, taste, shape and shrinkage of the product. The blanching of carrots at low-temperatures is modelled by Verlinden and de Baerdemaeker (1997). In this example firmness is translated into concentrations of different firmness components. A denaturing enzyme, E, catalyses the conversion of an unstable compound, C, in a stable product, R. Besides this enzymatic reaction the unstable compound degrades into products

$$
\begin{aligned}
Q(t) &= Q(0) + c_C + c_R, \\
C + E &\rightarrow R + E, \\
C &\rightarrow Prod, \\
E &\rightarrow E_{degr.}.
\end{aligned}
$$

These reactions result in a model that can be written as

$$\begin{aligned} \dot{x}_p &= K\, r, \\ x_p &= \begin{bmatrix} c_C \\ c_R \\ c_E \end{bmatrix}, \quad r = \begin{bmatrix} c_C \\ c_C c_E \\ c_E \end{bmatrix}, \quad K = \begin{bmatrix} k_1 & -k_2 & 0 \\ 0 & k_2 & 0 \\ 0 & 0 & k_3 \end{bmatrix}. \end{aligned} \tag{3.9}$$

The reaction rates were assumed to depend only on temperature and were described using an Arrhenius equation.

Example iv: Other product quality attributes
Not all product quality attributes can be described with respiration, enzymatic reactions and a degradation reaction. Some examples will be given of cases that do not fit in the proposed structure based on physical/chemical knowledge.
In modelling product colour sometimes so-called CIE-Lab indices (L,a,b) are related to a colour scale value with a (linear) regression model, as is done in Ávila and Silva (1999). For an extrusion process Bhattacharya et al. (1997) related these indices to temperature and screw speed with a regression analysis. These models require non-physical process state variables (e.g screw speed). This contradicts the assumptions made in this chapter.
Franke (1998) proposes a model to describe the product property crystallisation in the chocolate coating with a degradation reaction using the released heat of the crystallisation. The released heat depends on both the actual temperature and the heat that has been released up to the current time.
When there is a lack of knowledge about the underlying biophysical and biochemical mechanisms, the product properties can be modelled using black-box techniques. These include neural networks, fuzzy modelling and parametric relations. An example is modelling the wet-milling quality of grain in a drying process as done by Trelea et al. (1997a). They use a neural network to describe this product property. The model developed is used as a constraint in determining the optimal control strategy, see Trelea et al. (1997b).
The first examples can be described in the presented model structure. The quality attributes are subject to reactions in which a separation can be made between the influence of the primary, x_p, and the secondary (e.g. temperature), x_s, state variables. This illustrates the applicability of the model structure in a range of processes, varying from storage to heat treatments. As is illustrated in example *iv*, some cases may not fit in the proposed model structure. However, as the model structure is applicable in a range of processes with different types of product it can be used in developing a model-based controller methodology. This methodology should be sufficiently generic for a range of operations that process agro-material.

3.4 Extending the model structure

Processing agro-material involves different particularities, such as constraints on product states and reactions, irreversible behaviour, and variation in the quality properties. In this section the nominal (bulk) model structure from Section 3.3 is extended to incorporate these particularities. First, constraints will be discussed in Subsection 3.4.1. Variation in one state variable will be described in Subsection 3.4.2. Variation in more state variables is discussed in Subsection 3.4.3.

3.4.1 Handling constraints

Besides manipulation constraints there are limitations for the values of the process state. These limitations result from physical process boundaries, or from the product, excluding situations where undesired reactions inside the product occur,

$$x_{min} \leq \quad x \quad \leq x_{max}. \tag{3.10}$$

Irreversible behaviour can be reflected in the model structure by restricting the corresponding reaction rate to positive values as is done in *example iii*. The constraints should be included in the control problem to result in realisable controller actions in industrial practice, as e.g. can be done in constrained model predictive control.

3.4.2 Variation in one state variable

A first step towards the modelling of processing a population distribution is to allow for a variation in the initial condition in one primary state variable only. The process model is then constructed from two parts, namely the processing of the nominal product with a nominal process and a mapping of the initial variation (in one variable) into a variation in the product.
The nominal process in Section 3.3 is written as

$$\dot{x}_{p_0} \quad = \quad K r_0. \tag{3.11}$$

The variation or deviation of the product state Δx is defined as the maximum difference between the nominal product and another product. This can be described with

$$\Delta x_p = x_p - x_{p_0}, \qquad \Delta \dot{x}_p = \dot{x}_p - \dot{x}_{p_0} = K(r - r_0), \tag{3.12}$$

where r is a function of the primary state variables x_p and can be written as function of the nominal reaction rate r_0 and the variation in the product state

$$r = r_0 + \Delta r \quad = \quad r_0 + \left.\frac{\partial r}{\partial x_p}\right|_0 \Delta x_p, \tag{3.13}$$

where the derivative is evaluated for the nominal product, which is exactly valid in the linear case. In case the nominal model is non-linear Equation (3.13) is a linearisation around the nominal trajectory. However, as variation is relatively small as compared to the evolution of the nominal product, this linearisation will be sufficiently accurate in most cases. From Equations (3.11)-(3.13) the dynamic behaviour of the variation in the product state as a result of the initial variation can be described with

$$\Delta \dot{x}_p \quad = \quad K \left. \frac{\partial r}{\partial x_p} \right|_0 \Delta x_p. \tag{3.14}$$

Combining the two parts of description for variation in Equation (3.14) and the nominal model description in Equation (3.11) results in

$$\begin{bmatrix} \begin{bmatrix} \dot{x}_p^m \\ \dot{x}_p^a \end{bmatrix} \\ \Delta \dot{x}_p \end{bmatrix} \quad = \quad \begin{bmatrix} K & 0 \\ 0 & K \end{bmatrix} \begin{bmatrix} r \\ \left. \frac{\partial r}{\partial x_p} \right|_0 \Delta x_p \end{bmatrix}. \tag{3.15}$$

This result illustrates that the nominal model structure can be easily extended to describe variation in one state variable, without changing the structure. In Section 3.5 this model extension will be illustrated with a case study.

3.4.3 Variation in several state variables

Quality attributes in processing agro-material could show variations that cannot be described sufficiently accurate with only one primary state variable as is done in Section 3.4.2. The distribution must be included. A complicated continuous distribution model with the main primary state variables as stochastic variable is not a valid possibility as that would often be difficult to quantify with the available (limited) number of measurements.

Alternatively, a three step approximation procedure is presented that, even in a non-linear case, can be sufficiently accurate. The modelling as presented here is to allow for variation in initial conditions of more than one state variable. The first step is to discretise the interval of one chosen state variable. In this description it is assumed that the most important variable that is discretised is a main primary state variable. Nominal (bulk) behaviour for the products is described in each separate interval. This step is motivated by the fact that measurements or quality judgements are often performed in terms of quality classes. This means that the discretisation step in this modelling approach will not restrict the model accuracy required in these cases. The projection of variation in the other state variables onto the discretised one-dimensional subspace (of the main primary variable) results in transfer between the classes. The second and most difficult step is to model this transfer of products between the different classes. The main assumption is that the products within a class are homogeneously distributed. The third and final step is to formulate the variation in all product states as an extension to the nominal model structure.

Step 1: discretisation in quality classes
A main primary state variable is picked as a class specifying variable. The discretisation step in the main primary state variable, x_p^m, is performed, as is illustrated in Figure 3.2, where class intervals are defined and the number of products in each class is shown. The advantage of the discretisation of the quality attribute state space into small intervals is that it allows the approximation of the variation in the quality attributes in these small classes with simplified models, like presented in Subsection 3.4.2.
Dynamic class boundaries are introduced that change in time following the nominal model. In this way product transfer between classes is only caused by variation in the other state variables, in this section an assisting primary state variable. The drawback of dynamic class intervals is that these intervals not necessarily correspond with the quality classes that are measured. Therefore, the intervals should be defined carefully in such a way that at the end of the processing the class intervals correspond with the discrete classes of the quality attributes as they are used in practice.

Step 2: transfer of products
In the second step the transfer of products between the classes is modelled. Due to the dynamic class boundaries, transfer between the classes of the main primary state variable is caused only by the variation in the additional primary state variable in a certain class. The number of products in a class changes due to the transfers and is modelled with

$$\dot{n}_j \quad = \quad -\hat{n}_{j,j+1} + \hat{n}_{j+1,j} - \hat{n}_{j,j-1} + \hat{n}_{j-1,j}, \tag{3.16}$$

where e.g. $\hat{n}_{j,j+1}$ represents the flow from class j to class $j+1$. This is illustrated in Figure 3.2 where the marked areas represent the products that transfer to a neighbouring class. To determine the transfer from a class to the neighbouring class the projection or effect of the variation in the additional state, x_p^a, onto the main state, x_p^m, must be considered. Using the result of Equation (3.14) this effect or projection can be written as

$$\dot{x}_p^{am} \quad = \quad K\,(\frac{\partial r}{\partial x_p^a}\Delta x_p^a)\Big|_{boundary}, \tag{3.17}$$

which is evaluated at the class boundary. The effect $\dot{x}_p^{am}$ represents the variation in $\dot{x}_p^m$ due to the variation in the assisting state variable, x_p^a. The distribution of this assisting primary state variable within a class with respect to the other state variables is assumed to be homogeneous. For sufficiently small class intervals this is a valid approximation as either the number of products that transfer is small compared to

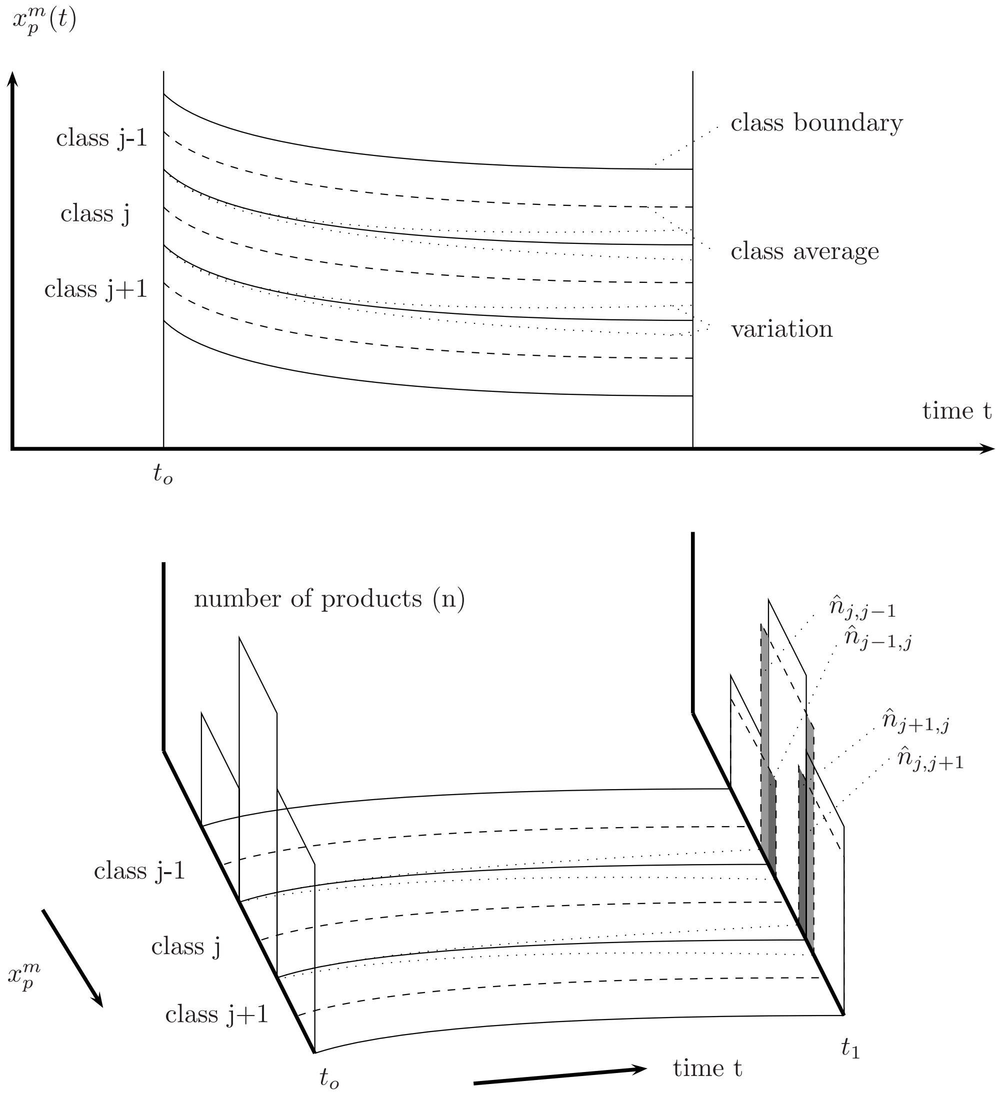


Figure 3.2: *Class behaviour*

the number of particles in a class or the effect of the variation, $\dot{x}_p^{am}$, is small.
The behaviour at the upper class boundary is approximated by

$$\Delta x_p^a\big|_{boundary} \quad = \quad \frac{1}{2}(\Delta x^a_{p_{i+1}} + \Delta x^a_{p_i}). \tag{3.18}$$

The change of Δx_p^a can be modelled similar to Equation (3.14).
For a product in class j to be transferred to the upper class $j+1$, it must fulfill two requirements. First, the assisting primary state variable must be above its nominal value, to assure a positive value for $\dot{x}_p^{am}$. Otherwise, no class boundary

can be crossed meaning that only half of the products can be candidate for transfer to the upper class (the other half may be transferred to the lower class). Second, the product must be in $\Delta x_p^{am}(\Delta t)$ from the class boundary to enable product transfer in time interval Δt. Outside this area the effect of variation in the additional state variable on the main state variable is too small to cause transfer. In the upper plot of Figure 3.2 variation is the maximum $\Delta x_p^{am}(\Delta t)$ in the time interval $t_1 - t_0$. Assuming a homogeneous distribution within a class the average effect of variation in the additional state variable on the main state variable is half of this maximum. Therefore, the proportion of products to be transferred from class j to $j+1$ is

$$P_{j,j+1} = \frac{1}{2}\frac{\frac{1}{2}\dot{x}_{p_j}^{am}}{\Delta x_{p_j}}, \tag{3.19}$$

where Δx_{p_j} is the class width that is defined with $\frac{1}{2}(x_{p_{j+1}} - x_{p_{j-1}})$. Together with the number of products in a class it represents the density of products in the class interval. Using Equation (3.19) the transfer from class j to $j+1$ follows from

$$\hat{n}_{j,j+1} = P_{j,j+1} n_j, \tag{3.20}$$

where $\hat{n}_{j,j+1} \geq 0$. This can be done for all transfers in Equation (3.16) to describe the change of the number of products in a class. For a restricted period of time, $t < t_{limit}$, holds, $x_{p_{j-1}}^m < x_{p_{j+1}}^m$, and therefore $\Delta x_{p_j} > 0$, and the transfer in Equation (3.20) will not become infinite.

Step 3: model formulation
Extending the model structure with variation in several state variables leads to the following model structure

$$\begin{bmatrix} \begin{bmatrix} \dot{x}_p \\ \dot{x}_a \end{bmatrix} \\ \Delta\dot{x}_{var.} \end{bmatrix} = \begin{bmatrix} K & 0 \\ 0 & K \end{bmatrix} \begin{bmatrix} r \\ \Delta r_{var.} \end{bmatrix}, \tag{3.21}$$

with

$$\Delta x_{var.} = \begin{bmatrix} \Delta x_{p_j}^a \\ n_j \end{bmatrix}, \quad \Delta r_{var.} = \begin{bmatrix} \frac{\delta r}{\delta x_{p_j}^a} \Delta x_{p_j}^a \\ \frac{\delta r}{\delta x_{p_j}^a} \frac{\Delta x_{p_j}^a \big|_{boundary}}{\Delta x_{p_j}} n_j \end{bmatrix},$$

where the dimensions of $\Delta r_{var.}$ depend on the number of classes that is chosen in step 1 of the procedure. Equation (3.21) may be simplified using a Taylor approximation around a chosen reference class width, $x_{p_{j_{ref}}}$. Using only the first term on the right hand side of such an approximation results in

$$\frac{(\Delta x_{p_j}^a)\big|_{boundary}}{\Delta x_{p_j}} \approx \frac{(\Delta x_{p_j}^a)\big|_{boundary}}{\Delta x_{p_{j_{ref}}}}, \tag{3.22}$$

that simplifies $\Delta x_{var.}$ in Equation (3.21). Higher order terms can be neglected if $\Delta x_{p_j} \approx \Delta x_{p_{j_{ref}}}$, otherwise they should be included in the model. From Figure 3.2 it can be seen that an extra term for the nominal or average behaviour in the most upper and lower class is necessary with respect to the variation as otherwise transfer from these classes would lead to defining new classes. Half of the effect, as described in Equation (3.17), should be added to the nominal or average behaviour of the upper and lower classes.

With the extensions to the nominal model structure, variation in the main product state that results from variation in the initial values for the other state variables can be described. This will be illustrated with an industrial case study.

3.5 An industrial example

In *example iii* in Section 3.3.3 a model of the potato sugar content, S, as the main quality attribute in potato storage is discussed. This model is used for control purposes as presented in Verdijck et al. (1999b). In this section the model is extended to describe the variation, ΔS, in the primary state variable. First, only the variation in the sugar content is considered and the result in Subsection 3.4.2 can be used. Second, the result from Subsection 3.4.3 is used to model the variation in more state variables.

In the approach with variation in one primary state variable the total model can be written as

$$\begin{bmatrix} \dot{S} \\ \dot{En}_{cold} \\ \dot{En}_{sene} \\ \Delta\dot{S} \end{bmatrix} = K \begin{bmatrix} S \\ En_{cold} \\ En_{sene} \\ \Delta S \end{bmatrix}, \; with\; K = \begin{bmatrix} k_1 & k_2 & k_3 & 0 \\ 0 & k_4 & 0 & 0 \\ 0 & 0 & k_5 & 0 \\ 0 & 0 & 0 & k_1 \end{bmatrix}, \qquad (3.23)$$

where the temperature dependency of the reaction rates k_i is described with Arrhenius type equations. Model parameters used in the simulations are taken from Hertog et al. (1997).

In Figure 3.3 the storage temperature is shown for a time period of eight months. In the beginning of the storage process the temperature is relatively high for two weeks. After this time period the temperature starts to decrease to reach the optimal storage temperature. Reaching the end of the storage process temperature rises, as is common practice in these processes. In Figure 3.4 the simulated and measured frying colour of the potatoes are shown. The frying colours were measured off-line by taking samples at fourteen different moments at three different locations in the storage facility. This measurement technique introduces measurement variance that is relatively large. Values for the colour index that are too high result in unwanted

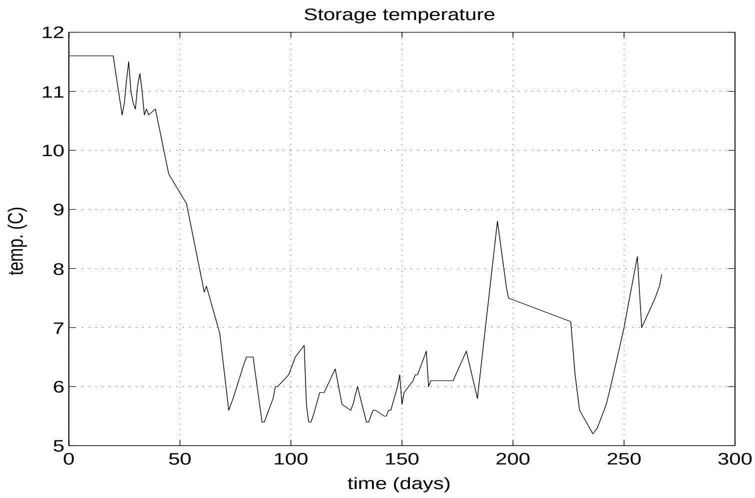


Figure 3.3: *Temperature in storage*

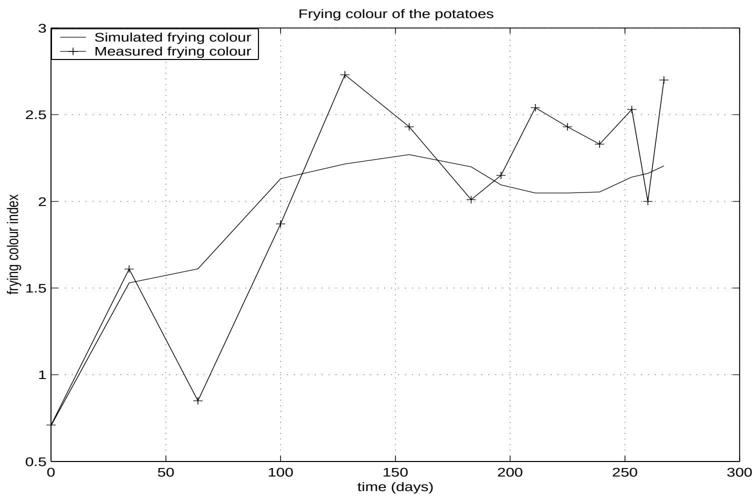


Figure 3.4: *Frying colour in storage*

dark products in the processing industry. The colour index depends on the actual sugar concentration in the product

$$\textit{Colour index (Q)} = \left(\frac{c_s}{0.02}\right)^{\frac{1}{2.047}}. \tag{3.24}$$

In Figure 3.5 the simulated and measured sugar concentrations are shown in time, both for the nominal or average sugar content and the variation in the sugar content.

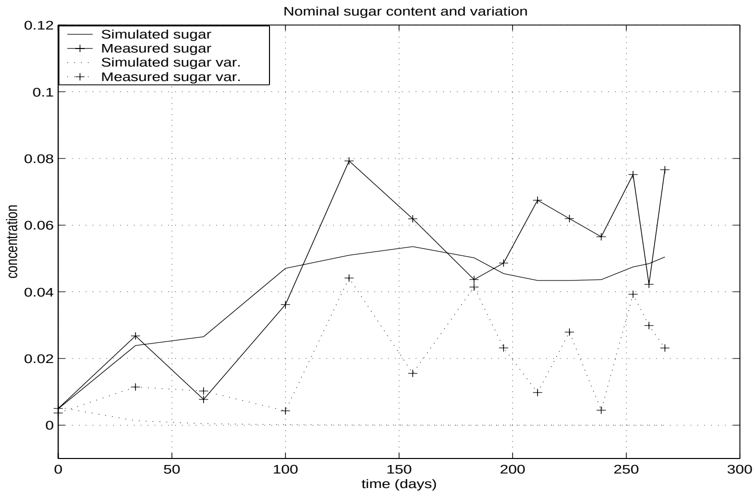


Figure 3.5: *Sugar content in storage with variation in one variable*

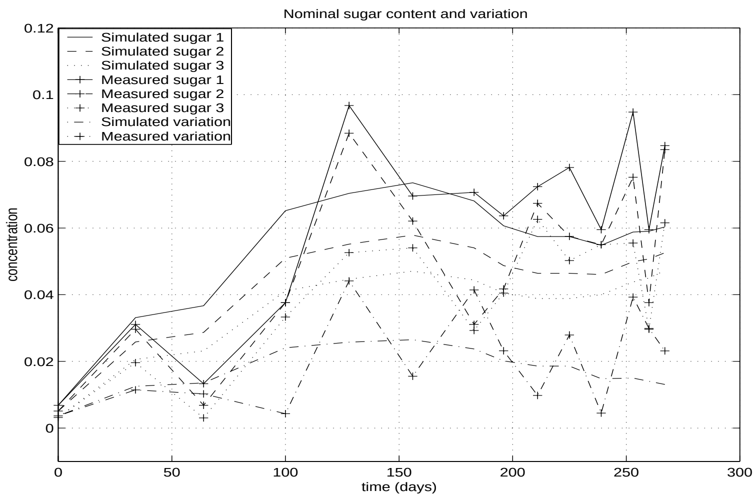


Figure 3.6: *Sugar content in storage with variation in more variables*

The results with variation in one variable are not very satisfying. This corresponds with the experience that products with similar sugar concentrations may end up with different sugar concentrations due to variation in other variables. Therefore, the results from Section 3.4.3 are used to model the effect of variation in more state variables. In this case study the variation in other variables is assumed to be accumulated in the assisting primary state variable En_{cold}. Three different classes are defined based on the (measured) initial variation in sugar content. The modelling structure is used from Section 3.4.3 with sugar content and both enzyme concentrations for each class, number of products for each class and the variation in the enzyme concentration En_{cold} in each class as the state variables. The results obtained with this model are shown in Figure 3.6. The results using the different classes improve the understanding of the behaviour of the product in the storage process with respect to the sugar content. The sugar contents for the different classes are within the measurement accuracy. The simulated variation shows similar behaviour as the measured variation between the measured samples. Differences can be explained by measurement noise. The (small) decrease of variation shown at the end of the simulations corresponds with empirical knowledge. This also explains the transfer of products between the classes (not shown) that shows a decrease in variation.

3.6 Conclusions

In this chapter a modelling structure is presented for describing the dynamics of product quality in processing agro-material. The objective of this model structure is to describe the most important dynamics of the product quality properties. This enables the development of a model-based control methodology that is dedicated to the product and product quality. Therefore, in the model a separation is made between the influence of the primary and the other state variables. Some often occurring reactions were described that are responsible for the dynamic behaviour of the product properties to motivate the presented model structure. Examples of processing agro-material were given that could be modelled using the proposed model structure. Furthermore, the nominal model structure was extended to include constraints and variation in one or more state variables. The extended model structure was used in a case study for the storage process of potatoes. This illustrated the applicability of the proposed model structure.
This chapter focused on the product properties, where the influence of the product environment is considered to be known. In the development of a control methodology, a modelling approach for the product environment and the important interaction between product and its environment must be developed. Eventually, this will enable the development of a model-based control methodology that shortens control design and development time for operations that process agro-material and improves product quality in these processes.

Notation

D	degrading component
Enz	enzyme concentration that acts as assisting primary state variable
K	system matrix
$Main$	main primary state variable
P	transfer probability $[s^{-1}]$
$Prod$	reaction product from reactions inside the product
Q	quality attribute
T	temperature $[^{\circ}C]$
c	concentration
f	function
j	class number
k	reaction rate $[s^{-1}]$
n	number of products
$\hat{n}$	product transfer between classes
r	reaction components
q	quality function
t	time $[s]$
x	process state
y	measurable outputs
z	non-measurable outputs of interest
Superscripts:	
a	assisting
am	projection of assisting state variable on main state variable
m	main
Subscripts:	
0	nominal value
$boundary$	boundary value
$degr.$	degradation
m	measurement
max	maximum value
min	minimum value
p	primary state variable
r	reconstruction from measurements
ref	reference value
s	secondary state variable
$var.$	variation

Chapter 4

A Modelling and Control Structure for Product Quality Control

abstract

In this chapter a modelling and control structure for product quality control is presented for a class of operations that process agro-material. This class can be characterised as climate controlled operations, such as storage, transport and drying. The basic model consists of three parts. These are the quality and behaviour of the product, and its direct and indirect environment. This decomposition is reflected in the proposed control structure. The significance of the explicit inclusion of product behaviour is that the control is much more geared to the demands of the product. The applicability and potential advantages of the proposed structure are illustrated in different industrial cases, such as the storage of potatoes and the transport of apples in reefer-containers.

G.J.C. Verdijck, G. van Straten

A Modelling and Control Structure for Product Quality Control in Climate Controlled Processing of Agro-material, Control Engineering Practice, 10(5):533-548,2002.

4.1 Introduction

Tighter demands on the efficiency of post-harvest processes as well as quality requirements require a dynamical operation that directly includes the relevant product characteristics. Present process controllers aim at keeping climate variables, such as temperature, as close as possible to setpoints. These setpoints are determined *a priori* and are constant, or, at best, adjusted according to pre-set blueprints. The dynamical aspects of product behaviour with its quality attributes are not directly controlled in processing agro-material. Furthermore, the present controllers act as lower-level subsystems that are not interconnected. This makes it difficult to incorporate input/output constraints into the design, which is essential if an optimal but practical solution is to be found (Katebi and Johnson (1997)). In contrast, model-based (supervisory) controllers allow for connecting sub-systems and incorporating constraints. These developments enhance the opportunity for a new controller methodology for processing agro-material, as is also stated e.g. in Galara and Hennebicq (1999) and for drying operations in Achanta and Okos (1996). Using models of the process and product in the controller (e.g. in Model Predictive Controllers) enables the use of prediction and optimisation techniques to determine the most appropriate control action. The goal of the new controller methodology is the use of the maximum knowledge about process and product quality to design controllers that are safe, energy efficient, reduce quality variation and maximise product quality. The first step in the development of such controllers is to define a generic modelling and control structure.

In this chapter such a structure will be presented that is fit to a special class of climate controlled post-harvest processes. This class is characterised by different time scales (as in most post-harvest processes involving agro-material), and disturbance and control inputs that only drive the product environment and not the product directly. The model and control structure must be dedicated to product and product quality. Furthermore, it should be sufficiently generic in order to shorten development time and reduce cost of the controllers for a range of processes.

In Section 4.2 the modelling of operations that process agro-material is presented. The control structure is presented in Section 4.3. In Section 4.4 the control structure is used in industrial cases to illustrate the applicability of the developed structure. This chapter ends with conclusions and suggestions for further research on the development of a generic controller methodology for processing agro-material.

4.2 Modelling

First principle based modelling starts with the conservation laws for the extensive variables energy, mass and momentum. The model in extensive variables is reformulated in terms of intensive variables, such as temperature and concentration, resulting in a set of differential equations for the process state. From this set the following (physically oriented) separation of the process state in sub-states can be deduced,

- primary product states, x_p, that are subject to reactions of biological and/or chemical components in the product representative for the product quality attributes, Q, such as colour, shape, taste and smell,
- secondary product states, x_d^p, that are not directly involved in the reactions, but indirectly through the reaction constants, such as temperature and moisture content of the product,
- direct climate states, x_d^c, that are directly in contact with the product, such as temperature and humidity of the air directly surrounding the product, and
- indirect climate states, x_i, that are not directly in contact with the product, such as temperature and humidity of the air in air channels, air rooms etc.

The sub-states for the secondary product states and the direct climate states can be considered together as one environment. This is motivated by the observation that the time scales for these state variables are of the same order of magnitude. The fast equilibrium between these state variables makes them behave as one entity. Consequently, the system can be separated into three sub-states

- primary sub-state (x_p),
- direct environment sub-state (x_d) that directly interacts with the primary state variables,
- indirect environment sub-state (x_i) that does not affect the product directly, but only through the direct environment.

This separation in the process model is particularly suited for control purposes as aimed at here. The relations between the different classifications into sub-states are illustrated in Figure 4.1. In Figure 4.2 the relations between the different components of the model structure are shown. The structure of the process is strictly hierarchical whereby the primary state variables are in the center, capsulated by the direct environment state variables of the containing unit. The indirect state variables

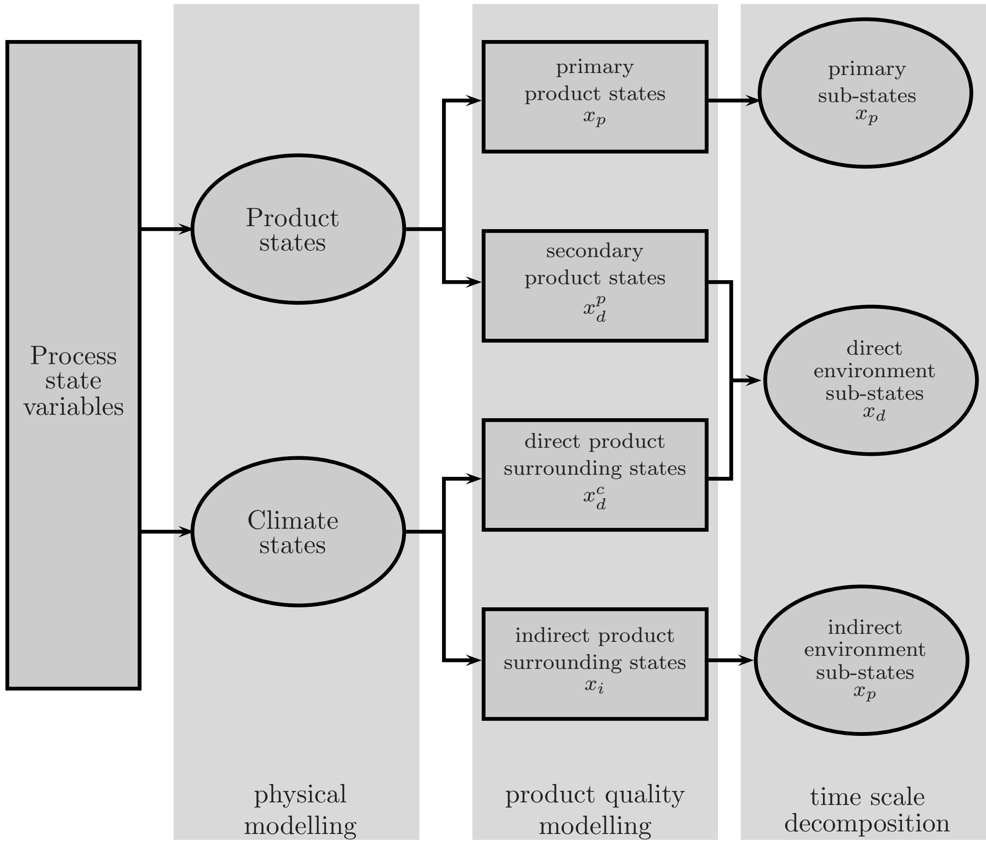


Figure 4.1: *Relation between the different classifications of sub-states*

form yet another outer shell enclosing the unit completely. As it is, the plant input, that can be manipulated only, is sequentially linked together with the primary state variables, which are the target, with the environments in between. This observation is characteristic in operations that involve agro-material. In Table 4.1 time scales are presented that are representative for storage, transportation and drying. The differences between the time scales of the sub-states enable the development of a decoupled control structure.

Thus, in this section a classification of the whole system into three sub-states is made. An example of the proposed classification in three hierarchically coupled sub-states as developed here is in potato storage where the sugar content is the primary state variable. The direct environment consists of a non-quality product component (e.g. product temperature) and a climate component (e.g. air temperature). Air temperatures in the air channel and air room belong to the indirect environment.

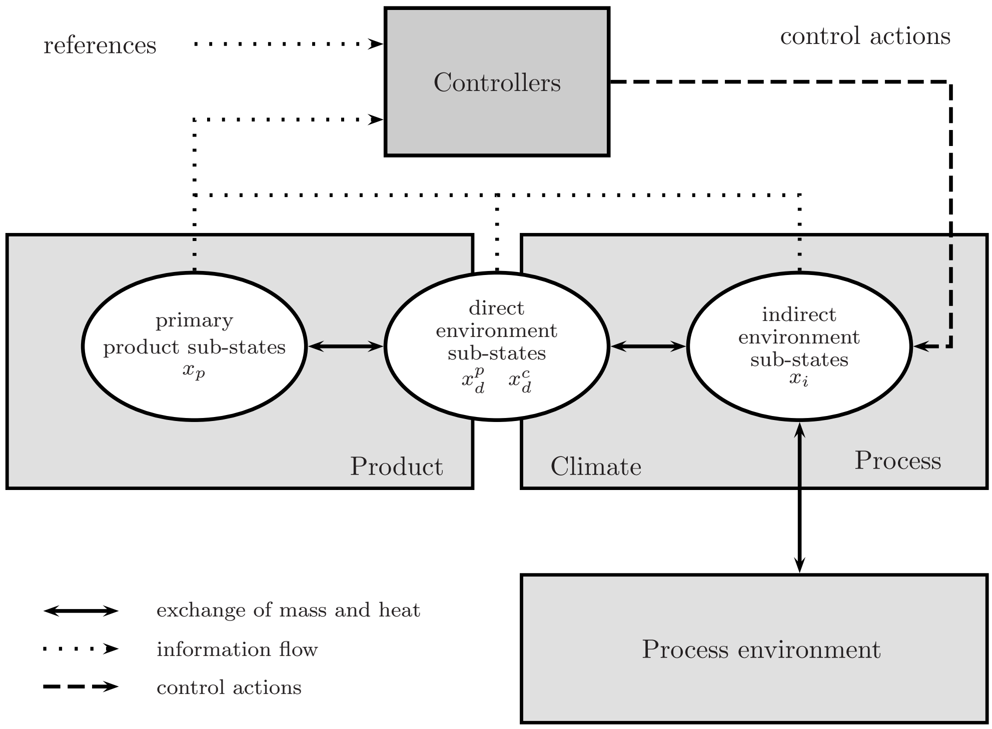


Figure 4.2: *Relation between model components*

Table 4.1: *Time scales of agro-processes*

time scales sub-states (τ)	storage	transport	drying
product (τ_p)	days/weeks	hours/days	seconds/minutes/hours
direct environment (τ_d)	hours/days	hours	seconds/minutes
indirect environment (τ_i)	minutes	seconds/minutes	seconds
hardware controllers (τ_h)	seconds	seconds	seconds

4.2.1 Primary sub-state

The primary state variables are subject to reactions that take place inside the product. These reactions cause changes in the state variables and, therefore, in the quality attributes. The product model describes the dynamics of the primary state variables, x_p. It can be shown that the product model is defined by

$$\dot{x}_p = Kr, \tag{4.1}$$

where the vector r is a vector valued function of the primary state variables and the matrix of functions K consists of the reaction constants that may depend on the direct environment states

$$\begin{aligned} r &= r(x_p), \\ K &= K(x_d). \end{aligned} \tag{4.2}$$

For example, the rate of the reactions, that take place inside the product, depend on product temperature. More details on modelling the product quality attributes are given in Verdijck et al. (2001). The main assumption in Equation (4.2) is that the state variables in the direct environment are not limiting for the reactions inside the product.

4.2.2 Direct environment sub-state

The direct environment consists of a product component, x_d^p, and a climate component, x_d^c. Both can be constructed from the conservation laws for mass and energy. These balances result in ordinary differential equations for the temperature and mass concentrations of the different components. Examples of state variables in the product component are temperature and total mass. Product temperature influences reaction rates in the product and product mass is important in considering undesired weight-loss of the product. Weight-loss can not only decrease product quality, but may also be important for the financial yield of the product after transport. The dynamics of the state variables of the product component can be written as

$$\dot{x}_d^p = f_d^p(x_p, x_d). \tag{4.3}$$

These state variables are not controlled directly, but only through the manipulation of the climate component. Furthermore, they are not subject to outside disturbances, that is, these disturbances only affect the product component indirectly .
The dynamics of the state variables of the climate part, such as temperature and oxygen concentration of the air, can be written as

$$\dot{x}_d^c = f_d^c(x_p, x_d, x_i). \tag{4.4}$$

In case an interaction between x_d^p and x_d^c can be considered infinitely fast, an algebraic relation is added to the system description that reduces the dimension of this sub-state. Such a relation can be written as

$$0 = f_c(x_d^p, x_d^c). \tag{4.5}$$

In the proposed model approach only lumped state variables are considered. In case gradients inside the product or its environment are too important to be neglected,

a spatial distribution could be considered. This step results in separate lumped (sub-)systems that together approximate the gradients and still fit in the proposed sequential model structure.
The non-linearities in this model component are located in state dependent model coefficients, e.g. temperature dependencies of heat transfer coefficients.

4.2.3 Indirect environment sub-state

The state variables in the indirect environment may be controlled directly and their dynamics can be written as

$$\dot{x}_i = f_i(x_d^c, x_i, u, v_{md}, v_{ud}), \tag{4.6}$$

where u represents control actions, and the measured and unmeasured disturbances are represented by v_{md} and v_{ud} respectively. The indirect environment in these processes has relatively fast dynamics. This is caused by the relatively low thermal mass in this part of the process. Examples of this indirect environment are the air room and air channel in potato storage (Verdijck et al. (1999a)), and the headspace in container transport, respectively.
The model may have non-linear terms in the control inputs. This occurs as e.g. both flow rate and incoming temperature of this flow act as controlled input. This would lead to a non-affine system (non-linear in the control input) which requires special care in choosing the control algorithms, as is mentioned in Mutha et al. (1997).

4.2.4 Model structure

Equation (4.2) through (4.6) have been written in the presented form in order to show the (sequential) interaction between the sub-states and their effect upon product quality. The system can be described as a sequence of interacting sub-systems.
The complete state space model is summarised by

$$\begin{aligned} \dot{x}_p &= Kr, \\ \dot{x}_d &= f_d(x_p, x_d, x_i), x_d = [x_d^p \;\; x_d^c]^T, \\ \dot{x}_i &= f_i(x_d^c, x_i, u, v_{md}, v_{ud}), \\ 0 &= f_c(x_d^p, x_d^c), \\ r &= r(x_p), \\ K &= K(x_d), \end{aligned} \tag{4.7}$$

with the output relations

$$y = f_m(x), \;\; x = [x_p \; x_d \; x_i]^T,$$

$$
\begin{aligned}
z &= f_r(y), \\
Q &= f_q(y, z),
\end{aligned}
$$

where z represents the unmeasured process outputs to be reconstructed from the available measurements that are represented by y. The function $f_m(x)$ is the so-called measurement equation and the function $f_r(y)$ represents a reconstruction filter. As product quality, Q, often is a complex function of process outputs, both measured and reconstructed, an additional quality equation $f_q(y, z)$ is added to the model structure.

4.3 Control structure selection

Improving process control involves:

- the formulation of the control objective,
- building the necessary models,
- selection of the control structure,
- design of the selected controllers,
- validation of the control system and
- implementation of the controller.

The selection of a control structure is an important step, although this step is often not given much attention. It determines the inputs and outputs of the control components, the objectives of the different control components and the control performance. In this section a control structure will be proposed for the class of operations that is discussed in this chapter. The control structure is applicable in an industrial environment, as will be shown in Section 4.4.
The control structure is not a trivial choice for the type of processes, discussed in this chapter, as there are different time scales, uncertain information and practical constraints in the design procedure. A non-optimal control structure results in a non-optimal control design and, therefore, in non-optimal operation of the controller and the process. The selection of a control structure can be seen as an optimisation problem where the objective is to determine or select the control structure with low complexity without loss of performance. This involves the aspect of time scales that may occur in the process and the separation of time scales, if possible, and the optimal use of available information while considering the uncertainty of this information. Also, to achieve the desired process performance the system must be in the span of the controller. For the industrial application it is important to guarantee a certain

degree of robustness and reliability, as the processes operate with a large variance in the product. These aspects will be discussed in the Sections 4.3.3 and 4.3.4 after a discussion of practical constraints that affect the selection procedure in Section 4.3.2. First, in Section 4.3.1, the total control structure is presented for the class of operations that is discussed in this chapter.

4.3.1 Control structure

In selecting a control structure in climate controlled processing of agro-material, all aspects must be considered that are mentioned earlier in this section. In Figure 4.3 the general control structure is illustrated with a control component for each substate of the process model from Section 4.2. In short, the indirect environment is controlled by the local controllers. The direct environment is controlled by the short-term controller. The short-term controller calculates the setpoints u_s for the lower level control components. The primary state variables are controlled by the long-term controller that performs an economical optimisation resulting in reference trajectories, u_l^{ref}, and settings for variables that are not controlled on the short-term level, u_l^{set}, the so-called partial control,

$$u_l \quad = \quad [u_l^{ref} \; u_l^{set}]^T. \tag{4.8}$$

Examples of the different controlled variables will be discussed in more detail in the case studies. In the container case, u_l^{ref} represents the product respiration trajectory, u_l^{set} e.g. the relative air humidity, and u_s the temperature and oxygen concentration in the container. In the following sections motivation and details for this control structure will be discussed.

4.3.2 Practical constraints

Often in an industrial environment, practical constraints are imposed on the control structure. One such constraint is that the model-based (supervisory) controllers may not control directly the process quantities of interest, but only by means of the settings of the local controllers. The advantage of this approach is that, in case of control system failure, the operator can return to the existing low level subsystems. Of course, the drawback is that the local control dynamics often can not be changed and must be taken into consideration in the development of the supervisory controllers. In the class of operations that is discussed in this chapter, it is assumed that it is necessary to cope with this practical restriction. In the case studies presented in this chapter this constraint will be illustrated.
In industrial practice there will be operating constraints for the controller. Constraints result from local controller performance possibilities, the product, outside weather

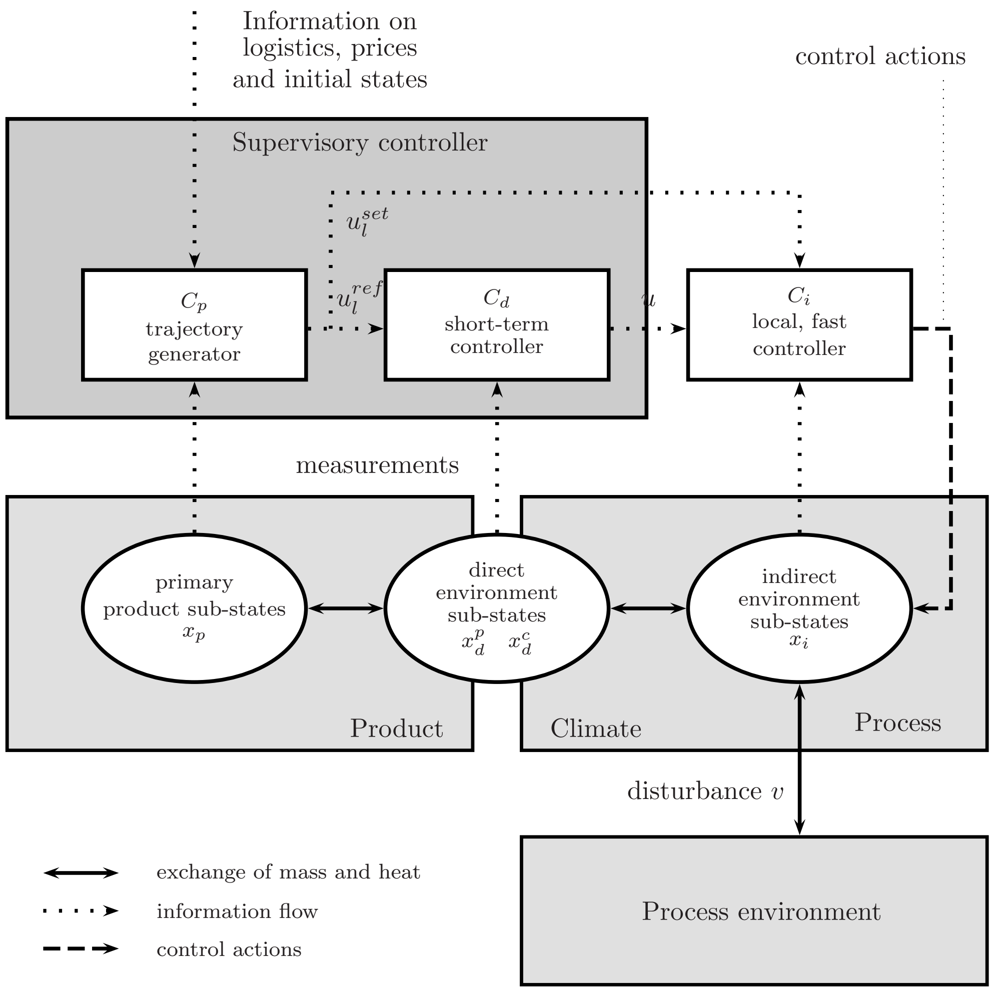


Figure 4.3: *General control structure*

and the process capabilities. These have to be included in the control problem of the supervisory control components.

4.3.3 Decoupling of time scales

Decoupling reduces controller complexity and improves understanding and insight in the controller and the process by the end-users. Decoupling is possible if there is a significant difference between the time scales in the process as illustrated in Table 4.1. On a supervisory control level the fast dynamics in the process can often be ignored by assuming a pseudo-steady state, while studying slow dynamic behaviour.

This is a valid approximation in the presence of slowly fluctuating inputs. In this approximation the time for the fast dynamics to settle in the pseudo-steady state is ignored and the different time scales are decoupled. It should be noted that, in presence of fast fluctuating inputs, this could give rise to non-optimal control performance, as discussed in van Henten (1994) in the optimal control of greenhouse operation based upon singular perturbation theory.
The decoupling of dynamics, as done here, is supported by practical considerations for the class of operations in this research. These are that desired changes in the state variables by the controlled inputs are constrained to relatively slowly changing values to prevent product stress and that external disturbances only slowly affect the environment of the product. In transport and storage processes the expected disturbances often are the outside weather conditions that may change rather fast. However, due to insulation fast outside disturbances only affect the inside conditions with slow dynamics. Also in drying operations disturbances of outside conditions often are relatively small due to the factory building where the operation is located. The main disturbance in this process is the product flow, which often has slow dynamics. This motivates the choice for the decoupled control structure. The fast dynamics of the indirect environment are dealt with on the local control level. The relatively slow dynamics of the direct environment and the product are dealt with on the supervisory control level.

4.3.4 Availability of information

As presented in Subsection 4.3.1, on the supervisory control level there are sub-controllers for the different sub-states. These are the short-term controllers. Furthermore, there is a long-term controller or trajectory generator.
The different control components require process and product information. Together with the effect of the candidate inputs, the availability of this information determines which variables are controlled in each control component. There are essentially two types of problems regarding the availability of information in processing agro-material. The first type of problems is that necessary information is not always available or is rather uncertain. E.g., exact information on the outside weather conditions is only available at the actual time, predictions are available for five days at most and only averages over several years are available for long-term objectives. The first type of problems are solved by the separation in long-term and short-term control components. Information on weather averages over several years is used by the long-term controller to determine the trajectories for the process state. Weather predictions could be used in the short-term controllers to anticipate on this process input.
The second type of problems is that the influences of the different system inputs on

product quality are not known with equal accuracy and that there often are more outputs than inputs of the system. The second type of problems are solved by the use of some of the long-term controller outputs directly as setpoints for the local controllers, and some as reference trajectories for the short-term controller. The reference trajectories, u_l^{set}, are used to control the main outputs exactly. Other process outputs, that outnumber the remaining inputs, are set directly by the long-term controller, u_l^{ref}. Of course, these outputs can only be kept within certain domains. Such a separation of controllable inputs could be evaluated in terms of partial control, see Kothare et al. (1998). The choice whether or not the selected inputs should be controlled at all and by which controller is difficult to quantify. For uncertain systems robust analysis may answer this question, see e.g. Braatz et al. (1996). However, in the processes that are discussed in this chapter, often more information is available than only unmodelled dynamics. The model structure is often known. The selection of the controlled inputs for the controller components on the supervisory level is determined by the effect a candidate input has on the output y. A candidate input is controlled by the short-term controller if its effect on the output is sufficiently large. The effect of a candidate input can be calculated with

$$\frac{u_0}{y_0}\left.\frac{\partial y}{\partial u}\right|_{u_0,p_0}, \quad with \quad y \in \Re^i, u \in \Re^j, \tag{4.9}$$

resulting in a $i * j$-matrix, with i the number of process outputs, j the number of inputs, and where u_0 and p_0 represent the operating conditions and nominal expected model parameters. The inputs with the larger effect are controlled by the short-term controller, in u_s. Otherwise they are controlled by the long-term controller, in u_l^{set}, or stay fixed. An example will be given in the case studies in Section 4.4.

4.3.5 Limitations of the control structure

The control structure that is presented in this chapter assumes slowly changing control inputs and disturbances. If this assumption is not met decoupling the sub-states could be inappropriate depending on the effect of the input on the system.

In general model-based control performance strongly depends on the quality of the models and that is also true for the processing of agro-material. Especially choosing or determining the model structure and the state variables of interest should be given enough attention. An inappropriate model structure would minimise the control performance. In case there is an appropriate model structure parameters in the model may be unknown, uncertain, or changing in time. This requires the use of a type of estimator, either on-line or off-line. This should improve the control performance as will be shown in the case study on potato storage.

4.4 Industrial examples

4.4.1 Potato storage

Storage is an important part of the production cycle in the food industry. Although harvesting is season-bound, the food industry demands year-round supply of potatoes. During the storage period product quality declines. In potato storage, product quality is defined as the sugar content that is expressed in the so-called frying colour index. The industry is enforced to improve process control to increase the added value of processing/storing potatoes.

Model

The models of the process components enable on-line product quality prediction and are used for model-based control purposes. The model of the potato storage process is presented in Verdijck et al. (1999a). The main primary state variable is the sugar content, x_p^m, and the concentrations of two enzymes are the assisting primary state variables. These enzymes cause cold-induced, x_{p1}^a, and senescent sweetening, x_{p2}^a, as presented in Hertog et al. (1997) together with the model parameters. The direct environment state variable is the product temperature, x_d^p. Total mass as product component, and air temperature, x_d^c, and humidity (and CO_2) as climate component can also be considered as direct environment state variables. Product temperature determines the reaction rates changing the quality states and weight-loss. This weight-loss is mostly determined by evaporation and is important for the financial yield after storage and for the overall product condition. Air humidity drives the evaporation or condensation and too high CO_2 concentration causes quality decline of the product. This is an unmodelled feature handled by a (knowledge-based) constraint. The indirect environment state variable is the air temperature in the air channels, x_i. In Equation (4.10) the differential equations are written for the primary state variables, and for the direct and indirect environment state variables, with respect to temperature. This model is used for a time scale analysis in the control structure selection. In simulation studies a more complicated nonlinear model is used.

$$
\begin{aligned}
\dot{x}_p^m &= k_1(x_d)x_{p1}^a + k_2(x_d)x_{p2}^a - k_3(x_d)x_p^m, \qquad (4.10)\\
\dot{x}_{p1}^a &= -k_4(x_d)x_{p1}^a,\\
\dot{x}_{p2}^a &= k_5(x_d)x_{p2}^a,\\
\dot{x}_d^p &= \frac{1}{(1-\epsilon)\ \rho_p\ Cp_p}[R + UA(x_d^c - x_d^p)],\\
\dot{x}_d^c &= \frac{1}{\epsilon\ \rho_a\ Cp_a}[\rho_a\ F\ Cp_a\ (x_i - x_d^c) + UA(x_d^p - x_d^c)],
\end{aligned}
$$

$$\begin{aligned}\dot{x}_i &= \frac{1}{\rho_a\ Cp_a}[\rho_a\ F\ Cp_a\ (u - x_i)],\\ y &= x_p^m,\\ Q &= f_q(y),\end{aligned}$$

where evaporation and conduction are neglected. The process output y represents the sugar content of the product. The control input u is the air temperature entering the air channel that is manipulated by the local controller. Product quality is referred to as a frying colour index and depends on the process output

$$Q = (\frac{y}{0.02})^{\frac{1}{2.047}}. \tag{4.11}$$

The eigenvalues, time constants and eigenvectors of the system matrix (with terms smaller than 10^{-8} set to zero) are shown in Table 4.2. From this table it

Table 4.2: *Time scales potato storage*

sub-states	description	eigenvalue	time constant	eigenvector		
primary	sugar content	$-8.9 * 10^{-9}$	10^8 (s)	[-0.999	$1.33 * 10^{-4}$	$1.06 * 10^{-5}$
				-0.0269	-0.0233	0]
	En_{cold}	$-5.93 * 10^{-8}$	10^8 (s)	[-0.883	0.468	$7.57 * 10^{-6}$
				-0.0238	-0.0206	0]
	En_{sens}	$2.031 * 10^{-7}$	10^7 (s)	[$5.4 * 10^{-4}$	$-1.4 * 10^{-8}$	1
				$1.5 * 10^{-5}$	$1.3 * 10^{-5}$	0]
direct env.	product	$-4.55 * 10^{-5}$	10^4 (s)	[$4.749 * 10^{-4}$	$4.15 * 10^{-6}$	$1.38 * 10^{-6}$
				-0.7565	-0.6539	0]
	air around the product	-1.888	1 (s)	[0	0	0
				$-1.8 * 10^{-4}$	1	0]
indirect env.	air channel	-9.720	10 (s)	[0	0	0
				10^{-6}	$-3.27 * 10^{-2}$	0.999]

can be concluded that the primary state variables have the slowest dynamics, as was expected. The unstable assisting state variable, x_{p2}^a representing senescent sweetening, will not lead to problems regarding the time scale of interest for the storage period (max. 10 months). The product temperature is a direct environment state variable with medium dynamics, while air temperature around the product has faster dynamics. The indirect environment state variable has the most fast dynamics. The time constants for the main primary state variable, sugar content, can also be approximated by

$$\tau_p = \frac{x_{p_{max}} - x_{p_{min}}}{[\frac{dx_{p_{max}}}{dt}]_{x_{p_{min}}}}, \tag{4.12}$$

as is used in Weijers (2000). In Figure 4.4 the response of the sugar content in time as function of storage temperature is presented. This result is used to approximate the time constant for the primary sub-state with Equation (4.12). Also, in this figure the step response (after 100 days) to a temperature change from 5 to 7 degrees is shown that illustrates the slow dynamics of the sugar content.

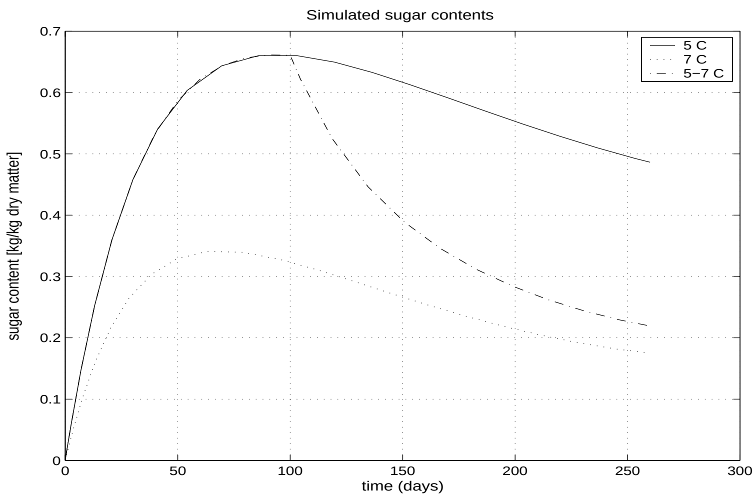


Figure 4.4: *Sugar content in time as function of temperature*

Control structure selection

The new controller structure developed along the line presented in this chapter aims at improving product quality while at the same time restricting energy consumption. In the past the local controller was the only controller in the potato storage process controlling a fixed air temperature. The incorporation of the local controller was a practical constraint for the new control structure.
Due to the different time scales a time scale decomposition is performed. Through the strong interaction (heat exchange) between product and air direct in contact with the product and the relatively slow and small influence of other variables (e.g. ambient temperature) on product temperature, product temperature follows the air temperature. This can also be seen from the eigenvectors where the influence of the air temperature on product temperature is relatively large in the eigenvector corresponding with the eigenvalue of the product temperature. As the values in the eigenvectors for the direct and indirect environment state variables refer mainly to the state variables in the same environment, this motivates the separation in

different control components. The control structure is shown in Figure 4.5. From Equation (4.9) the effect of temperature shows the highest impact on the system output (sugar content) and is selected to be controlled by the short-term controller, u_s. The long-term controller calculates the reference sugar trajectories, u_l^{ref}, (x_p^*),

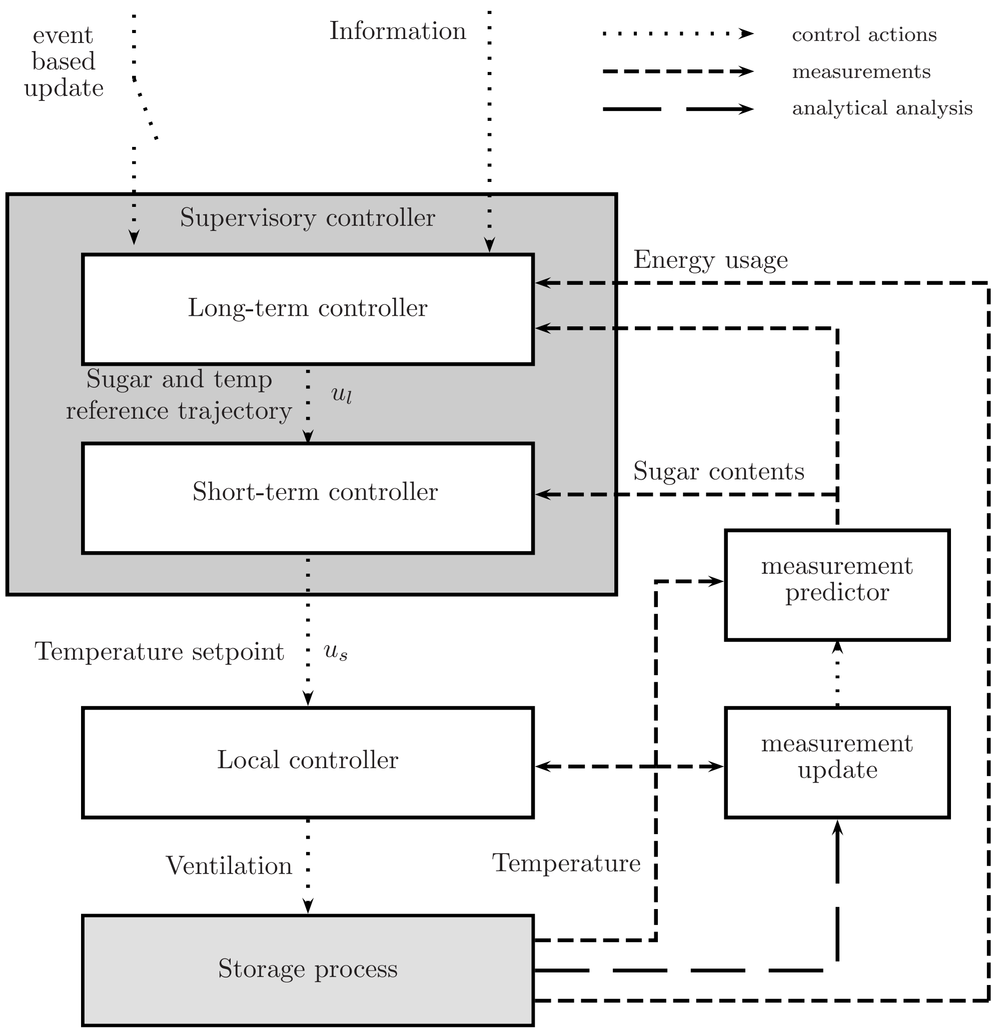


Figure 4.5: *Control structure in potato storage*

and also the expected long-term temperature, (x_d^*), both used by the short-term controller. Compared with the general control structure in Figure 4.3 sugar content is not only considered in the long-term controller, but also in the short-term controller with a prediction horizon of two weeks. This is motivated by the desire to control product quality and the presence of unexpected outside weather conditions. These may result in off-setpoint operation in case of cooling with outside air (instead of applying mechanical cooling). No outputs of the long-term controller are used directly by the local controller, $u_l^{set} = [-]$. The sugar reference trajectory is calculated at the start of the storage process. The calculation can be repeated in case of unexpected situations such as, an extreme cold winter, ventilation problems, product diseases, changing storage periods or a large update in the model parameters. This update is event based. The short-term controller is a linear model predictive controller and determines the optimal process condition (storage temperature), using the short-term control output as an adaptation on the expected long-term temperature, that keeps the primary state variable sugar content as close as possible to its reference trajectory with limited energy usage. The calculation of the temperature setpoint is performed weekly. Measurements of the sugar content are estimations with a product model that is regularly updated/adapted with analytical data of product samples.

Control components

Long-term controller
The long-term controller or trajectory generator optimises the long-term overall economic objective of the process using e.g. the weather averages over several years. This controller uses information that would not be usable in a short-term approach. The long-term controller calculates the desired trajectories of the states by calculating the objective function for different pre-defined temperature trajectories. The objective function can be written as

$$\min_{u_l} J \quad = \quad -P(Q(t_f))M(t_f) + \int_{t_0}^{t_f} L(x, u_l, v, \tau)d\tau, \tag{4.13}$$

subject to Equation (4.7), with P the price of the product that depends on the end-quality $Q(t_f)$, $M(t_f)$ the end-mass of the product and the integral with cost function L represents the cost that are made to achieve the desired primary state variables and direct and indirect product environment in presence of disturbances. The cost function is discussed in more detail in Chapter 6. This objective function tries to achieve maximum product quality, minimum weight-loss and minimum cost to result in a maximum performance. Inputs are information on the final process time, t_f, energy supply and prices, and initial conditions of the primary state variables. In the solution lower level controllers and dynamics are assumed ideal, e.g. the indirect environment sub-state is assumed infinitely fast and $x_i = x_i^*$. Outputs are realisable setpoints for (partial) control to the local hardware controllers (in this case $u_l^{set} = [-]$) and realisable desired trajectories (x_p^* and x_d^*) for the short-term controller. Realisable setpoints and reference trajectories are, to a certain degree, guaranteed by incorporation of practical constraints in the long-term controller.

Short-term controller
The objective of the short-term controller is to reach and maintain the process at the desired trajectories with minimum cost. Undesired disturbances must be rejected. The controller must optimise between achieving the setpoint and cost (energy usage). This leads to a short-term objective function that can be written as

$$\min_{u_s} J \quad = \int_t^{t+H} ((x - x_{ref})^T W_x (x - x_{ref}) + \Delta u_s^T W_u \Delta u_s) dt, \tag{4.14}$$

where W are the weighing factors that relate differences between actual, x, and desired behaviour, x_{ref}, to each other and to changes in the control actions, Δu_s. These weighing factors are tuned such that the result is an acceptable trade-off between financial yield and amount of risk for product damage/loss. The time horizon of this controller is denoted with H. There will be constraints on the process state (frost damage, excessive browning) and the short-term control inputs u_s (realisable, condensation),

$$x_{min} \leq x \leq x_{max}, u_{s_{min}} \leq u_s \leq u_{s_{max}}, |\Delta u| \leq \Delta u_{max}.$$

Equation (4.14) is a quadratic objective with constraints and this allows the formulation of a control problem in standard notation. This short-term controller is a MPC type controller with time intervals of one week and a control and prediction horizon of a few weeks for this storage process. The length of these two horizons is chosen in agreement with the model confidence. The first calculated control action is used for the process as is common for predictive controllers. Inputs are reference trajectories from the long-term controller (sugar content), and actual state values from measurement information or from the state estimation. Outputs are setpoints (storage temperature) for the lower-level control components.

Local hardware controllers
The local controller continuously tries to accomplish the target storage temperature from the model predictive controller. The local controller uses ventilation with external or internal air to keep storage temperature as close as possible to the setpoint by switching the ventilation units on or off.
The objective of the local hardware controllers is to minimize the error between the desired and actual indirect environment sub-state. Inputs are setpoints from the supervisory controllers. Probably, some settings could also be set by the supervisory controllers, e.g. bandwidths. Outputs are control actions that act upon the process. As said before, the dynamics of this control level are considered ideal at the upper control level.

Results and perspectives

The proposed, supervisory, controller is compared with the current controller in a simulation study. Results are shown in Figures 4.6 and 4.7. From these figures it can be concluded that the storage process is improved using the new controller. Not only product quality in terms of the sugar content is monitored and controlled, also energy usage in terms of hours of ventilation is reduced in this simulation with about 10 %. These savings could be obtained thanks to the fact that the new method shows that a change of operating conditions in this particular batch of potatoes was possible without a significant decrease in quality. As agro-material exhibits large variations between different batches and seasons it can be expected that either a significant energy reduction or prevention of unacceptable loss of product quality will be achieved using the new controllers in most situations.

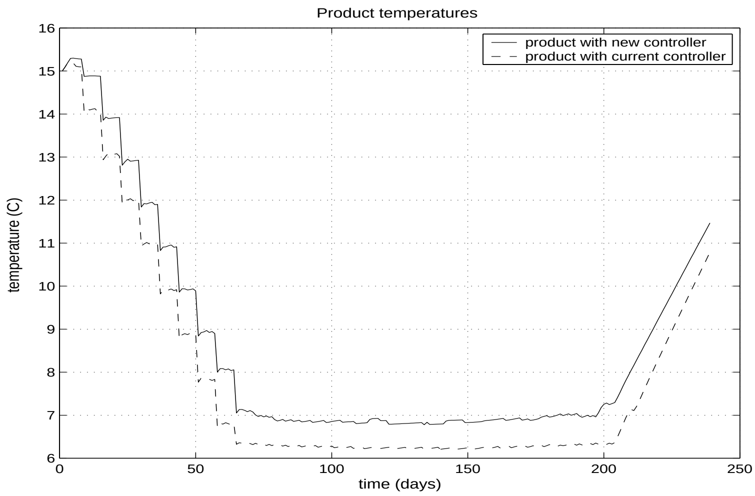


Figure 4.6: *Temperature in potato storage*

The proposed control structure was implemented in two industrial storage facilities. The controller monitors product quality and takes the appropriate control actions.
The temperature setpoints that are calculated by the short-term controller (MPC) are shown in Figure 4.8 together with the realised temperature in the storage facility. Due to unsufficient cooling capacity with outside air there is a difference between realised and desired temperature. This is caused by the differences between actual outside temperature and the temperature averages over several years.
In Figure 4.9 the reference trajectory for the sugar content is shown that is calculated by the long-term controller together with the realised sugar content. In the beginning

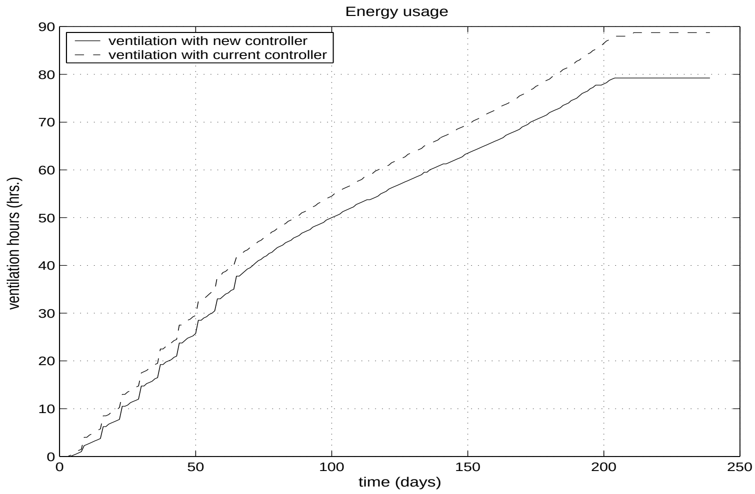


Figure 4.7: *Energy usage in potato storage*

of the storage period, the model adaptations are relatively large. This requires the calculation of a new reference sugar trajectory by the long-term controller resulting in step-wise changes as can be seen in the figure. These adaptations were expected, because the initial model parameters are calculated using only a few real measurements.

Although the controller performance strongly depends on the quality of the models,

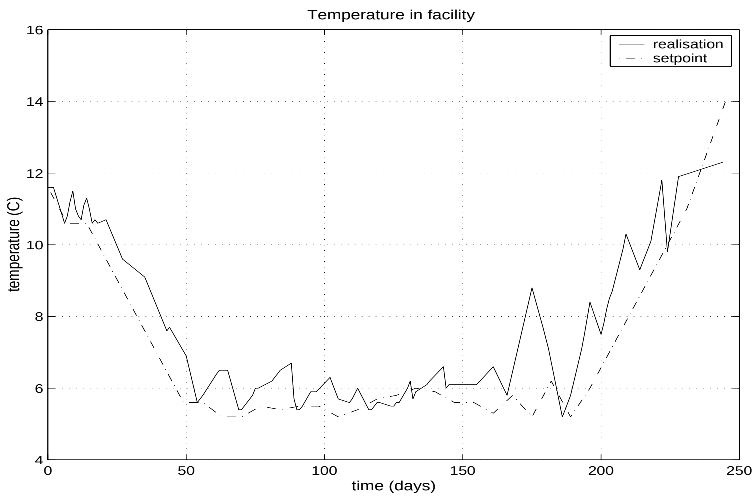


Figure 4.8: *Temperature in potato storage*

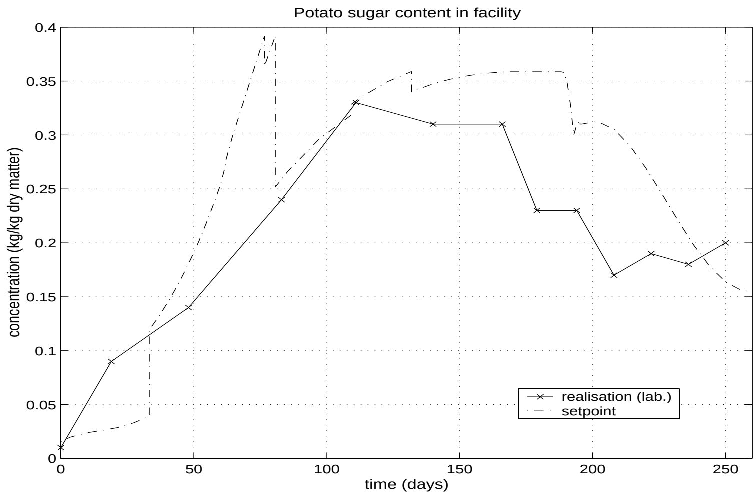


Figure 4.9: *Sugar content of the product in potato storage*

the new controller better assures optimal storage with respect to product quality and usage of energy than the old controller, that acts on user input only.

4.4.2 Container transport of apples

Climate controlled container transport of agro-material is a common way to get products at their desired location. During this transport the product quality changes due to time and transport conditions like temperature, relative humidity and concentrations of oxygen, carbon dioxide and ethylene.

Model

Product quality is defined by respiration and bacterial/microbial activity. In this case study respiration is modelled with an algebraic relation as function of the oxygen concentration in the direct environment sub-state. Details on the respiration model are mentioned in Chapter 5. The bacterial/microbial concentration acts as primary sub-state. The direct environment sub-state consists of product temperature, x_d^p, and moisture content as product component, and the air temperature, x_d^c, and humidity, and concentrations of oxygen and carbon dioxide as climate component. A compartment model is built consisting of three parts to represent the spatial distribution that is caused by the inhomogeneous air flow inside the container. The indirect environment sub-state consists of e.g. the air conditions in the T-bar floor, x_i, and the head space. The differential equations for the sub-states are shown in Equation (4.15). For the direct and indirect environment only the equations for temperature are shown as those for the moisture content, O_2 and CO_2 would be similar. The model shown here is used for a time scale analysis. In the simulation studies a nonlinear model is used.

$$\begin{aligned}
\dot{x}_p^m &= k_1(x_d)x_p^m, \\
\dot{x}_d^p &= \frac{1}{M_p\ Cp_p}[R + UA(x_d^c - x_d^p)], \\
\dot{x}_d^c &= \frac{1}{M_a\ Cp_a}[\rho_a\ F\ Cp_a\ (x_i - x_d^c) + UA(x_d^p - x_d^c)], \\
\dot{x}_i &= \frac{1}{M_{T-bar}\ Cp_{T-bar}}[\rho_a\ F\ Cp_a\ (u - x_i)],
\end{aligned} \tag{4.15}$$

where conduction and evaporation is neglected. In Table 4.3 the eigenvalues, time constants and eigenvectors for this case study are shown.

Table 4.3: *Time scales container transport*

sub-states	description	eigenvalue	time constant	eigenvector			
primary	bacterial	$10^{-6} - 10^{-9}$	$10^6 - 10^9 (s)$	$[1 * 10^{-8}$	0	0	0]
direct env.	product	$-1.51 * 10^{-5}$	10^4 (s)	$[-6.64 * 10^{-9}$	0.75	0.67	0]
	air	-0.006	100 (s)	[0	-0.02	1.00	0]
indirect env.	T-bar	-0.0034	100 (s)	[0	-0.01	0.23	0.97]

Control structure selection

Currently, transport is controlled by local controllers that try to stay as close as possible to the fixed setpoints that are given at the beginning of transportation. Product quality is not directly incorporated in the controller. To minimise quality decline, usually high rates of ventilation with outside air and/or circulation of internal air are used. This leads to unnecessary high cost, and to a high evaporation rate and weight-loss. Therefore, a new control structure is developed that is illustrated in Figure 4.10. In the control structure selection the incorporation of the local controllers was a practical constraint, like in the potato storage case in Section 4.4.1. A time scale decomposition is made that results in a long-term controller that calculates optimal and realisable reference trajectories, u_l^{ref}, and settings u_l^{set}, and a short-term controller. The short-term controller calculates the desired indirect environment settings, $u_s\ (x_i^*)$. This is motivated by the eigenvectors in Table 4.3 as the eigenvectors are related mainly to the state variables of the corresponding environment. The local controllers control the indirect environment state variables. Product temperature

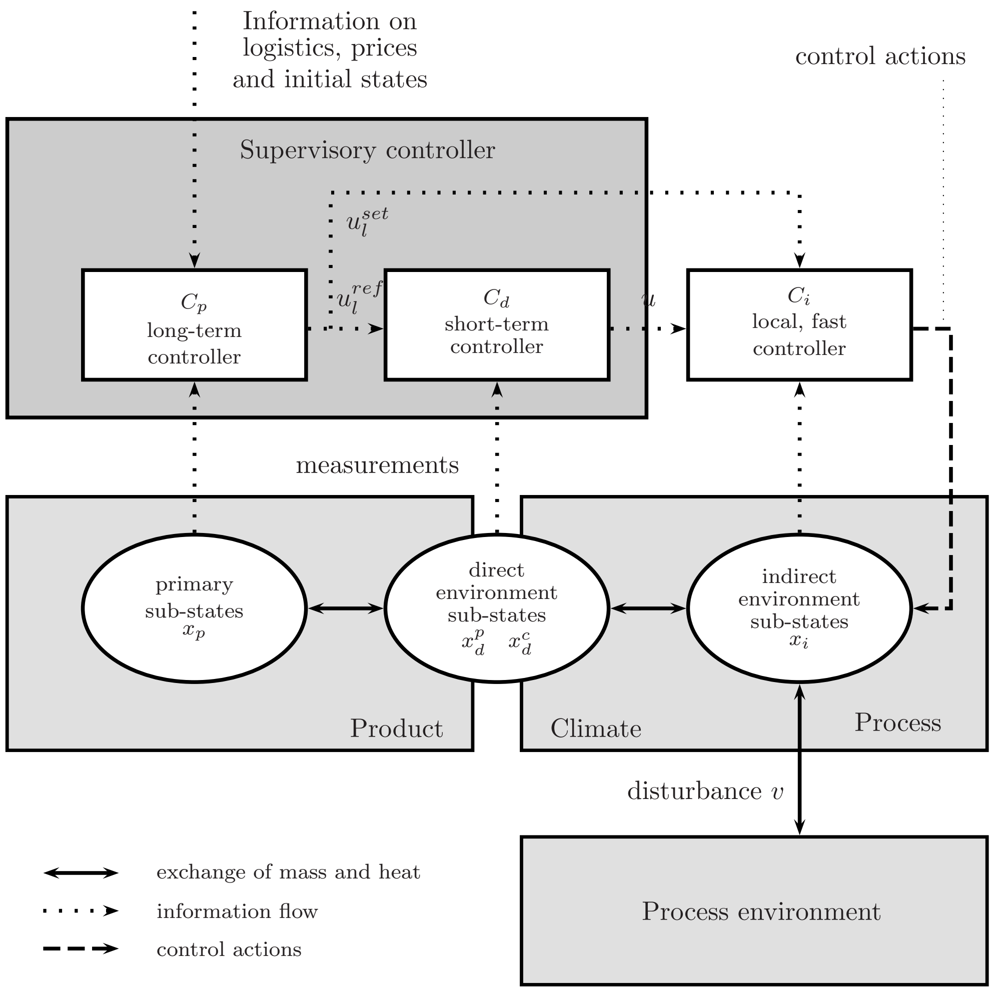


Figure 4.10: *Control structure in container transport*

follows the direct surrounding air temperature closely, as other variables have less effect (low disturbance effects due to insulation). This can also be seen from the eigenvectors in Table 4.3.

Equation (4.9) is used to select the control variables for the short-term and long-term controller in u_s and u_l^{set} respectively. Results with this equation for the effect of the candidate inputs temperature, oxygen, carbon dioxide and relative humidity on product respiration are shown in Table 4.4. This resulted in the control inputs temperature and oxygen concentration for the short-term controller, as they are measurable and have the highest effect on the product quality. To limit the usage

Table 4.4: *Effect of candidate inputs on respiration*

effect	oxygen	carbon dioxide	temperature	relative humidity
$\frac{u_0}{y_0}\frac{\partial y}{\partial u}\vert_{u_0,p_0}$	10^{-2}	10^{-4}	10^{-3}	–

of energy resources not only the desired average temperature should be set, but also the allowed temperature differences in the container. The control variables relative humidity and CO_2 concentration are in u_l^{set} as they have less influence on the primary state variables and are used to restrict evaporation, condensation, and several product diseases within domains.
The control components have the same objectives as in the potato storage case presented before. Only, the time intervals for the predictive controller were one hour and the controller has multi-inputs and multi-outputs.

Results and perspectives

In the selected control structure, product quality is directly incorporated in the controller and this enables container settings that are more appropriate for the product (Elstar apples) that is transported. In Figures 4.11-4.14 simulation results with the new controller are shown and compared with the current controller. All reference trajectories are constant i.e. that the controller aims at keeping all process outputs at the corresponding operating point (5 °C and 2% O_2). Temperatures are shown for the three parts in the compartment model that correspond with a

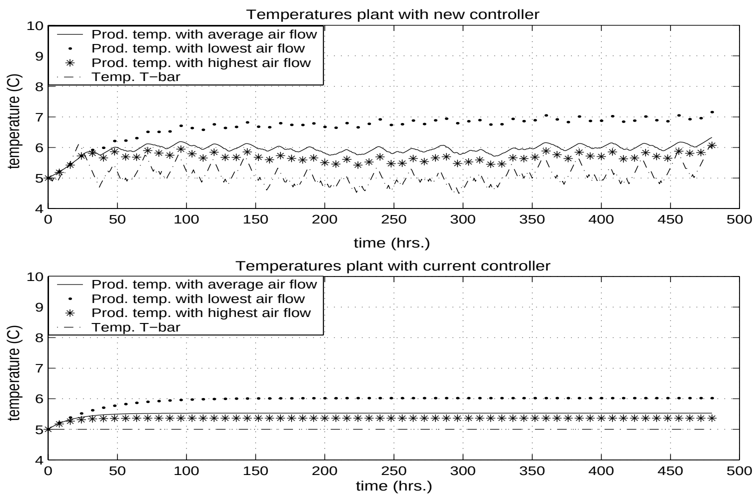


Figure 4.11: *Temperatures in load and setpoint in container transport*

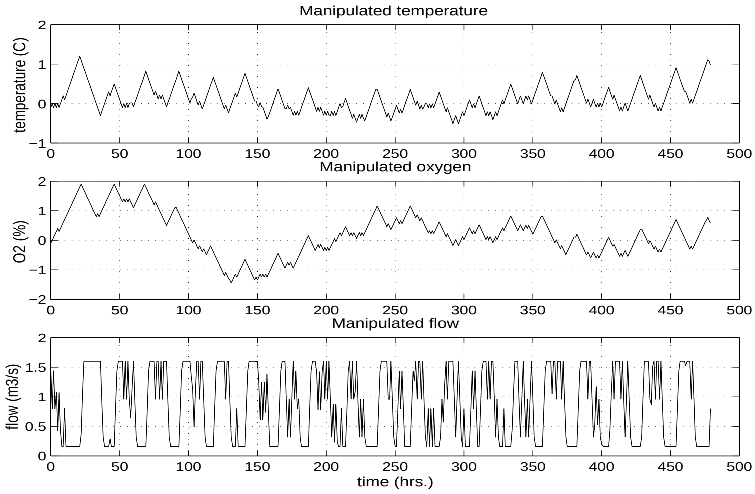


Figure 4.12: *Manipulated variables in container transport*

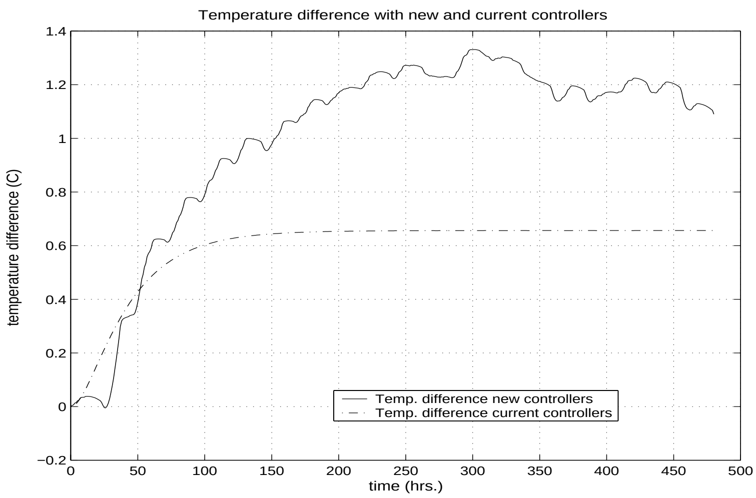


Figure 4.13: *Temperature differences within load in container transport*

minimum air flow, a maximum air flow and nominal air flow for the bulk load (Figure 4.11). As can be expected product temperature with a high flow rate follows most closely the setpoint that is generated from the predictive controller. The manipulated variables, around the operating point (5 °C and 2% O_2), that are calculated by the new controller, are shown in Figure 4.12. The flow in this figure is normalised with the maximum flow (flow in current practice) and has an order of magnitude of 1 m^3s^{-1}.

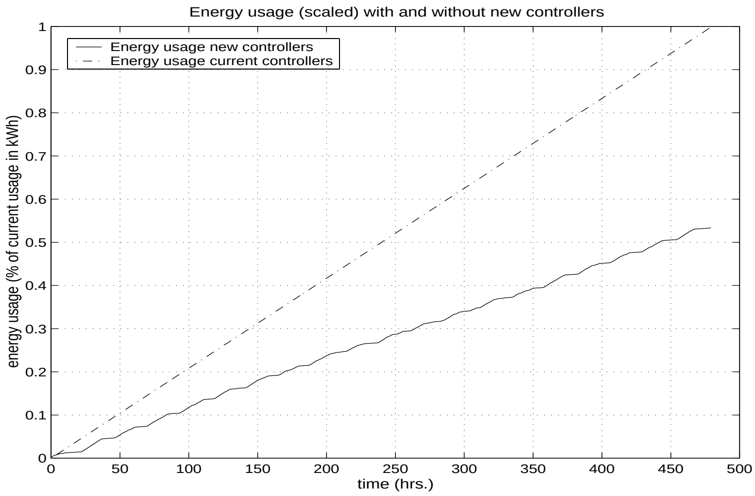


Figure 4.14: *Energy usage in container transport*

In Figure 4.13 temperature differences between the parts in the compartment model are illustrated and in Figure 4.14 the energy usage is shown. A reduction of up to 20-25 % may be achieved.

The control structure will reduce quality loss as this is directly controlled and decrease energy usage by reducing over-circulation and -ventilation. This will decrease weight-loss from the product through evaporation. The cost one has to pay for these results are higher temperature gradients in the container load. However, limited temperature differences are allowed as long as they do not affect product quality too much. This is discussed in more detail in Chapter 5. Again, the explicit inclusion of the quality model in the controller structure makes it possible to realise savings that otherwise would not have been exploited.

4.5 Conclusions and further research

In this chapter a modelling and control structure is presented for the class of climate controlled operations that process agro-material. This class is characterised by the presence of different time scales (as most post-harvest processes) and inputs -both disturbance as well as control inputs- that only drive the slow dynamics of the process. The modelling distinguishes between primary state variables, direct and indirect environment. This leads not only to more insight in the process, but also to localised information that is useful for time scale decomposition. Time scale decomposition allows for (goal-based) controllers with improved economic performance.

The presented control structure is mainly characterised by the decoupling of the different time-scales that are involved in the process, resulting in a separation of the control structure into long-term, short-term and local controllers. Furthermore, the subject of partial control is handled. The control structure is applied in industrial case studies that show the applicability and benefits in an industrial environment. To improve the processing of agro-material in this class of processes the control structure directly incorporates (dynamic) product behaviour. Because of this direct control it is possible to operate these processes closer at the operation limits, leading to improved process performance with respect to both quality and cost.

The ideas and structures discussed in this chapter could be useful in other classes of operations that process agro-material. The next step for the processes considered in this chapter will be the further improvement of control algorithms for the different controller components dedicated to the characteristics of the class of operations that is considered. These algorithms should be sufficiently generic to enable their use in the whole class of processes, thereby significantly reducing development cost of model-based (supervisory) controllers that are dedicated to the product and its quality.

Notation

ϵ	product-air ratio
ρ	density [$kg\ m^{-3}$]
τ	time constant [s^{-1}]
A	exchange area [m^2]
Cp	specific heat [$J\ kg^{-1}$]
F	air flow [$m^3\ s^{-1}$]
H	time horizon [s]
K	system matrix
M	total product mass [kg]
P	product price [$dfl.\ kg^{-1}$]
Q	quality attribute
R	respiration [$J\ kg^{-1}\ s^{-1}$]
U	heat exchange coefficient [$J\ kg^{-1}\ m^{-2}$]
W	weighing factor
k	reaction rate [s^{-1}]
r	reaction components
t	time [s]
u	input
v	disturbance
x	process state
y	measurable outputs
z	non-measurable outputs of interest
Superscripts:	
c	climate
i, j	number of process outputs, inputs
p	product
ref	reference value
set	setpoint
Subscripts:	
$T-bar$	T-bar in container
a	air
d	direct environment state variable
c	climate
h	hardware controller
i	indirect environment state variable
l	long-term
m, md	measurement, measured disturbance
max, min	maximum, minimum value
p	primary state variable
q	quality
r	reconstruction from measurements
s	short-term
set	setpoint
ud	unmeasured disturbance

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Part III

Control Components

Chapter 5

Direct Product Quality Control

abstract

A (model-based) Product Quality Controller is presented for climate controlled operations involving agro-material, such as storage and transport. This controller belongs to the class of Model Predictive Controllers and fits in a previously developed hierarchical control structure. The new Product Quality Controller rejects disturbances and tracks the product quality by means of the product responses respiration and fermentation. To achieve an energy efficient operation the presented controller is closely linked with the (existing) local controllers. Local optimisation on the level of these local controllers allows (controlled) high-frequent climate fluctuations. This results in significant energy savings. The Product Quality Controller and the energy efficient local controllers are implemented in small-scale and full-scale industrial case studies on CA-container transport of apples. This yields direct control of product quality and a significant reduction in energy consumption.

G.J.C. Verdijck, G. van Straten, H.A. Preisig

Direct Product Quality Control for Energy Efficient Climate Controlled Transport of Agro-material, Journal of Process Control, 2002, submitted.

5.1 Introduction

Process operations involving agro-material are confronted with tighter demands on energy efficiency and environmental pressure as well as quality requirements. These demands can not be met by the current (local) controllers. The setpoints are determined off-line in advance and are usually constant, or, at best, manually adjusted as conditions change out of the normal. In contrast, quality variables, which are the key indictors for the performance of the overall process, are measured off-line, if measured at all, but are usually rather slow. Thus their use in control applications introduces time delays that may result in periods where the process is not operating on specifications. This chapter focuses on the class of climate controlled operations like storage, transport and drying. These operations have in common the presence of different time scales and the property of controlling the slowly reacting product with a fast-reacting environment.

To illustrate the importance of improving control in these climate controlled operations, transport of agro-material is considered in more detail. Transport of agro-material, and in particular fresh agro-food products, constitutes a significant part of the world-trade. In 1998 total value of export of these products in sea containers alone was 58.5 Billion Euro for 27.7 Million ton of product (Penfold (2000)). These transport operations operate at a relatively high level of energy use, which significantly contributes to the environmental pressure. Penfold (2000) estimated that in 2010 the transport of 41 Million ton of bananas, hard fruit, citrus, milk products and tropical fruits would require 3542 Million kWh. Following Heap and Lawton (1999) to calculate the contribution of this specific transport to the global warming problem (in TEWI - Total Equivalent Warming Impact in kg CO_2) and using a transformation factor of 0.77 from kWh to kg CO_2 results in a conversion of 2728 Million kg CO_2 each year.

The tighter demands both on energy efficiency and reduction of environmental pressure, and on the quality requirements ask for an integrated control approach, which directly aims at low-cost and low energy consumption while still full-filling the product quality demands. This requires the on-line assessment of the product's quality and a model for its prediction to provide information on a completely different level about the process.

In (petro)-chemical industry Chen et al. (1998) propose a multivariate statistical controller for on-line quality improvement. Product quality is modelled performing a principal component analysis to calculate optimal setpoints for the climate variables. To overcome the problems with measuring product quality a lot of research has been done on inferential control in (petro)-chemical industry. An overview on this topic can be found in Ohshima and Tanigaki (2000) and Joseph (1999).

In climate controlled operations monitoring product quality by means of the product responses respiration and fermentation is discussed in e.g. Hertog et al. (1998b), Wareham and Persaud (1999) and Bower et al. (1998), but these responses were not used for control purposes. Perrot et al. (1998) used a fuzzy rule-based model for the prediction of the quality degradation in drying of rice and maize as a crude measure for product quality. This measure was, however, not used for direct control of product quality. Trelea et al. (1997b) use a kinetic product quality model as a constraint in a constrained model predictive controller, but no direct control of product quality was achieved. Examples of off-line optimisation of the process operation considering product quality can be found in Pan et al. (1998) for quality of carrots and Kajiyama et al. (1998) for vitamin C content and non-enzymatic browning of a model food. Both are applied to drying operations. Although these developments could improve operations in food industry two problems remain. Firstly, the quality measurement is not used for feedback control, and secondly energy usage and environmental effects of the process are not considered at all.

In this chapter a novel (model-based) Product Quality Controller is presented that directly controls product quality by means of the product responses respiration and fermentation. This controller defines the setpoints for the local, underlying controllers in the scheme. The local controllers are optimised for energy efficiency without harming the product.

The design of the controllers utilises a system model that will be discussed in Section 5.2. The presented controllers are part of a hierarchical control structure that is briefly discussed in Section 5.3. In Section 5.4 the control problem is stated and different types of nonlinearities are considered. In Section 5.5 the controllers are discussed in more detail. The applicability of the presented controller is shown using container transport of apples as an industrial case study in Section 5.6. Finally, this chapter ends with a discussion on the results with direct Product Quality Control.

5.2 Modelling the system

The system model is constructed for the analysis, simulation and design of the (model predictive) controllers. In this section the (sub)-models for the industrial case study of container transport are discussed illustrating the specific common properties of this type of processes.

Physical phenomena, especially in operations involving agro-material, occur at different time scales. A time-scale analysis of the process identifies three different scales: one of the product, being the slowest, one of its intermediate environment being significantly faster and on the outer domain a very fast containment for the product, the large (indirect) climate space. Assigning the state variables in climate controlled operations with agro-material, such as container transport, to their corresponding time scales leads to the following classification:

- primary sub-state, x_p, with slow dynamics that consists of reactive mass concentrations (the product quality attributes), n_r,
- direct environment sub-state, x_d, with medium dynamics that consists of product and air temperatures, T_p and T_d, and non-reactive mass concentrations, n_n,
- indirect environment sub-state, x_i, with fast dynamics that consists of temperature, T_i and mass concentrations in the air.

The (sub)-models of these state variables will be briefly discussed.

5.2.1 Model of the primary sub-state

Equations for the dynamic behaviour of the product quality attributes are written as

$$\begin{aligned} \dot{x}_p &= K\,r, \\ r &= r(x_p), \\ K &= K(x_d). \end{aligned} \tag{5.1}$$

The first equation states that the rate of change of the primary state x_p is separable into a self-referring term (the kinetics) and an environment dependent gain.
Nonlinearities are present in the gain matrix K and depend on environment state variables, x_d. Also, nonlinearities are involved in the vector r that depends on the primary state variables, x_p. The model in Equation (5.1) is discussed in detail in Verdijck et al. (2001).

5.2.2 Model of the environment sub-states

The environment sub-states are modelled using mechanistic models deduced from energy and mass conservation laws. In the container transport case the environment sub-states are $x = [T_{product}\ T_{air}\ O_2]$. They are controlled by the indirect environment states $x_i = [T_{in}\ O_{2in}\ flow_{in}]$, which act as the controls u on this level, i.e. $u = x_i$. The system is also subject to disturbance $d = T_{out}$. The basic equations are

$$\begin{aligned} \dot{x}_1 &= \frac{1}{Cp_p}\left[\frac{1}{R_{pa}}(x_2 - x_1) + E_{evap} + E_{resp}\right], \\ \dot{x}_2 &= \frac{1}{Cp_d}\left[\frac{1}{R_{flow}(u_3)}(u_1 - x_2) + \frac{1}{R_{pa}}(x_1 - x_2) + \frac{1}{R_{dist}}(d - x_2)\right], \\ \dot{x}_3 &= \frac{1}{Ma}\left[\frac{1}{R_{flow}(u_3)}(u_2 - x_3) + F_{resp}\right]. \end{aligned} \tag{5.2}$$

Resistances against heat and mass flows are denoted by R. The equations state that the product temperature is determined by the exchange with the air in the direct vicinity, and by energy sources (or sinks when negative) due to respiration and evaporation, denoted by E. The rate of change of the air temperature in the vicinity of the product is determined by heat exchange by ventilation with incoming air, and by conductive heat exchange with product and outside environment. The rate of change of the oxygen in the air depends upon the ventilation and the respiration term F_{resp}. More details can be found in Sman and Verdijck (2001).

Because of the presence of the flow dependency, the model in Equation (5.2) is non-linear in the control. Even when the resistance to exchange by flow is inversely proportional to the ventilation flux, which would make the model input-state control affine, it may still be input-output control non-affine, depending upon the outputs (see Section 5.2.3). While models that are control affine can be linearised easily, without higher order terms, it may be desirable to retain higher order terms in the non-affine situation. A linearised model is needed in the model predictive controller (MPC), developed later.

The linearisation of a state space system

$$\dot{x} = f(x, u), \tag{5.3}$$

with $x \in \Re^n$ and $u \in \Re^m$, and f an n-dimensional vector function around a point x_0, u_0 at the nominal trajectory is given by a Taylor series expansion of f:

$$\begin{aligned} \dot{x} \quad \approx \quad & f(x_0, u_0) + \left.\frac{\partial f}{\partial x}\right|_{x_0,u_0} \Delta x + \left.\frac{\partial f}{\partial u}\right|_{x_0,u_0} \Delta u + \\ & \frac{1}{2!}\sum_{j=1}^{n}\sum_{k=1}^{n} \left.\frac{\partial^2 f}{\partial x_j \partial x_k}\right|_{x_0,u_0} \Delta x_j \Delta x_k + \frac{1}{2!}\sum_{j=1}^{n}\sum_{k=1}^{m} \left.\frac{\partial^2 f}{\partial x_j \partial u_k}\right|_{x_0,u_0} \Delta x_j \Delta u_k + \\ & \frac{1}{2!}\sum_{j=1}^{m}\sum_{k=1}^{m} \left.\frac{\partial^2 f}{\partial u_j \partial u_k}\right|_{x_0,u_0} \Delta u_j \Delta u_k, \end{aligned} \tag{5.4}$$

where the superscript indicates evaluation at the linearisation point, and $\Delta x = x - x_0$ and $\Delta u = u - u_0$. Since Equation (5.2) is linear in x the first second order term on the r.h.s. is absent. The mixed second order term (fifth term on the r.h.s.) is small with respect to the last term. This follows because R_{pa} is much larger than the input dependent term R_{flow}, as shown in Table 5.3 in Section 5.6. With these considerations, the system model of Equation (5.2) simplifies to

$$\dot{x}_d = A\ x_d + B\ u + \frac{1}{2!}\sum_{j=1}^{m}\sum_{k=1}^{m} \left.\frac{\partial^2 f}{\partial u_j \partial u_k}\right|_{x_0,u_0} \Delta u_j \Delta u_k, \tag{5.5}$$

where A is the $n * n$ linearised system matrix given by $\left.\frac{\partial f}{\partial x}\right|_0$, B the $n * m$ input matrix $\left.\frac{\partial f}{\partial u}\right|_0$, and where the summation term is an n-dimensional column vector. In the MPC, to be developed later, an approximate linear model is required in order to be able to derive closed solutions. This can be achieved by further approximating the last term in Equation (5.5) by dropping all cross-correlation terms:

$$\frac{1}{2!}\sum_{j=1}^{m}\sum_{k=1}^{m}\left.\frac{\partial^2 f}{\partial u_j \partial u_k}\right|_{x_0,u_0} \Delta u_j \Delta u_k \approx F_{uu} diag(\Delta u)\ \Delta u, \tag{5.6}$$

where

$$F_{uu} = \begin{bmatrix} \frac{\partial^2 f_1}{\partial u_1 \partial u_1} & \cdots & \frac{\partial^2 f_1}{\partial u_3 \partial u_3} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f_n}{\partial u_1 \partial u_1} & \cdots & \frac{\partial^2 f_n}{\partial u_m \partial u_m} \end{bmatrix}, \tag{5.7}$$

is an $n * m$ matrix of second derivatives. Substitution of Equation (5.6) into Equation (5.5), and dropping the deviation notation, finally leads to the pseudo-linear control model

$$\dot{x}_d = A\ x_d + (B + \overline{B})\ u, \tag{5.8}$$

with

$$\overline{B} = F_{uu} diag(\Delta u). \tag{5.9}$$

Model (5.8) will be used in the MPC in Section 5.5. The derivation given above typically suits all sorts of climate controlled operations involving flows.

5.2.3 Output relations

The outputs of the control model are product and air temperatures, oxygen concentration, and respiration and fermentation

$$y_d = C\ x_d \tag{5.10}$$

where

$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & f_{resp} \\ 0 & 0 & f_{ferm} \end{bmatrix}, \tag{5.11}$$

and f_{resp} and f_{ferm} represent the quality relations that will be described next.
Although product quality of agro-material is a complicated matter, an important measure for product behaviour is the activity of the product by means of respiration

and fermentation. These mechanisms are the two metabolic pathways that provide agro-material with energy. This energy is used for maintenance or in other words: to stay alive. The usual metabolic pathway is respiration, but in case of oxygen shortage fermentation may take over. More details on respiration of apples, the product that will be used in the case studies, are discussed in Peppelenbos (1996)). Monitoring and control of respiration/fermentation is related to control of product quality evolution and may have practical value. Of course, product quality evolution has many more aspects that have little to do with respiration and/or fermentation. Control of these other quality aspects is primarily hampered by lack of reliable measurement techniques. In this chapter only respiration and fermentation are considered.
Below the reactions for respectively respiration and fermentation are shown

$$\begin{aligned} C_6H_{12}O_6 + 6O_2 &\rightarrow 6CO_2 + 6H_2O + E_r, \\ C_6H_{12}O_6 &\rightarrow 2CO_2 + 2C_2H_5OH + E_f, \end{aligned} \tag{5.12}$$

with E_r and E_f representing heat produced by the corresponding reactions. Peppelenbos (1996) describes the kinetics of these reactions with the following equations

$$\begin{aligned} respiration\ rate &= \frac{Vm_{O2}\ O_2}{Km_{O2} + O_2}\ [nmol\ kg^{-1}\ s^{-1}], \\ fermentation\ rate &= \frac{Vmf_{CO_2}\ Kmf_{O2}}{Kmf_{O2} + O_2}\ [nmol\ kg^{-1}\ s^{-1}], \end{aligned} \tag{5.13}$$

with O_2 in [%]. Because in the MPC controller a (pseudo-)linear model is needed in order to be able to use an explicit control law, Equations (5.13) were linearised in order to obtain expressions for f_{resp} and f_{ferm} in Equation (5.11). Values for the parameters are shown in Table 5.1 for apples (Elstar) at 20°C .

Table 5.1: *Parameters product model*

parameters	values	units
Vm_{O2}	$4.97 * 10^4$	$[nmol\ kg^{-1}\ s^{-1}]$
Km_{O2}	14.8	[%]
Vmf_{CO2}	0.212	$[nmol\ kg^{-1}\ s^{-1}]$
Kmf_{O2}	0.4	[%]

5.2.4 System analysis

In this section the stability and controllability of the previously described system model are investigated.

Stability

In this subsection the stability of the control model in Equation (5.8) is discussed briefly using the first method of Lyapunov:

For linear systems the equilibrium point, x_0, is locally asymptotically stable if the matrix A has all its eigenvalues in the open left half plane.

Table 5.2 lists the eigenvalues of the model described mathematically in Equations (5.2 and 5.8). The eigenvalues indicate that the process is stable. Each of the eigenvectors

Table 5.2: *Time scales container transport of apples*

state variables	eigenvalues	time constant (s)
product temperature	$-2.778 * 10^{-7}$	$O(10^6)$
air temperature	$-5.5177 * 10^{-4}$	$O(10^3)$
oxygen concentration	$-1.2577 * 10^{-1}$	$O(10^1)$

is dominated by one of the state variables. Therefore, each time constant is associated with an individual state variable.

Controllability

The controllability analysis must include the higher order terms that were approximated with the the matrix $\overline{B}$ in Equation (5.6). As the input matrix depends on the actual values for the manipulated variables, u_3 in Equation (5.2), controllability is analysed for a typical set of values covering the possible application range. In the case of container transport it is assumed that temperature changes with a maximum of 5 °C, oxygen concentration with 5 % and air flow with 25 % around the operating point.
The rank of the controllability matrix, $[B, AB, A^2B]$, is calculated for three different models representing the average and the extreme vertices of the operating range. These models are: $\overline{B}_{min}$ with minimum values for the inputs u, $\overline{B}_{nom}$ for nominal input values and $\overline{B}_{max}$ for maximum input values. Also, the rank of the observability matrix, $[C, CA, CA^2]^T$, is calculated. Both matrices have full rank. Therefore, it can be concluded that the process model is controllable and that the full state can be reconstructed from the available measurement.

5.3 Hierarchical control structure

In the process three different time scales can be recognised, as was already mentioned in the system modelling. Therefore, a large multivariable controller for the whole

process operation would not be an acceptable solution for reasons of long computation time, lack of knowledge in the field of application and incomplete state feedback on the required time intervals. Instead, mirroring the model structure results in a hierarchical control structure where the time-scale of the controller decreases as one moves down in the cascade of controllers. Verdijck and van Straten (2002a) discuss the detailed background of arguments and applicability of the concept and illustrate the validity of the time-scale separation.
As a result the control structure consists of three levels that act as a sort of cascade control with:

- optimisation on the slowest time scale (C_p),
- control on the intermediate time scale (C_d),
- local control on the fastest time scale (C_i).

This allows the control of product quality in order to fulfill the quality requirements, while trying to operate in the most (energy) efficient way. On every time scale state constraints can be incorporated (e.g. prevention of condensation) in their corresponding control component. The control structure is shown in Figure 5.1. In the next section the control problems on the different time scales will be discussed briefly.

5.4 Control Problem formulation

The hierarchical control structure of Section 5.3 introduces a number of different control components. In this section the individual control problems for these control components are discussed in more detail. In the remaining sections of this chapter setpoints and/or reference trajectories from the slow time-scale optimisation are assumed known and the focus will be on the design of the controller on the intermediate time scale and its interaction with the local controllers on the fast time-scale.
The system as a whole can be modelled by the following set of equations

$$\begin{array}{rcll} \dot{x}_p & = & K(x_d)r(x_p), & \textit{dynamics of product quality attributes} \\ \dot{x}_d & = & f_d(x_p, x_d, x_i), & \textit{dynamics of direct environment} \\ \dot{x}_i & = & f_i(x_d, x_i, u, d). & \textit{dynamics of indirect environment} \end{array}$$

The third equation shows that the controls act upon the indirect environment, which drives the direct environment in the second equation, which in turn drives the primary sub-state in the first equation.
There are constraints on both the process state, the manipulated variables u and the

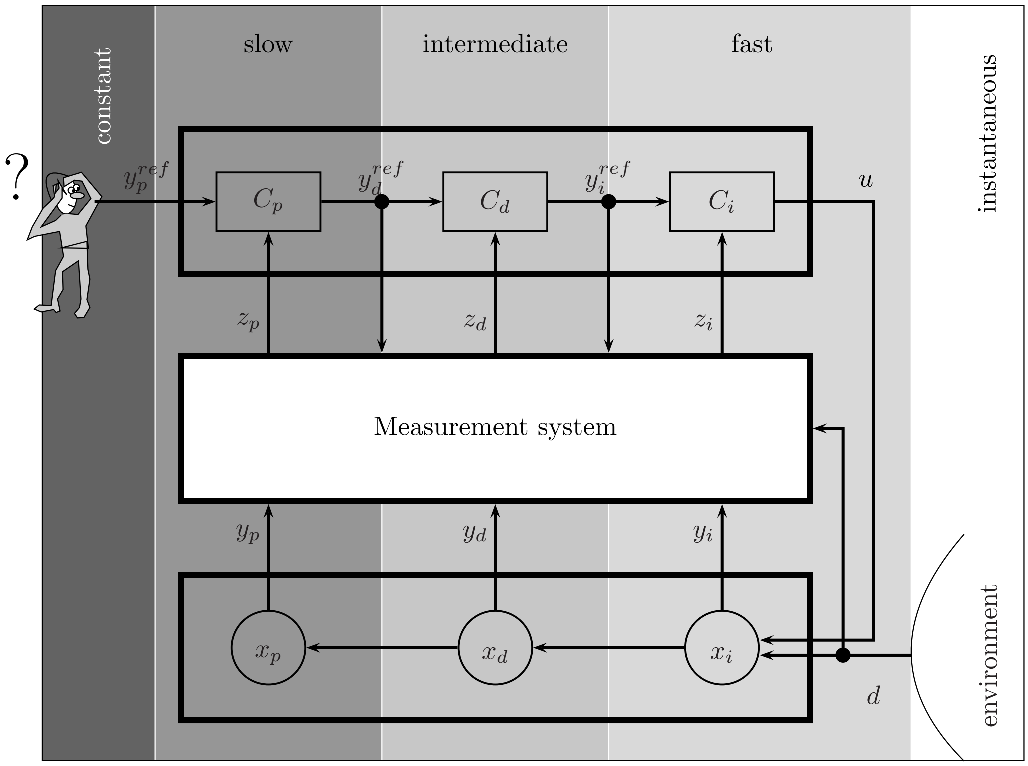

Figure 5.1: *General control structure*

control moves Δu,

$$x_{min} \leq x \leq x_{max},\ u_{min} \leq u \leq u_{max},\ |\Delta u| \leq \Delta u_{max}.$$

From these equations and constraints the control problems on the separate time-scales can be deduced.

5.4.1 Optimisation on the slowest time scale

On the highest level an economic objective is optimised

$$\min_{y_d^{ref}} J = P(Q_{t_f})M(t_f) + \int_{t_0}^{t_f} L(x_d, d, t)\ dt, \tag{5.14}$$

where the first term represents the financial yield of the process and the second term the costs made during the process. The parameter P is the product price ($Euro/kg$) valid for the final quality Q_{t_f}. The quality directly depends on the primary state variables, $Q = f_q(x_p)$. M_{t_f} is the total product mass (kg) at the end of the process that mainly changes by evaporation of water from the product. The costs, L, are computed by assuming that the intermediate and fast time scale controllers perform their tasks fast enough with respect to the relevant time scale of the slow process. The result of the optimisation is an optimal trajectory of the outputs of the direct environment, y_d^{ref}, that serves as a setpoint for the intermediate controller.

5.4.2 Control on the intermediate time scale

The objective of the controller on the intermediate time scale is to reach and maintain the process at the desired trajectories as calculated on the slow time scale. Undesired disturbances must be rejected. At this level a quadratic objective function is selected

$$\min_{y_i^{ref}} J \quad = \int_t^{t+H} ((y_d - y_d^{ref})^T W_y (y_d - y_d^{ref}) + (\Delta y_i^{ref})^T W_u \Delta y_i^{ref}) dt, \tag{5.15}$$

where W are the weighing factors that relate differences between actual and desired behaviour to each other and to changes in the control actions. The time horizon of this controller is denoted with H. Δy_i^{ref} is included to represent cost of control and to prevent unwanted chattering of the controller.

The objective function is subject to the following set of equations

$$\begin{aligned} \dot{x}_d &= f_d(x_p, x_d, x_i), && \textit{direct environment} \\ 0 &= f_i(x_d, x_i, u, d), && \textit{indirect environment} \\ y_i &= y_i^{ref} \ \forall t, \end{aligned}$$

assuming the indirect environment, x_i follows its setpoint immediately when considered on the intermediate time scale. The y_i^{ref} are updated by the MPC with an interval of 1 hour. The pseudo-steady state for x_i holds on average over this interval. The condition assures that objective function (5.15) is minimised if the controlled indirect environment is on average on the calculated setpoint during the control interval. In fact, the hierarchy decouples the desire to control the indirect environment as closely as possible to the settings that are optimal for quality assurance, while on the lowest level it still leaves room for minimising energy with the local controllers.

There will be constraints on the state variables x_d and the outputs of the controller y_i^{ref},

$$x_{min} \leq x_d \leq x_{max}, \; y_{min}^{ref} \leq y_i^{ref} \leq y_{max}^{ref}, \; |\Delta y_i^{ref}| \leq \Delta y_{max}^{ref}. \tag{5.16}$$

Equation (5.15) is a quadratic objective with constraints and this allows the formulation of a control problem in standard notation. The intermediate controller is a Model Predictive Controller (MPC), which is a discrete-time equivalent of Equation (5.15) with piecewise constant controls. The advantages of an MPC approach are:

- integrated use of feedback and feedforward structures,

- multi-input multi-output character,
- explicit inclusion of constraints in the control problem.

Inputs for the intermediate controller are reference trajectories from the slow time scale optimisation, and actual state values from measurements or from the state estimation. Outputs are setpoints for the outputs of the indirect environment state variables, y_i^{ref}, used by the lower-level control components.

5.4.3 Local control on the fastest time scale

The local controller continuously tries to accomplish the target settings for the indirect environment state variables, y_i^{ref}, from the intermediate time scale. The local controller performs local control actions, such as usage of ventilation with external or internal air for cooling purposes and/or by switching the ventilation units on or off. On the fast time scale the local controllers are mostly single-input single-output and control directly the variable of interest in the indirect environment sub-state. Other control approaches on this level would not add much to the control performance. Furthermore, leaving existing and currently used on-off or PID-controllers in place as local controllers, constitutes an advantage for acceptance of the hierarchical control structure in practice.

5.5 Solving the control problem

In Section 5.3 a hierarchical control structure was shown consisting of three layers of control. This was followed by the formulation of the control problem on each layer. In this chapter setpoints and/or reference trajectories from the slow time-scale optimisation are assumed known (for details on this optimisation is referred to Verdijck et al. (2002b)) and the focus will be on the design of the controller on the intermediate time scale and its interaction with the local controllers on the fast time-scale.

5.5.1 Intermediate control level

The controller designed for the intermediate control level is a Model Predictive Controller. The formulated control problem leads to a quadratic programming problem. For more details on solving such problems in predictive control is referred to Maciejowski (2002). The MPC-algorithm used in this chapter is based on the nonaffine control algorithm described in Mutha et al. (1997). Using the approximation for the input matrix in Equation (5.6), an iterative procedure is needed since $\overline{B}$ requires knowledge about future control moves. This leads to an iterative control algorithm that consists of the following steps:

- Build the necessary matrices and vectors.
- Update the approximated input matrix ($\overline{B}$).
- Perform optimisation using linear control techniques.
- If $\Delta(y_i^{ref,k+1} - \Delta y_i^{ref,k})^T N(y_i^{ref,k+1} - \Delta y_i^{ref,k}) > norm$, update approximated input matrix and repeat optimisation, otherwise terminate the iteration and implement the first control move. In here, k indicates the iteration counter. N is a diagonal normalisation matrix. The variable norm is the termination threshold explained below.
- Go to the next time interval.

The termination value norm was selected such that the difference between the old and new value for each of the calculated controls was within 1% of the expected level. Calculations with the model using an appropriate value of N show that norm should be set to 10^{-2} for the transport operations discussed in this chapter.

5.5.2 Fast control level

The local controllers on the fast time scale are locally optimised to achieve energy savings. These energy savings may result from nonlinear product behaviour and from the characteristics of the conditioning equipment. For linear product behaviour heat production and heat removal does not change with fluctuating conditions. However, as most product behaviour is nonlinear energy savings may result from allowing high-frequency fluctuations. Most equipment operates most energy efficient when operating at full power. Instead of continuous heat removal, cycling or switching procedures can be used. Of course, this results in fluctuating conditions in the indirect environment. However, as these conditions fluctuate with a frequency that is relatively high, it would not influence product quality. This can be understood by the fact that product behaviour is evaluated on the slowest time scale. Solving Equation (5.1) for the primary sub-state results in

$$x_p(t_f) = x_p(t_0) + \int_{t_0}^{t_f} K(x_d) r(x_p) dt. \tag{5.17}$$

So, every pattern of $x_d(t)$ which yields the same integral in Equation (5.17) yields the same change in x_p over the total time and hence the same economic value in the objective function on the slow time scale in Equation (5.14). On the intermediate time scale, any pattern of $x_i(t)$ which yields the same x_d over time ($\int f_d dt$) leads to the same quality result seen for the product on the slow time scale. This allows for local optimisation on the fast time scale. Results with this approach in an industrial environment will be shown in Section 5.6.2.

5.6 Application

The methodology developed in this chapter was applied to CA-container transport of apples with two objectives in mind. First, to show that it is possible to monitor and control product quality by means of the product responses respiration and fermentation. Second, to illustrate the possibilities for a more energy efficient operation by allowing (controlled) climate fluctuations on the fast time scale. Therefore, two different experiments are conducted. First, a small-scale experiment that will show the applicability and benefits of direct product quality control on the intermediate time scale. Respiration and fermentation are estimated using a Kalman filter. Details are discussed in Timmer et al. (2001). Second, a full-scale experiment that will show the benefits with respect to energy efficient operation and reduction of environmental pressure, achieved by locally optimising the (existing) fast time scale controllers.

5.6.1 Small-scale experiment

Experimental setup

In the experiment the applicability of product quality control and its benefits on the intermediate time scale will be shown. Therefore, a specially built small-scale experiment is used. Manipulated variables, which are controlled by the local controllers, are O_2, CO_2 and temperature, although temperature is kept close to its origin of 20 °C. The small-scale facility has a volume of 70 *liters* with 20 *kg* of product. The product used in the experiments are Elstar apples. Figure 5.2 presents a schematic view of the small-scale facility. In the figure the product and its direct environment (intermediate time scale) are shown. The Model Predictive Controller calculates the desired setpoints for the indirect environment, y_i^{ref} with an interval of 1 *hour*. The air in the direct environment of the product is analysed and its gas concentrations are measured. Inputs are the (estimated) levels of respiration and fermentation, and the setpoints for the direct environment, y_d^{ref}. The levels of respiration and fermentation are estimated from the differences in incoming and outgoing concentrations of O_2 and CO_2. The air conditioning behaves as the indirect environment (fast time scale). Local controllers act upon the valves manipulating gas concentration with intervals of about 10 *sec*.

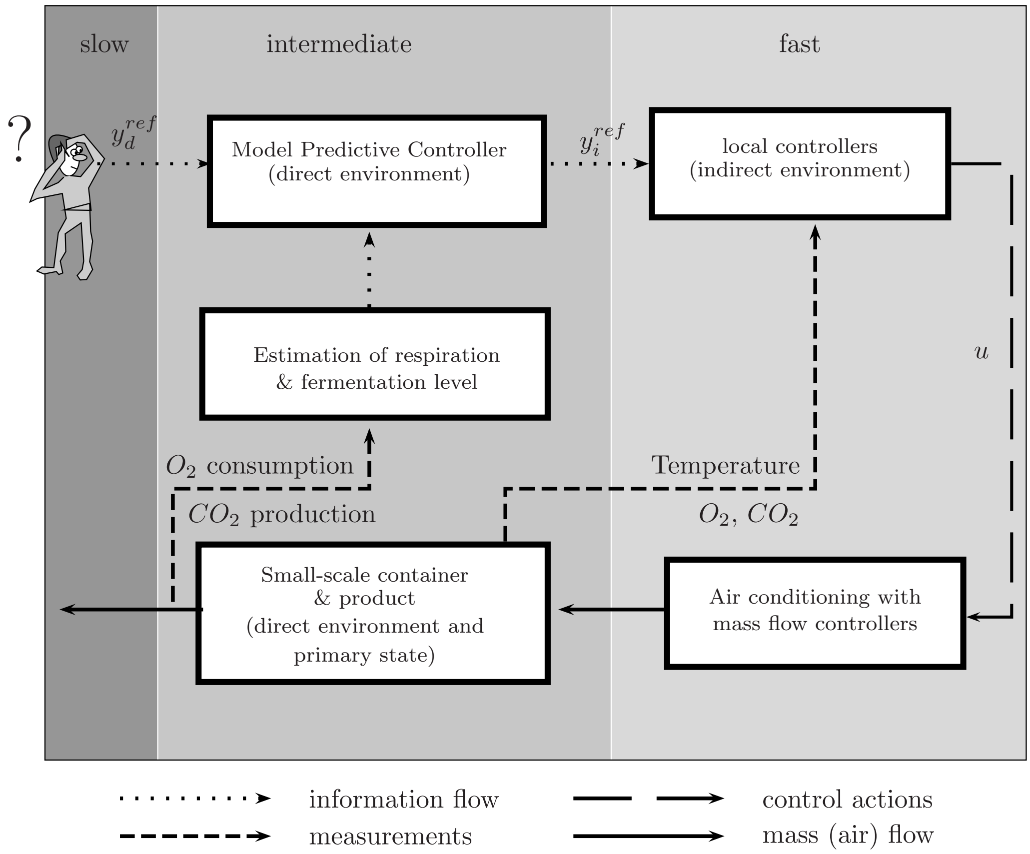

Figure 5.2: *Small-scale experiment*

Modelling and control

The model developed for this small-scale experiment is shown in Equation (5.2). Parameters for the small-scale model are shown in Table 5.3 (Sman and Verdijck (2001)). The controller is built using the Matlab Model Predictive Control Toolbox, which is extended with the nonaffine algorithm shown in Section 5.5. The predictive controller uses the model to calculate the required setpoints for the local controllers. The predictive controller has control intervals of an hour and a prediction and control horizon of thirty hours in three blocks of each 10 hours. The length of these two horizons is chosen in agreement with the model confidence and the time constants of the corresponding state variables.

Table 5.3: *Values for the model parameters*

parameter	value	units
Cp_d	390	$[J\ kg^{-1}\ K^{-1}]$
Cp_p	$4 * 10^3$	$[J\ kg^{-1}\ K^{-1}]$
E_{evap}	-	$[J]$
$E_{respiration}$	$1.04 * 10^{-5}$	$[J\ s^{-1}]$
$P_{respiration}$	$2.027 * 10^{-9}$	$[kg\ s^{-1}]$
R_{flow}	$1 * 10^{-3}$	$[s\ J^{-1}]$
R_{pa}	$6 * 10^{-5}$	$[s\ J^{-1}]$
R_{dist}	$0.5 * 10^{-3}$	$[s\ J^{-1}]$

Results

The model and controller are first tested in a series of simulation studies with the non-linear model acting as virtual reality. After that the controller was implemented in the small-scale facility and tested in an experiment.

Simulation study

For the small-scale experiment 5 outputs are being controlled. These are the product and air temperatures, oxygen concentration, and the levels of respiration and fermentation. The manipulated variables are temperature, oxygen concentration and the mass flow of the incoming air. In this simulation the oxygen concentration is the main manipulated variable to enable a comparison with the experiment at constant temperature. Results of the simulation are shown in Figures 5.3-5.7 around the operation conditions of 20 °C, 5% oxygen and 300 $[ml\ min^{-1}]$ air flow. In this simulation temperature is relatively high, however, these conditions were also used in the experiment. To test the behaviour of the controlled system the step response to a change in the level of respiration with 15 $[nmol\ kg^{-1}\ s^{-1}]$ is simulated, as shown in Figure 5.3. The resulting behaviour of the manipulated variables is shown in Figure 5.4. Because the effect of oxygen concentration on the level of respiration is relatively large a desired change in level of respiration will, as shown in the figure, lead to a change in this input. The respiration is shown in Figure 5.5. The mismatch between control and plant model is due to the nonlinear relation between respiration and oxygen concentration as described in Equation (5.13). Temperature behaviour for both the plant and control model are shown in Figure 5.6. The noise in the control model is caused by an additional disturbance input for the outside temperature with fluctuations of up to 4 °C. In the plant model the effect of this disturbance is more

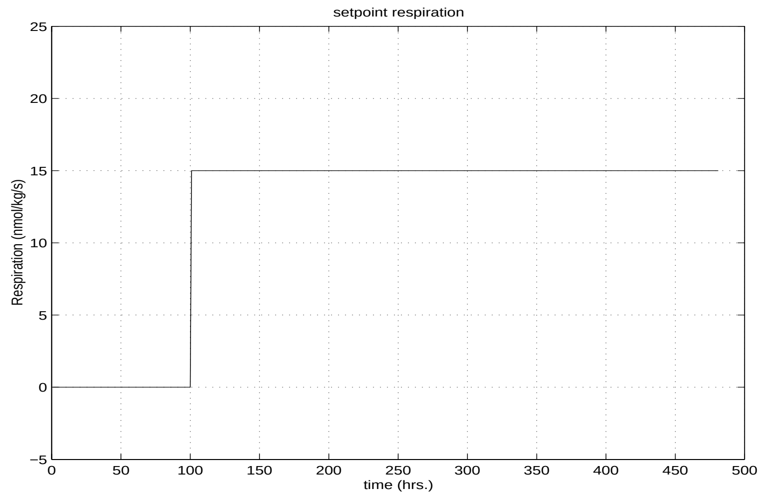

Figure 5.3: *Setpoint for respiration in simulation*

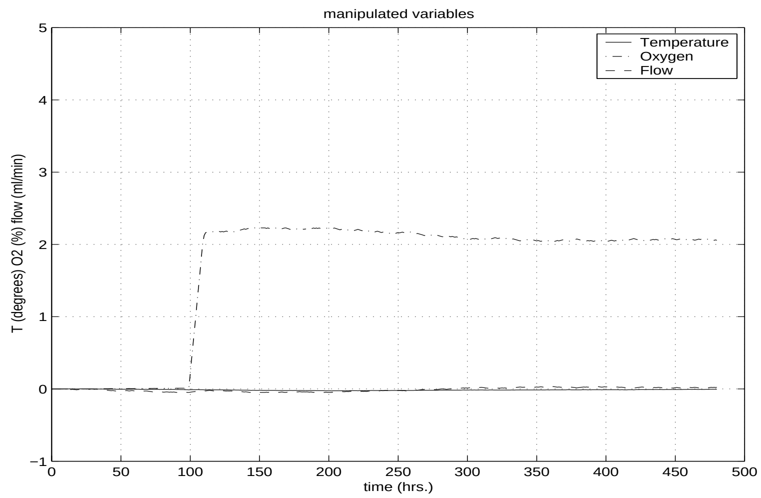

Figure 5.4: *Manipulated variables in simulation*

damped. The level of fermentation around its starting condition is shown in Figure 5.7. The off-set between control and plant model is caused by the nonlinear behaviour of the product.
From the results it can be concluded that the controlled process functions as expected. Since the differences between the nonlinear model and the locally linearised control model are acceptably small the latter will be used in the experiment.

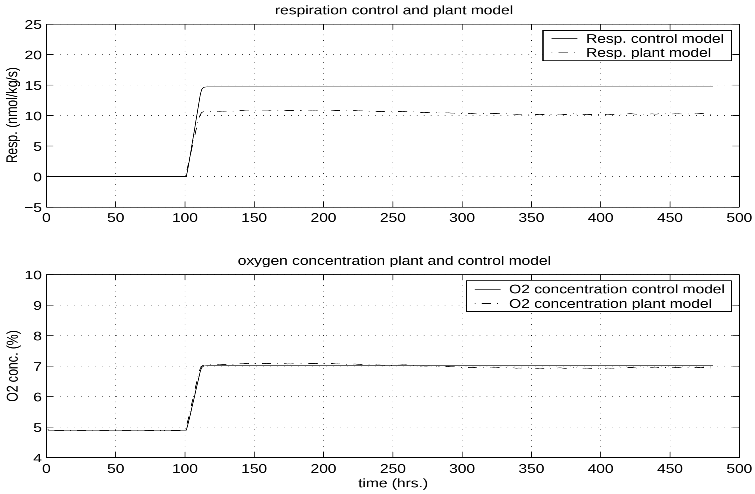

Figure 5.5: *Respiration and oxygen concentration in simulation*

Experimental study

The model predictive controller is implemented in the small-scale facility to test the applicability of monitoring and control of the levels of respiration and fermentation. As mentioned, details on monitoring of respiration and fermentation are discussed in Timmer et al. (2001). In the experiment the step response to a change in the level of respiration with 15 [$nmol\ kg^{-1}\ s^{-1}$], as shown in Figure 5.8, is tested similar to

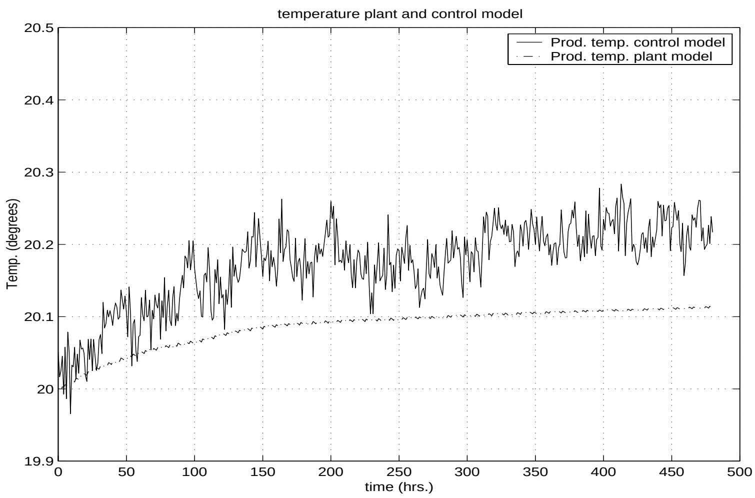

Figure 5.6: *Temperatures in simulation*

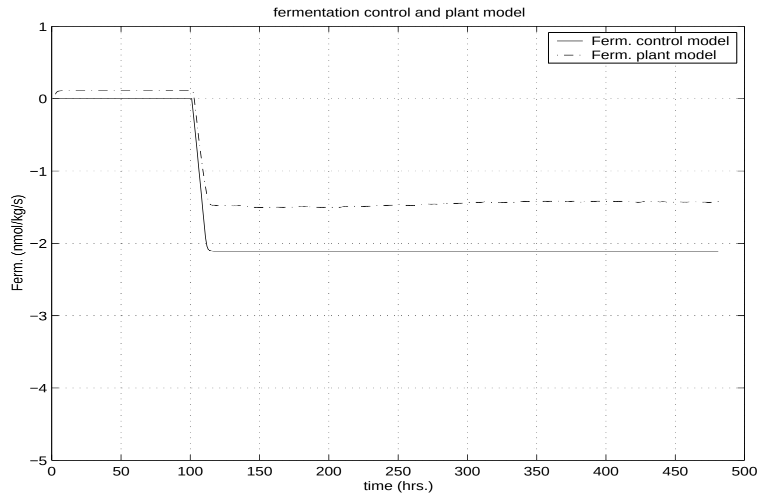

Figure 5.7: *Fermentation in simulation*

the simulation study. The results of the experiment are shown in Figures 5.8-5.11. The resulting behaviour of the manipulated variables is shown in Figure 5.9. In the

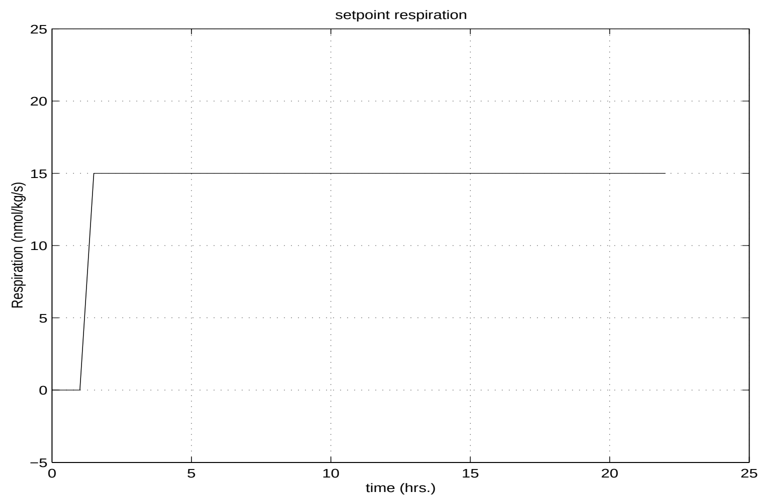

Figure 5.8: *Setpoint for respiration in experiment*

experiment, O_2 is increased to maintain the respiration at the desired setpoint. The level of respiration is shown in Figure 5.10. Temperature differences in the experiment were not measured. The level of fermentation around its starting condition is shown in Figure 5.11. The experimental results resemble those of the simulation. From the results one may conclude that it is possible to monitor and control product responses respiration and fermentation and thereby the quality evolution of the product.

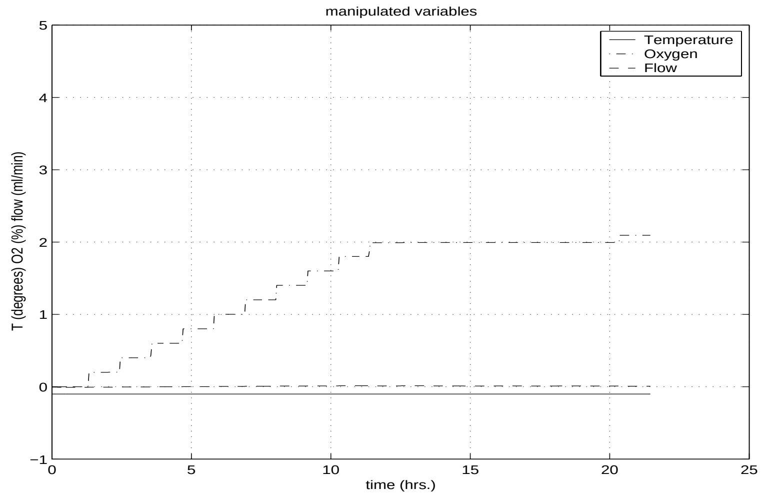

Figure 5.9: *Manipulated variables in experiment*

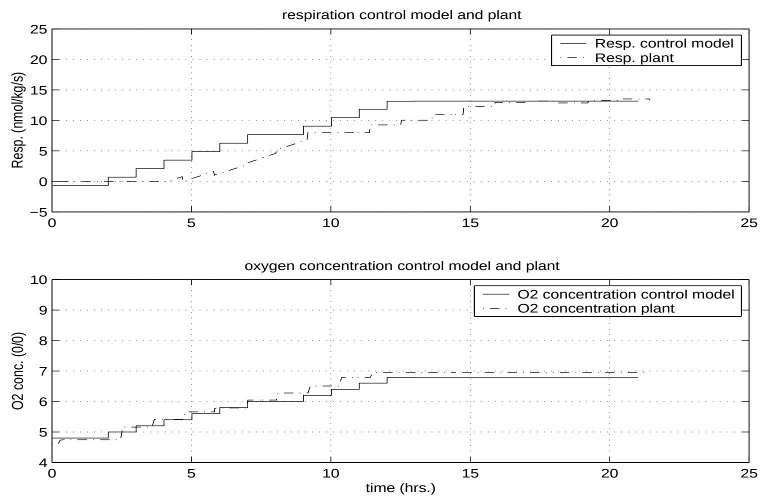

Figure 5.10: *Respiration and oxygen concentration in experiment*

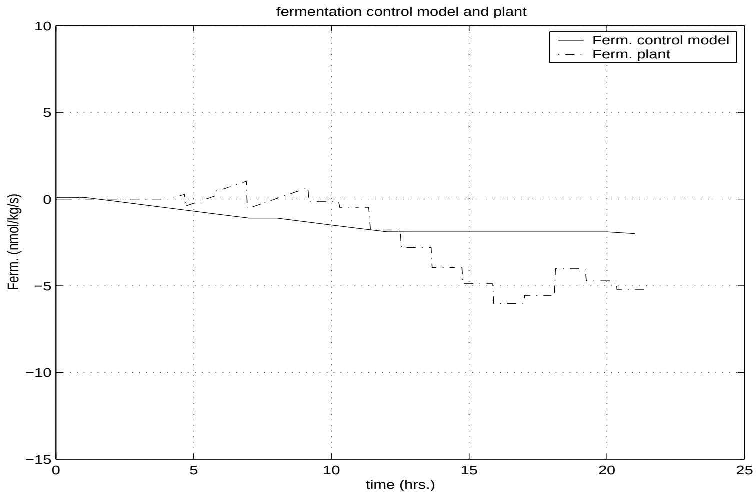

Figure 5.11: *Fermentation in experiment*

5.6.2 Full-scale experiment

Experimental setup

The full-scale experiment focused on reduction of energy consumption in a transport of 20 *tons* of apples during 33 days.

Modelling and control

The models that are used consist of the three sub-states as presented in this chapter. Equations for the direct and indirect environment are deduced from the conservation laws. The direct environment consists of the product state variables temperature and moisture content, and the climate state variables air temperature, RH, O_2, CO_2. The indirect environment consists of e.g. the air conditions in the headspace. In this case study, a large model, discussed in more detail in Sman and Verdijck (2001), is used for simulation of the transport operation.

Results

The model and controller are first tested in a series of simulation studies with the non-linear model acting as plant. These results will be shown first. The focus will be on the reduction in energy usage allowing for high frequent fluctuations in the direct environment of the product that are not harmful for product quality. After that the controller was implemented in a full-scale experiment of which also results will be shown and discussed.

Simulation study
In simulation studies a container transport of apples from New Zealand to The Netherlands is simulated for different conditions. Results with the simulation model are shown in Table 5.4. Details of the simulation are discussed in Sman and Verdijck (2001). From the table it can be concluded that significant energy savings can be

Table 5.4: *Levels of energy consumption in the simulation*

phase	characteristics	Average energy consumption (kW)
I	current practice	4.6
II	high-frequent temperature cycling	1.8

achieved allowing for high-frequent temperature cycling. Energy savings result from both the nonlinear product behaviour and more efficient operation of the equipment. To test the applicability of this high-frequent cycling and its effect on product quality a full-scale experiment has been conducted.

Experimental study
The experiment was performed in November and December 2001. Previous to the experiment the apples (Elstar; 2nd harvest) from a grower in The Netherlands were stored for 1 month under CA conditions. Apples were transferred from bulk storage to standard transport boxes (LxBxH is 40x30x24 cm) which were put on pallets (9 layers with each 10 boxes). Products were kept at ambient air (5 - 10 °C) before refrigerated transport to the experimental facility. Common climate conditions for a container transport would be a RH of 90-95%, an O_2 of 21% and a CO_2 of 0-4%. To enable a comparison of product quality between the container transport with new local controllers and the standard approach with fixed setpoints and extensive circulation of air, two pallets were stored as a reference batch at a constant temperature of 5 °C and 90 % RH. Firmness of the product in this reference batch was monitored during and after the experiment.
In Figure 5.12 the locations of the different type of sensors (O_2, CO_2, temperature, pressure, relative humidity, condensation) that were used in the experiment are shown. In total 48 temperature-, 5 pressure-, 6 condensation- and 8 relative humidity-sensors were used. Also, at 5 different locations air samples were automatically and regularly taken and analysed for CO_2 and O_2 concentrations.
In the experiment separate phases are defined that were tested consecutively:

- A: Cooling full speed,
- B: Cooling half speed,

- C: Transport period with cycling.

The separate phases correspond with transport in full speed, half speed and half speed

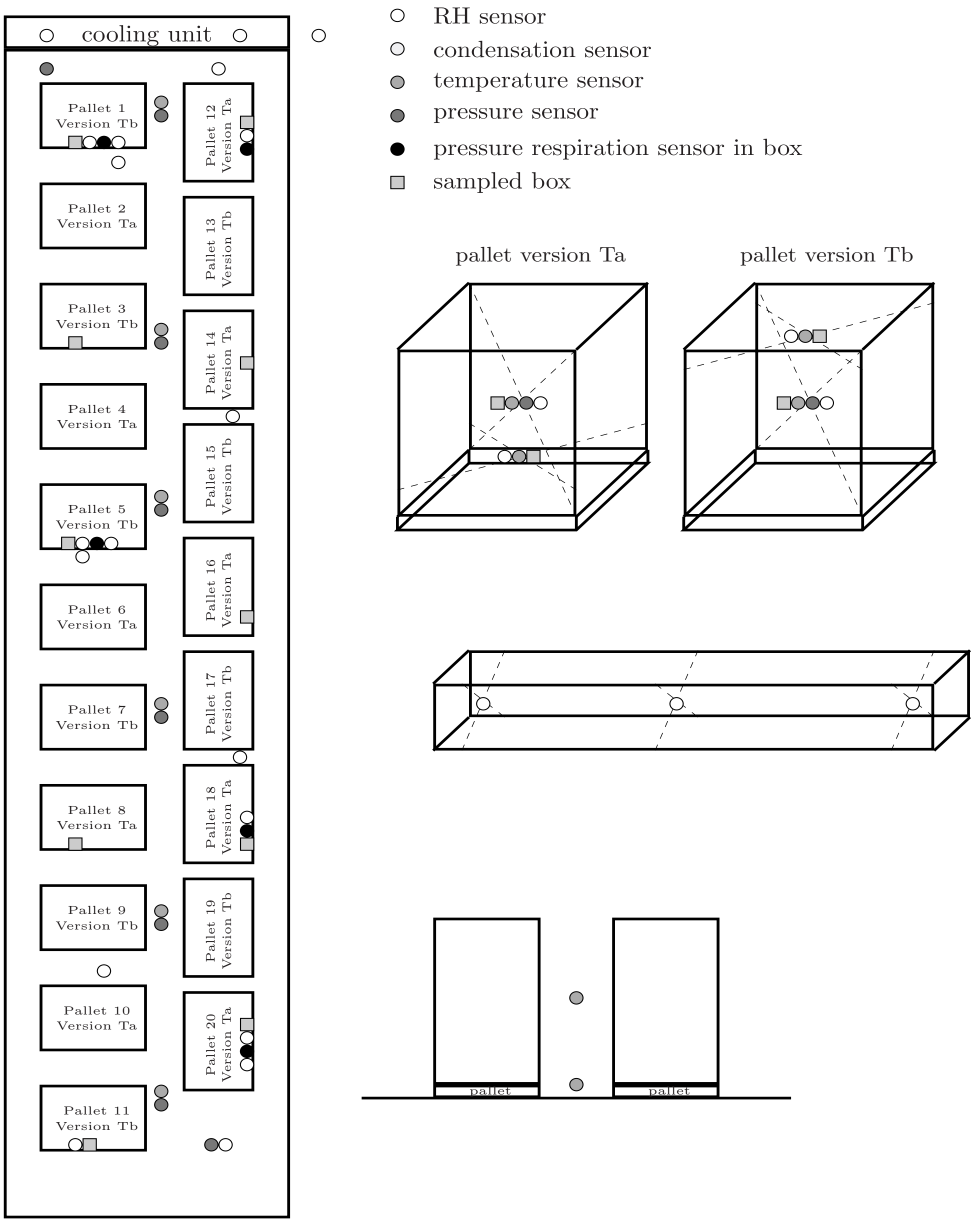

Figure 5.12: *Sensor locations in the full-scale experiment*

with cycling. In the cycling period the cooling is put on and off. In the not-cooling periods the supply air temperature follows the return air temperature up to a limit. In the cooling periods the supply air temperature is 0.5 °C (freezing temperature for these apples around -1.5 °C). In Figure 5.13 the temperature trajectories for the return air and two locations inside the pallet are shown for a period with high-frequent temperature cycling. The high temperature peaks in the return air result from a

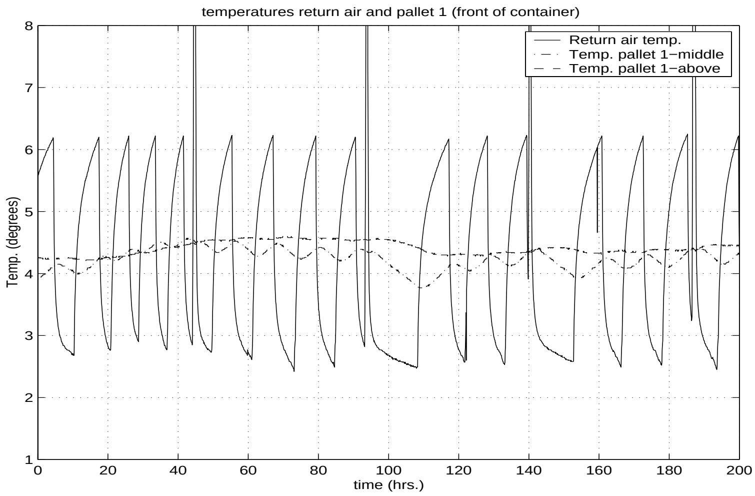

Figure 5.13: *Temperature trajectories in the full-scale experiment*

defrost period required from the unit. The periods with and without cooling are clearly visible and correspond with periods when the cooling either operates at full power or not at all. In Table 5.5 the resulting levels for energy consumption in the different phases are given. During the periods in which energy consumption is

Table 5.5: *Levels of energy consumption in the experiment*

phase	characteristics	Average energy consumption (kW)
A	cooling full speed	4.907
B	cooling half speed	2.896
C	transport period with medium frequent cycling	1.806

measured, the unit was in steady state. The duration of the different phases are chosen such that all (uncontrolled) parameters (e.g. settings for cycling) stay fixed. This results in energy savings between phase A and C of 63%, of which 40% between phase A and B, and 23% between phase B and C.

Product quality was determined as firmness (most important quality parameter for apples). The firmness was measured at the end of the transport period in the center of 20 pallets (400 product evaluations) and in the lower and upper layer of 10 pallets (200 product evaluations for each layer) from different positions in the container as illustrated in Figure 5.12. The measurements from the container experiment were compared with firmness of apples from the reference treatment (25 product evaluations for each layer). No significant difference in firmness was found. Furthermore, no difference in amount of rot was found. The decay in firmness of apples in both the container and reference batch resembles that in small scale experiments.
From the results one can conclude that with the new local controllers, which use the tolerance of the product for "high" frequency climate fluctuations, energy consumption was largely reduced. It was shown to be possible without harming the product and its quality in the transport operation.

5.7 Conclusions

In this chapter improved control of the transport of agro-material is discussed directly considering both product quality and energy efficiency. A newly developed control methodology was used. Controllers were designed at two different time scales. A Model Predictive Controller directly controlled product quality by means of the product responses respiration and fermentation. On the fast time scale the local controllers were locally optimised to allow controlled climate fluctuations which do not harm the product. The developed control components were studied in simulations and implemented in both small-scale and full-scale applications for the transport of apples. With the new controllers product responses were monitored and controlled. Furthermore, a reduction of energy consumption of more than 50 % was realised.
Results with the new control components learned that direct control of product quality is possible. This will result in lower product damage and energy consumption. Furthermore, including the product directly in the control this allows for more flexible control of climate conditions, especially on the fast time scale. The new control components are not only applicable in container transport but also in other climate controlled operations as e.g. storage and drying operations.

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Notation

C	control configuration
Cp	specific heat $[J\ kg^{-1}\ K^{-1}]$
E	energy $[J\ kg^{-1}]$
F	oxygen consumption $[nmol\ kg^{-1}\ s^{-1}]$
H	time horizon $[s]$
J	objective function $[Euro]$
K	matrix with yield coefficients
L	costs of operation $[Euro]$
M	total product mass $[kg]$
Ma	total air mass $[kg]$
P	product price $[Euro\ kg^{-1}]$
Q	quality attribute
R	resistance $[J\ K^{-1}]$
T	temperature $[K]$
W	weighing factor
d	disturbance
$flow$	incoming air flow $[kg\ hr^{-1}]$
n	mass concentration $[\%]$
r	reaction components
t	time $[s]$
u	input
x	process state
y	measurable outputs
z	reconstructed state variables
Superscripts:	
k	iteration co-efficient
ref	reference value
Subscripts:	
a	air
d	direct environment state variable
$dist$	disturbance
$evap$	evaporation
$ferm$	fermentation
$flow$	incoming air flow
i	indirect environment state variable
max	maximum value
min	minimum value
n	non-reactive components
out	outside
p	primary state variable
r	reactive components
$resp$	respiration
u	input
y	output

Chapter 6

Optimisation of Product Quality and its variation

abstract

In this chapter an optimisation procedure is presented for direct control of product quality of agro-material and its variation. The procedure builds on a previously presented model structure, which is briefly reviewed, together forming a methodological framework for direct product quality control in climate controlled operations. We introduce an economic-based optimisation procedure that is part of a hierarchical control structure and utilizes the model structure to control product quality and its variation. The result is a trade-off between operational cost and product quality. The characteristic variation in natural products is included in the procedure following a lumped approach. This lumped approach makes use of discretised quality classes to describe not only product quality, but also include a measure for its variation. Although direct measurement of product properties is often difficult the approach is validated using simulated and measured data. The optimisation procedure using the model approach is implemented and tested in an full-scale industrial operation of storing large quantities of potatoes illustrating the applicability and benefits of the procedure.

G.J.C. Verdijck, G. van Straten, H.A. Preisig

Optimisation of Product Quality and its variation in climate controlled operations, Computers and Electronics in Agriculture, 2002, submitted.

6.1 Introduction

Climate controlled operations involving agro-material, such as storage and container transport, constitute an important class of operations. These operations are more and more confronted with the overall objectives of increased productivity and product quality. E.g. Trystram and Courtois (1994) state that specifically in food industry requirements on product variation and perishability must be considered. However, controllers that are currently used in these operations focus on maintaining (fixed) climate settings.

Realising the overall objectives asks for an economic-optimising control procedure directly including product quality and its variation. Such a procedure requires an economic objective function including product quality and its variation to perform an optimisation. Furthermore, models describing the evolution of product quality in the operation, in relation with the operational climate variables must be available. With the increasing availability of process and product models (Verdijck et al. (2001)) the use of such optimising model-based controllers has become more feasible.

Recently, the use of product models is more commonly accepted. In van Straten et al. (2000) the use of (mechanistic) product models describing crop growth in climate control of greenhouses is discussed. Next to a mechanistic model approach, black-box techniques can be applied to predict and monitor product quality and its variation. For monitoring product quality Statistical Process Control (SPC) techniques are used in, e.g., sugar quality monitoring (Ooi and McFarlane (1998)). Albert et al. (2001) use inferential (data-driven) quality assessment to estimate quality variables on-line to advice process operators in breakfast cereal production. Wang et al. (2002) use inferential quality assessment in the design of a control structure. In all these examples models that describe product behaviour are used. However, either product models are not considered explicitly in the process optimisation or are limited to product mass (or crop growth).

In literature several examples can be found where product models are used for trajectory optimisation for (batch) operations in food industry. They include the use of a Model Predictive Control approach for timber drying optimising temperature and moisture profiles (Musch et al. (1998)). Trelea et al. (1998) optimise the fruit refrigeration process for several economic objectives including mass loss. For batch operations Trelea et al. (1997b) use the wet-milling quality of corn for off-line optimisation. Fleurat-Lessard (2002) developed a decision support system for grain storage considering some quality aspects. Most of the mentioned examples perform, in a way, an off-line optimisation. Often the thereby optimised objective function does not include product quality or is limited to product mass and moisture content. Therefore, product quality is not controlled directly. Furthermore, variation is not

considered explicitly, although it is an important property for both process efficiency and product quality in operations involving agro-material.
In this chapter an optimisation procedure is presented that is part of a new hierarchical control structure and includes recent (mechanistic) quality models directly in the (economic) objective function. Furthermore, quality variation, defined as the difference in the product quality attributes of individual products, is included in the objective function using a lumped model approach. This approach enables the description and prediction of the time-evolution of the relevant quality attributes. The relation between product quality, its variation and product price enables the explicit trade-off between profits and cost of operation at the highest level of the control structure thereby meeting the overall objectives of increased productivity and product quality. Through the incorporation of the optimisation procedure in a hierarchical control structure the various levels of detail are accounted for on the corresponding control level.
The hierarchical control structure is briefly discussed in Section 6.2. Section 6.3 deals with modelling product quality and quality variation. In the next section the models will be validated using data from an industrial potato storage facility. In Section 6.5 this is followed by a discussion on direct Product Quality Control on the highest control level. Finally, the economic optimisation is applied to an industrial operation on potato storage.

6.2 Control structure

In operations involving agro-material, physical phenomena occur at different time scales. A large multivariable controller for the whole process operation would not be an acceptable solution for reasons of long computation time, unknown disturbances and incomplete state feedback on the required time intervals. Fortunately, from a time scale analysis it is concluded that a separation into three time scales is justified in the processing of agro-material. This leads to a three-stage hierarchical control structure with decreasing time scale, as discussed in Verdijck and van Straten (2002a). The corresponding sub-states, as will be shown in Figure 6.1, are defined on each separate time scale as:

- slow time scale: primary sub-state, x_p, with slow dynamics, consisting of slowly changing reactive mass concentrations, c_r, that determine product quality,

- intermediate time scale: direct environment sub-state, x_d, with intermediate dynamics, consisting of e.g. product and air temperatures, T_p and T_d, and non-reactive mass concentrations, c_n e.g. moisture content, and

- fast time scale: indirect environment sub-state, x_i, with fast dynamics, consisting of e.g. (indirect) temperature, T_i.

The structure of the process is strictly hierarchical. The product with its quality is in the center, encapsulated by the direct environment of the containing unit. The indirect environment forms yet another outer shell enclosing the unit completely. The plant input, that can be manipulated only, is sequentially linked together with the primary state variables, which are the target, with the environments in between.
On each time scale a separate control problem is formulated. On the slow time scale an economic optimisation problem is formulated, which is the main subject of this chapter. On the intermediate time scale a quadratic objective function is used to correct the desired settings and on the fast time scale local controllers try to reach and maintain the calculated setpoints, in order to reject disturbances; the latter being the technique currently in use. From the (relatively large) differences in time constants it is plausible that "loss" of control performance due to this separation of the control problem is limited. In Figure 6.1 the control structure with the different sub-states and control components is shown.
The highest control level focuses on the evolution of the product quality at the same time optimising an economic profit function. This results in an optimal state trajectory for both the product state as well as for the states representing the direct environment of the product. The latter is then used as setpoint or reference trajectory for a Model Predictive Controller (MPC) on the intermediate control level. This controller drives the process towards and then along the reference trajectory. Typical control horizons are one week for storage, one day for transport and one hour for drying operations. Inputs are reference trajectories, constraints and weighing factors from the slow time-scale controller, measurement information and the choice of some weighing functions. Outputs are setpoints and or constraints for the fast time-scale controllers, which maintain the conditions in the indirect environment of the product usually the container, room or equipment in which the process takes place. At this lowest control level the fast time-scale controllers often are the currently implemented controllers. An advantage of the presented control scheme is that the current controllers remain essentially unchanged. This will not only enhance acceptance from potential end-users, it will also allow for a modular approach that could benefit implementation.

The objective of the slow time-scale controller at the highest control level, which is the main target in this chapter, is to optimise the economic return of the process. Inputs for the slow time scale optimisation are logistic information including lead times, energy supply and prices, and initial values for the product state. Outputs are realisable setpoints, y_d^{ref} in Figure 6.1, for the lower-level controllers. The desired

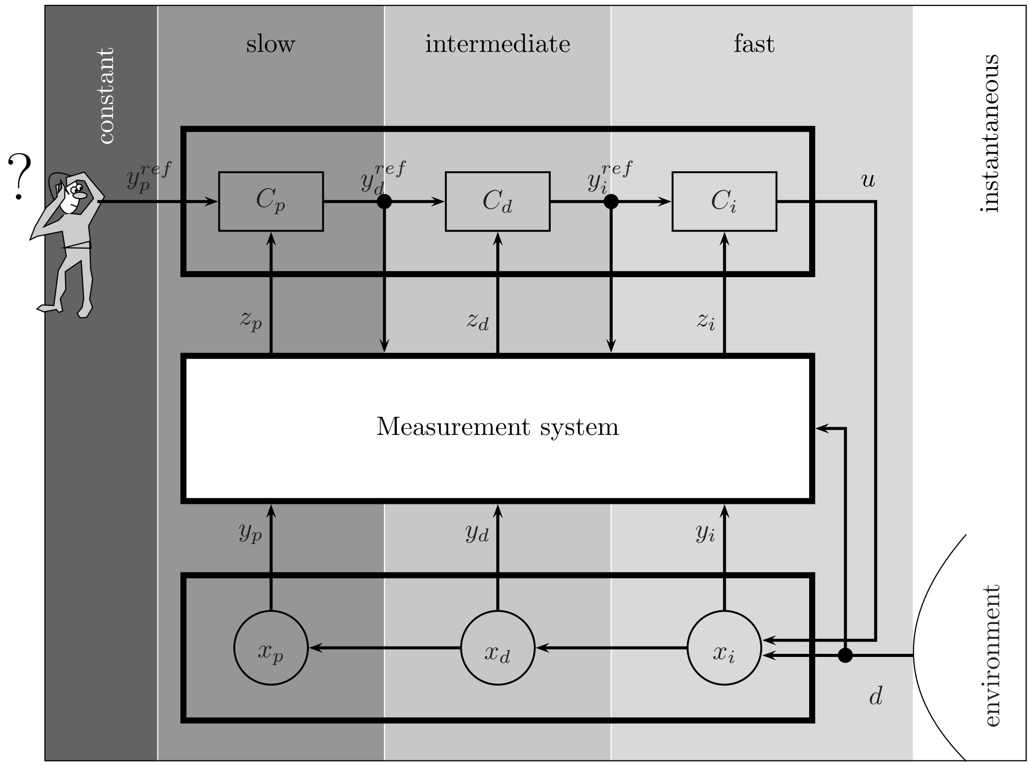

Figure 6.1: *Control structure with control components on different time scales*

state trajectories are calculated optimising an economic objective function that can be written as

$$\min_{y_d^{ref}} J = -P(Q(t_f))\ M(t_f) + \int_{t_0}^{t_f} L(x_d, d, t)dt, \tag{6.1}$$

where P is the price of the product that depends on the end-quality $Q(t_f)$, $M(t_f)$ is the end-mass of the product and the integral represents the cost that are made to achieve the desired primary and direct and/or indirect environment state variables ($x = [x_p\ x_d\ x_i]^T$), subject to disturbances, d. This objective function optimises financial yield and product quality against weight loss and costs of the operation. The objective function in Equation (6.1) is subject to the differential state equations:

$$\begin{aligned} \dot{x}_p &= f_p(x_p, x_d), \\ y_d &= y_d^{ref}, \end{aligned} \tag{6.2}$$

where the differential equations describe the quality attributes of the product and the dynamics of the direct environment are considered to be instantaneous at the slowest time scale. Algebraic equations describe the relations for the derived quantities Quality, Q, and total product Mass, M:

$$\begin{aligned} Q &= f_q(x_p), \\ M &= f_m(x_d), \end{aligned}$$

which are required in the objective function. The cost L is a function of the input u, which is acting at the fast time-scale of the process directly manipulating the indirect environment, which in turn affects the direct environment. Costs associated with these control actions, u, are e.g. energy consumption from fans and cooling equipment. It is assumed that on the slow time scale, that is discussed in this chapter, the indirect state variables, x_i, are equal to the direct state variables, x_d. Thus, for the evaluation of the cost function on the slow time scale an estimate of the control actions on the fast time scale must be made that depends on the output, y_d^{ref}, of the slow time scale controller. For a transport or storage operation this would require knowledge about the average heat produced by the product and the average heat exchanged with the surroundings. Together with the equipment characteristics this knowledge can be used to relate fast time scale control actions (u) to operation costs (L). This will be illustrated in the application.
One of the main problems when processing agro-material is the product variation. This variation requires "conservative" process settings to fulfill the minimal quality requirements, as in current operations no direct control of the variation is included. Further optimisation of these operations demands not only direct control of product quality but also should include quality variation. This can be done by extending the objective function in Equation (6.1) with a variation term, which penalises large variation or difference in values for the product state variables of individual products. In an industrial operation this can be realised by means of a penalty on product price as will be shown later when discussing the application of potato storage. Including variation in the objective function requires a model for individual products or classes of the product.

6.3 Modelling product quality and its variation

In this section first the nominal behaviour of the product is discussed. Then a lumped approach is illustrated that enables the inclusion of variation.

6.3.1 Nominal product behaviour

To include product quality directly in the process controller a model structure is necessary that captures the dynamics of the relevant state variables of the product.

In Verdijck et al. (2001) a nominal model structure is presented in which a product is considered to be a discrete entity that interacts with its environment. In this model structure an agricultural product is considered as a bioreactor where (biochemical) reactions take place, such as enzymatic reactions, degradation and respiration. Although these reactions are quite complex, most reaction mechanisms can be simplified to a limited number of basic reactions, which is a gross simplification of reality. However, due to limited knowledge about the mechanisms in quantitative terms and the fact that the model is to be used for control purposes, such a simplification is justified. It is assumed that the reactions inside the product together with the relation between state variables and quality attributes can be described by the following model structure:

$$
\begin{aligned}
\dot{x}_p &= K(x_d)r(x_p), \\
z &= f_z(y), \\
y &= f_y(x_p, x_d, x_i). \\
Q &= f_q(z),
\end{aligned}
\tag{6.3}
$$

where Q represents the quality attributes that depend on the primary state variables in the (reconstructed) process outputs, z. As often not all desired process outputs can be measured directly they need to be reconstructed from the available measurements, y, using the process models. The rate of change of the primary state variables, x_p, is separated in reaction rates and reaction components. Reaction rates, k, are the components in the matrix K and are a function of direct product environment state variables, x_d, such as temperature, pH and concentration of mass components. The reaction components, grouped in the vector r, directly take part in the reactions and are a function of the primary state variables only. This separation of the dependency on the dynamics of the primary state variables into primary and secondary state variables is of interest to control as these components are associated with different non-linearities and time scales.

6.3.2 Quality variation

Variation of product and product quality together with its control is not often considered in operations involving agro-material. Product variation is usually not described by distribution functions, but rather by (discrete) quality classes. Moreover, the use of distribution functions is not attractive because of computation time. As an alternative, a lumped procedure is proposed in Verdijck et al. (2001). In this approach:

- The state variables of the product are separated into a main primary state variable, x_p^m, such as e.g. the sugar content of potatoes or firmness of apples, and assisting state variables, x_p^a, such as e.g. enzyme concentrations.

- The main quality variable is discretised into intervals, called classes, thereby acting as class specifying variable. This is shown in Figure 6.2.

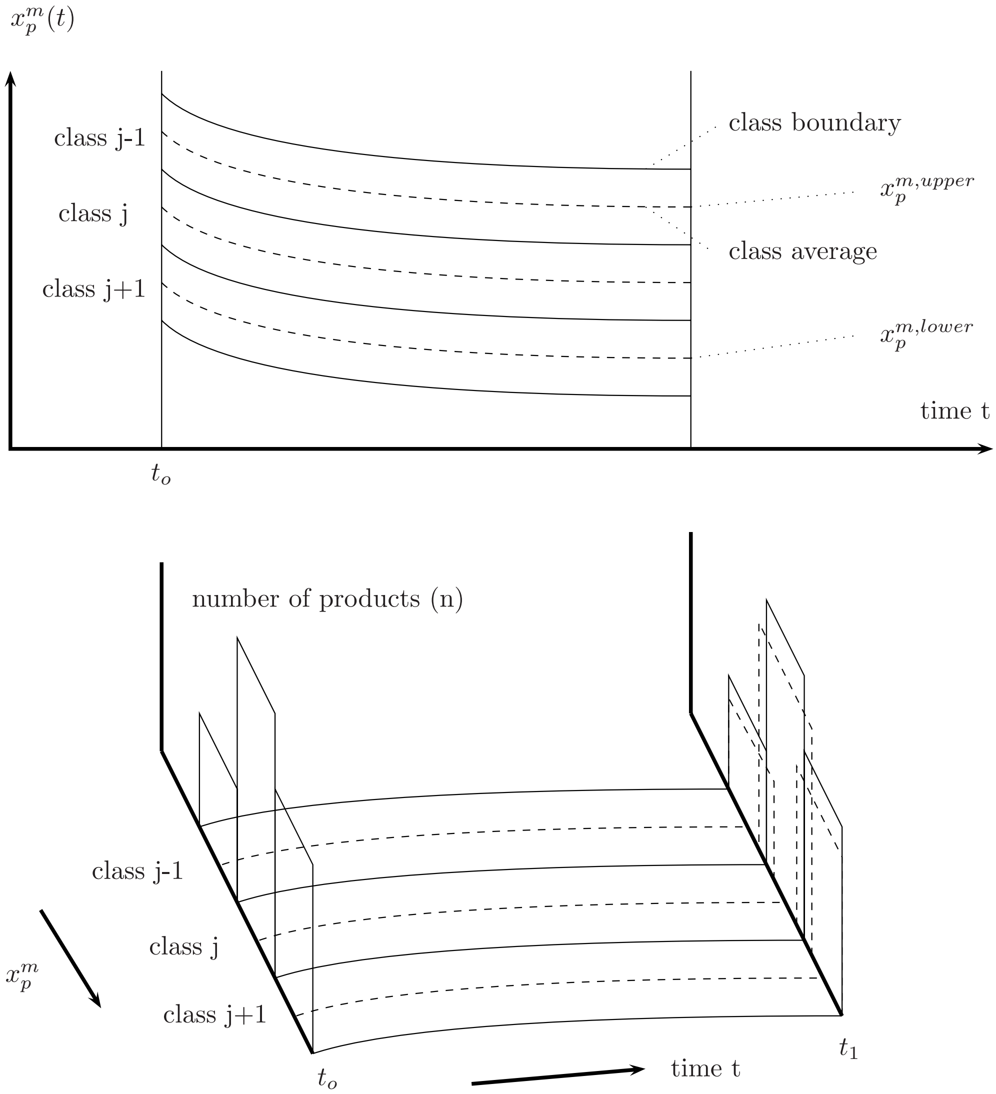

Figure 6.2: *Class behaviour*

- A nominal product in each class, that is a product with average initial values and and average behaviour for both x_p^m and x_p^a, corresponding to a specific class

j, defines the class middle $x_p^m(j)$ and its time-evolution.

- In this chapter variation, Δx_p^m, is defined as the difference in the main primary state variable between the nominal products of the most "upper" and "lower" classes,

$$\Delta x_p^m = x_p^{m,upper} - x_p^{m,lower}. \tag{6.4}$$

- Class boundaries are defined as the average of the neighbouring classes

$$x_p^m\big|_{boundary} = \frac{x_p^{m,j} + x_p^{m,j+1}}{2}. \tag{6.5}$$

  For the computation of the extreme boundaries additional information is derived from the conservation of the number of products and the fact that all products resides inside all the classes. The boundaries are thus given by the minimal and the maximal value of the main primary state in the population.

With the different classes, variation, Δx_p^m, in the main product state caused by initial variation in the main and assisting state variables can be described. This model will be used to control quality variations as will be shown when discussing the application on the storage operation.

6.4 Model validation

In this section the earlier presented modelling approach will be validated using a full-scale storage facility for potatoes as an example. First though, a simulation study is performed where a multi-product simulation is compared with the lumped-class model. In the multi-product simulation a large number of products exhibiting their own dynamics is simulated. Second, measurements from an industrial facility will be shown which are used to validate the lumped-class model for sugar content during the storage period.

6.4.1 Validation of lumped-class model with simulated data

The target for the lumped-class model was to reproduce approximately the same averaged trajectories and product variation as the more detailed multi-product model. As a full-scale test of the model with thousands of product evaluations would not be feasible a numerical study simulating 1800 of individual products was performed, the multi-product model. This simulation is compared with a simulation using the lumped-class model with three quality classes. For the multi-product and lumped-class simulations the same ranges for the product state variables were used (in this example sugar content S and enzyme concentration En_{cold}). Values, which are used in the simulations, are shown in Table 6.1. From the table it can be seen that both

Table 6.1: *Simulation parameters*

parameters	multi-product simulation	lumped-class simulation
number of state variables	5400	9
range of initial sugar concentrations	0.0022-0.0077	0.0022-0.0077
range of initial En_{cold} concentrations	0.1983-0.5163	0.1983-0.5163

simulations (multi-product and lumped-class) start with the same variation in sugar content, S, and enzyme concentration. In the lumped-class simulation, the classes are defined at the beginning, after which the time evolution of the classes is computed. In the multi-product simulation (1800 products) the time evolution of each product is computed. In Figure 6.3 the sugar concentrations for the three classes (lumped-class approach) are shown. In the same figure the average and the minimum and maximum sugar concentrations from the multi-product simulation are shown. As expected the

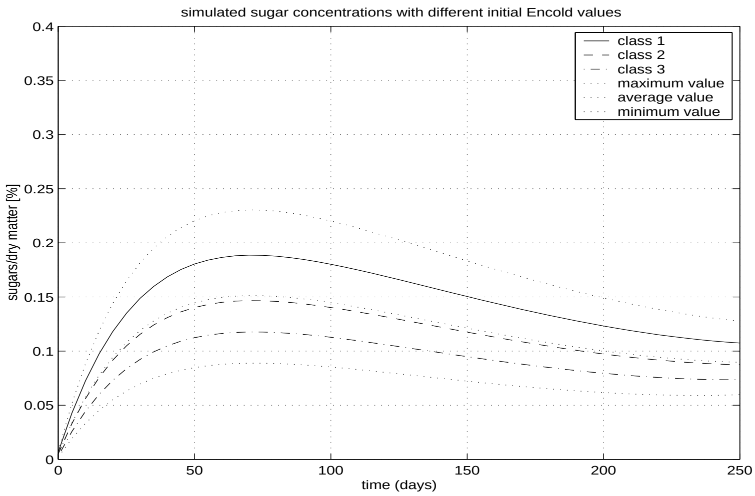

Figure 6.3: *Evolution of the sugar concentrations in the three classes*

average sugar concentration from the multi-product simulation corresponds with that of class 2 (middle class) of the lumped-class approach. From the figure it can be concluded that the lumped-class approach describes the nominal sugar concentrations in the three classes reasonably well. The lumped-class approach will be further validated using measured data in the next section.

6.4.2 Validation of lumped-class model with measured data

Measuring sugar concentration in an industrial facility is a laborious task. During the actual loading of the facility a number of products is grouped together as a sort of super-products, of which the weight is measured before storage and which are used for sampling during the storage operation. At several instances a sample is taken by removing one of the "super products" from the facility for analysis of sugar content. Since this analysis is destructive it has the drawback that individual products cannot be monitored during the entire storage period. However, at the moment this is the only method available for measuring sugar content in industrial storage facilities. The location of samples in the facility is related to different locations in the field. Therefore, carefully chosen locations in the facility may act as a measure for the variation in sugar concentration and can be used for validation purposes.
In Figures 6.4-6.5 the simulated and measured sugar concentrations, x_p^m, are shown in time, both for the nominal (average) sugar content for one of in total three sugar classes and the maximum variation in the sugar content between the classes, $\Delta x_p^m = x_p^{m,upper} - x_p^{m,lower}$. The model predictions are compared with the available measurements. At specific times, samples are taken from three different locations in the facility, corresponding to a class. In the storage period the frequency of sampling increases from every 4 weeks to weekly sampling towards the end of the storage period. In view of the available measurement data the definition of more quality classes would not be appropriate. The sugar concentrations in the remaining two classes show similar behaviour (not shown). The results with the model using the different classes show a fit with the measurement data that is reasonably well considering the measurement accuracy that is about 0.015 [*kg (kg dry matter)*$^{-1}$] at these low concentrations. The predicted evolution of the variation shows similar behaviour as the measured variation. In the beginning variation increases due to the effect of the enzyme En_{cold}. Towards the end of the storage period this enzyme is denaturated and both sugar concentration and its variation decline as temperature of the product stock in the storage facility rises, as shown in Figure 6.6. Again, differences can be explained by the limited accuracy of the measurements. The experimental results confirm the results of the simulation study with a large number of individual products. This shows that the lumped-class approach can be useful for control purposes. This will be the main topic of the remainder of this chapter.

6.5 Direct Product Quality Control

The general concept as outlined in Section 6.2 is now worked out in greater detail. First, the objective function for quality control of the nominal product is discussed.

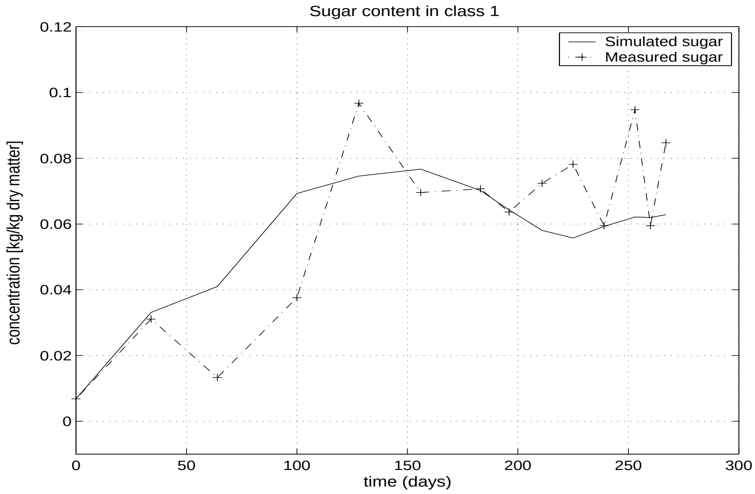

Figure 6.4: *Evolution of the sugar content in class 1*

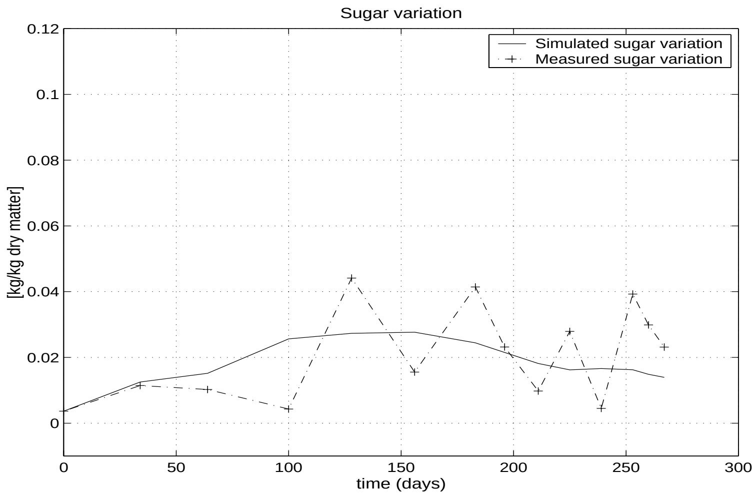

Figure 6.5: *Evolution of variation in sugar content*

Then, the method to include the quality variation is shown.

6.5.1 Optimising nominal quality

In the implementation of the optimal control problem outlined in Section 6.2 in practice, the following changes are made. First, the total time is divided into N

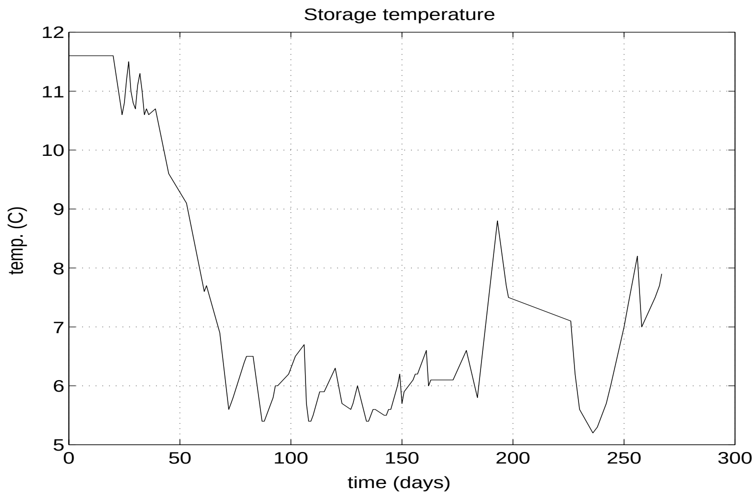

Figure 6.6: *Temperature history in storage*

equidistant control intervals, indexed by k, where $t_k = k\ \Delta t,\ k = 0, ...N-1$. Instead of the integral in Equation (6.1) it is more convenient to work with the Mayer formulation, which entails the definition of an additional state variable, $E(t)$

$$\frac{dE}{dt} = L(x_d, d, t),\ E(t_0) = 0. \tag{6.6}$$

Moreover, soft constraints are introduced on the piecewise constant controls, y_d^{ref}. First to allow recovery from harvest injuries a soft constraint is put on the control over the first interval,

$$W_0\ |x_{d,0}^{ref} - x_{d,0}^c|. \tag{6.7}$$

Similarly, at the end of the storage period a soft constraint is put on the control over the last, $N-1^{st}$ interval, to prevent injuries while unloading the storage facility,

$$W_f\ |x_{d,N-1}^{ref} - x_{d,f}^c|. \tag{6.8}$$

The parameters $x_{d,0}^c$ and $x_{d,f}^c$ represent the target temperatures at the initial and the final stage of the storage period, and W_0 and W_f are weighing factors. Finally, large control movements are penalised by

$$\sum_{k=0}^{N-1} \left(x_{d,k+1}^{ref} - x_{d,k}^{ref}\right)^2. \tag{6.9}$$

Together, the problem is now to find the N piecewise controls y_d^{ref} such that

$$\min_{y_d^{ref}} J = -P(Q(t_f))M(t_f) + E(t_f) + S, \tag{6.10}$$

where S represents the constraints in Equations (6.7-6.9). In the application the optimisation is performed assuming y_d^{ref} piecewise constant with a time interval of 5 days. The objective function is subject to

$$\begin{aligned} \dot{x}_p &= K(x_d)\ r(x_p), \\ y_d &= y_d^{ref}, \\ Q &= f_q(x_p), \\ M &= f_m(x_d). \end{aligned} \tag{6.11}$$

In general, a non-trivial optimisation problem asks for a numerical optimisation. Several approaches can be followed, such as nonlinear programming, dynamic programming and calculus of variations. Because of the availability of some time-efficient algorithms this last approach was applied, using Pontryagin's Minimum Principe. Details can be found in e.g. Bryson jr. and Ho (1975). Two different solution techniques may be used, gradient search methods and direct solution methods. Although direct solution methods converge faster to the optimum they require an initial estimate close to the optimal value. Therefore, a gradient search method, that is slower but more robust, is used (Bryson jr. (1999)). The gradient search method is implemented in Matlab using the Optimisation Toolbox. Weighing factors are determined by product price, cost of energy consumption, cost of quality variation (for details see the application in Section 6.6). Weighing factors for the constraints that are included in the optimisation problem are considered as tuning parameters.

6.5.2 Optimising quality variation

To include quality variation directly in the optimisation performed on the highest control level a penalty on product price, as function of the variation in product quality, is incorporated in the objective function in Equation (6.10)

$$\Delta P(\Delta x_p(t_f))M(t_f), \tag{6.12}$$

with the variation, $\Delta x_p(t_f)$, given by the lumped-class model as discussed earlier. This penalty is included in the objective function and is used in the optimisation in the application on potato storage that will be discussed in next section.

6.6 Application on potato storage

Potato storage is an important part of the production cycle in the food industry, because the industry demands a year-around supply of potatoes. The facility that is considered in this study is approximately 400 m^2 and the product is stacked 4 m

high. Air climate is maintained by ventilation with outside air, circulation of air or by a combination of both. The stored batch of potatoes shows an initial variation in product state variables, which is correlated to the location of the potatoes in the storage facility. The quality variable of interest is the frying colour index, which is related to the sugar content.

6.6.1 The quality model

The concentration of sugars, S, changes due to several reactions of which the most important are

$$\begin{aligned} S + O_2 &\xrightarrow{k_1} H_2O + CO_2, \\ Starch + En_{cold} &\xrightarrow{k_2} S + En_{cold}, \\ Starch + En_{sene} &\xrightarrow{k_3} S + En_{sene}, \\ En_{cold} &\xrightarrow{k_4} En_{cold_{non-active}}, \\ En_{sene} &\xrightarrow{k_5} En_{sene_{non-active}}. \end{aligned}$$

The first reaction represents the respiration, and the second and third reaction are enzymatic reactions with enzymes En_{cold} and En_{sene} representing cold-induced and senescent sweetening (Hertog et al. (1997)). Assuming first-order kinetics the following model is obtained for one quality class, using the model structure in Equation (6.3)

$$\begin{aligned} \dot{x}_p &= Kr, \\ x_p &= \begin{bmatrix} c_S \\ c_{En_{cold}} \\ c_{En_{sene}} \end{bmatrix}, \quad r = x_p, \\ K &= \begin{bmatrix} k_1(T) & k_2(T) & k_3(T) \\ 0 & k_4(T) & 0 \\ 0 & 0 & k_5(T) \end{bmatrix}, \end{aligned} \tag{6.13}$$

where $k_i(T)$ are the reaction rates that are assumed to be only temperature dependent following an Arrhenius-type equation. The state variables are expressed in mass concentrations with units *kg (kg dry matter)*$^{-1}$.

The variation in sugar concentration is assumed to be caused by initial sugar variation and the variation in the assisting primary state variable En_{cold}, while the concentration of the enzyme En_{sene} is assumed not to exhibit any variation. This can be motivated as in literature (Hertog et al. (1997)) differences in sugar content between batches are described with different (nominal) values for En_{cold}, while keeping the value for En_{sene} constant. Equation (6.13) applies to each class and differs in initial conditions only. In view of the available measurements, no more than three classes

can be distinguished, but this is sufficient to illustrate how quality variation can be included into the control structure.
The optimisation problem is defined in the objective function in Equation (6.10). Potato product price depends on the quality of the product. Quality is measured as the frying colour index that is directly related to the sugar content according to

$$Colour\ index\ (Q) = \left(\frac{c_s}{0.02}\right)^{\frac{1}{2.047}}. \tag{6.14}$$

Below an index of 4 a high price of about 0.07 Euro per kilogram of product will be paid, otherwise a low price of about 0.02 Euro. Other, more complicated, price-quality relations can be incorporated if necessary.
The moisture content of the product changes due to internal reactions inside the product and the evaporation of moisture from the product. Assuming that evaporation is the dominant process, the change of product mass per m^2 can be written as

$$\frac{dM}{dt} = \rho_{bulk}\ H\ k_{evap}\ A_{sp}\ \Delta P\ [kg\ H_2O\ (kg\ product\ day)^{-1}], \tag{6.15}$$

with parameters defined in Table 6.2, and where the driving force, ΔP, depends on humidity in the air directly surrounding the product (Rastovski and van Es (1987)). In the storage operation an average difference in relative humidity of 5 % is assumed. For the driving force this results in

$$\Delta P = 5\ (1.7011 + 7.7835\ e^{\frac{T_d}{17.0798}}). \tag{6.16}$$

The cost in the objective function depends on the local control actions, i.e. the amount of ventilation required to remove the necessary heat

$$\frac{dE}{dt} = n_{fan}\ p_{fan}\ P_e\ \frac{H_{cool} + H_{production} + H_{heat\ exchange}}{H_{removal}}\ [Euro\ day^{-1}], \tag{6.17}$$

with H_{cool} the heat for cooling the initial product temperature to the desired storage temperature. $H_{production}$ the heat produced by the product, which would lead to a temperature rise of 0.25 °C per day without ventilation. $H_{heat\ exchange}$ the heat exchange between storage facility and outside environment. $H_{removal}$ the heat that can be removed by ventilation with outside air. These can be calculated with

$$\begin{aligned}
H_{cool} &= H\ \rho_{bulk}\ Cp_{potato}\ (T_{t_0} - T_d^{ref}),\\
H_{production} &= 0.25\ H\ \rho_{bulk}\ Cp_{potato},\\
H_{heat\ exchange} &= k_{insulation}\ A_{facility}\ (T_{outside} - T_d^{ref}),\\
H_{removal} &= flow\ \rho_{bulk}\ Cp_{air}\ \Delta T,
\end{aligned}$$

with parameters given in Table 6.2. With Equations (6.14)-(6.17) the required relations are given for solving the objective function in Equation (6.10) including the penalty for variation.

Table 6.2: *Parameters in potato storage*

parameters	description	values
ΔT	temperature difference for ventilation	2 $[^oC]$
ρ_{bulk}	density of potatoes in bulk	650 $[kg\ m^{-3}]$
k_{evap}	specific evaporation co-efficient	2.0 10^{-5} $[kg\ day^{-1}\ m^{-2}\ Pa^{-1}]$
$A_{facility}$	specific heat exchange surface	1.2 $[m^2]$
A_{sp}	specific moisture exchanging surface	60 $[m^2\ per\ m^3 product]$
Cp_{air}	specific heat air	1003 $[J\ kg^{-1}K^{-1}]$
Cp_{potato}	specific heat potato	3600 $[J\ kg^{-1}K^{-1}]$
H	height of potato stock	4 $[m]$
H_{roof}	height of the roof	6 $[m]$
L	length storage facility	20 $[m]$
W	width storage facility	20 $[m]$
$T_{outside}$	average outside temperature	7.25 $[^oC]$
$flow$	air flow with ventilation	360 $[m^3\ hour^{-1}]$
n_{fan}	number of fans	5
$k_{insulation}$	insulation of storage facility	2.6 10^4 $[J\ m^{-2}\ K^{-1}\ day^{-1}]$
p_{fan}	power of fans	3 $[kW]$
P_e	price per kWh	0.12 $[Euro\ kWh^{-1}]$

6.6.2 Manipulation possibilities for control of variation

To explore the possibilities for manipulation of the variation in sugar content several simulation studies have been performed. These show the effect different values for the optimised variable (temperature) have on the variation in product quality. Simulations have been done for constant temperature regimes of 4, 7 and 10 ^oC. The results are shown in Figures 6.7-6.9. It can be concluded that changing the optimised climate variable T_d^{ref} (temperature) manipulates the product variation. Evolution of product quality variation decreases with increasing temperature. On the other hand, weight-loss will be larger. The optimal input for the storage operation should be a trade-off between cost, nominal or average sugar content, weight-loss and quality, as expressed in the objective function.

6.6.3 Optimisation of quality and variation control

In Chapter 4 the new hierarchical control structure not including variation is compared with the current controller. For potato storage a practical optimisation resulted in a 10 % reduction in energy consumption (Figure 4.7). The economic objective function that is (numerically) optimised in this chapter is given in Equation (6.10) including the penalty on product price in Equation (6.12). Results for the optimisation are shown in Figure 6.10 for the sugar content in the different classes. The sugar content is shown

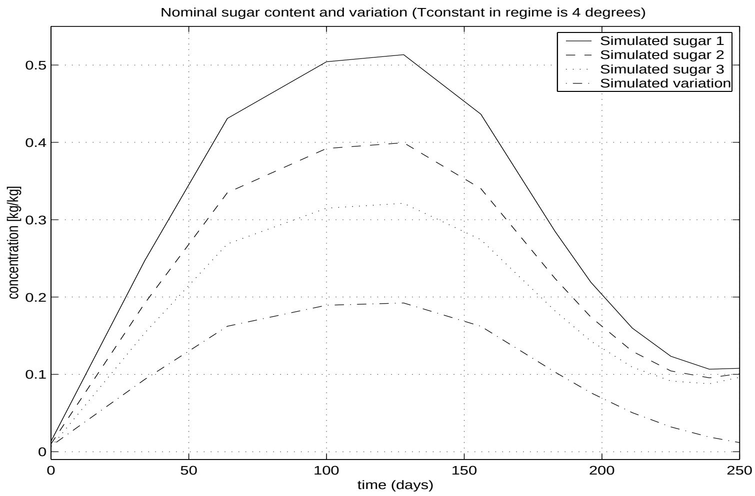

Figure 6.7: *Evolution of sugar content and variation (4 degrees)*

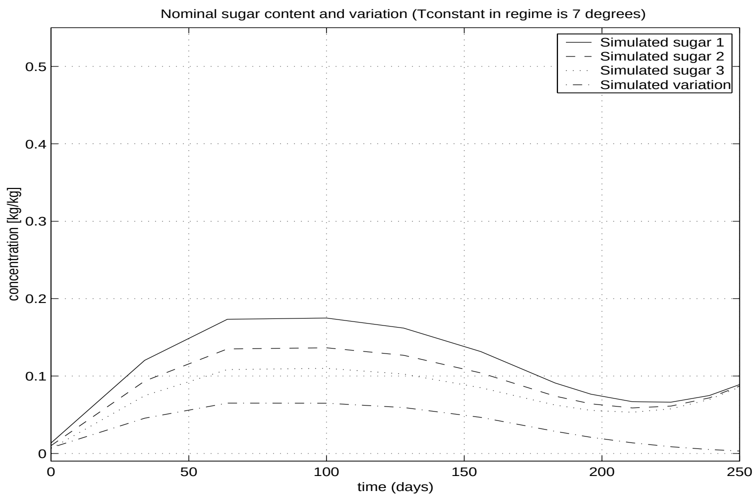

Figure 6.8: *Evolution of sugar content and variation (7 degrees)*

for the optimisation with the penalty for the variation set to 10^5 (small weight value that corresponds to a penalty of 0.005 Euro for a variation in sugar content of 0.01 [$kg\ kg\ dry\ matter^{-1}$]) in Equation (6.12). The (controlled) variation is shown as the maximum difference in sugar content between the classes. It changes dramatically when increasing the penalty to 10^6 (large weight factor), as shown in Figure 6.11. The value for the penalty on variation depends on product type, the intended further

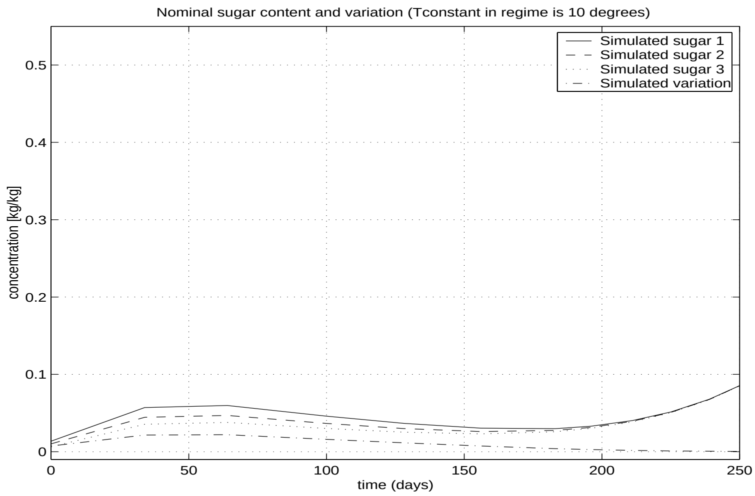

Figure 6.9: *Evolution of sugar content and variation (10 degrees)*

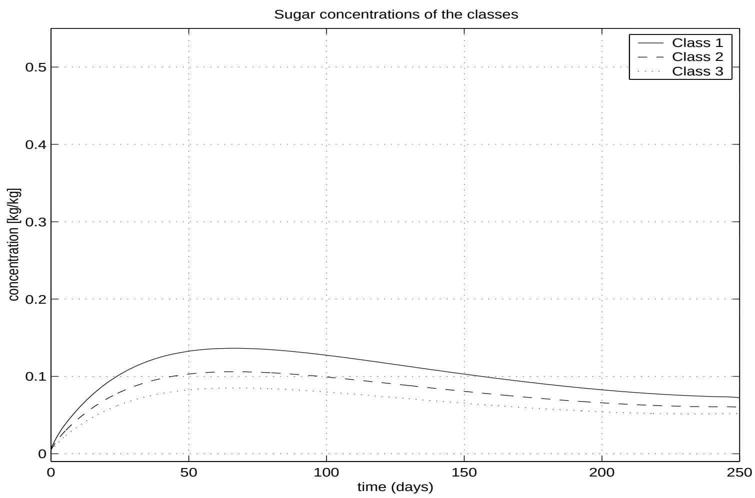

Figure 6.10: *Evolution of the sugar contents for the optimal temperature*

processing of product, the length of the storage period and the market situation. The temperature trajectories in Figure 6.12 are shown for the different penalties on quality variation and fulfill the initial and final constraints of 15 °C and minimal temperature fluctuations. In this study tight constraints are put on the temperature fluctuations to achieve confidence from the practitioners. Less strict constraints would result in more smooth temperature trajectories. Different climate conditions result, besides

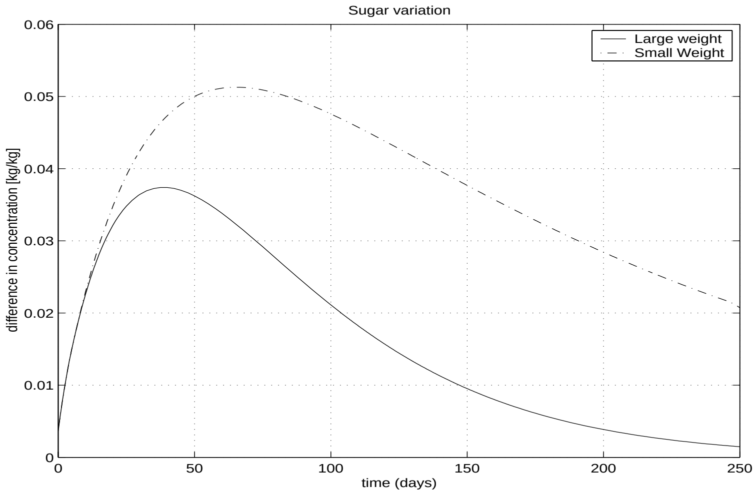

Figure 6.11: *Evolution of the variation in sugar content*

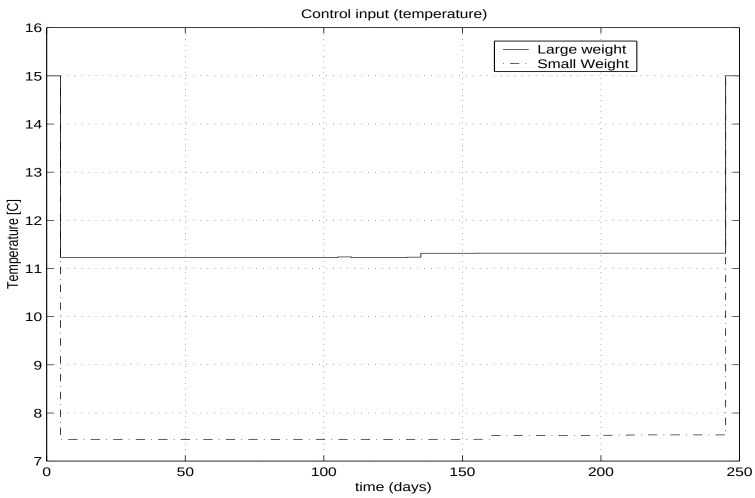

Figure 6.12: *Optimised temperature trajectories for different weight factors*

cost differences, in different behaviour with respect to evaporation of water from the product. The weight-loss at the lower temperature trajectory is 7363 kg less for the storage facility as a whole, which corresponds to a 20 % reduction of the weight-loss. For this case study this would amount to 515 Euro for this (relatively) low product price. In case the new controllers prevent quality to decline to the lower quality class the profit would amount to 52.000 Euro.

6.7 Conclusions and further research

In this chapter product quality is directly included on the highest control level. The control component on this level optimises an economic objective function, thus maximising the economic return of the process. The optimisation procedure uses a model structure that directly manipulates product quality. It was shown that mechanistic models, describing the relevant product dynamics and product quality, can be used to improve process operations involving agro-material. The relation between product quality and product price enables the explicit trade-off between profits and cost of operation. It was shown that a change in product price changes the optimal climate conditions to meet the overall objectives of increased productivity and product quality. Through the incorporation of the optimisation procedure in a three-stage hierarchical control structure the various levels of detail are accounted for on the corresponding control levels. Furthermore, product variation is included in the economic optimisation on the highest control level by introducing a penalty function for product variation. The (industrial) applicability was shown for potato storage. By switching to other climate conditions it was shown that it is possible to reduce the variation by incorporating a penalty on quality variation thereby improving the average product quality when further processing the potatoes into french fries and chips.

Notation

Δ	variation
E	energy function
J	(economic) objective function $[Euro]$
K	system matrix $[s^{-1}]$
L	cost function $[Euro]$
M	product mass $[kg]$
P	product price $[Euro\ kg^{-1}]$
Q	quality attribute
S	constraints function
T	temperature $[°C]$
W	weighing parameter
c	concentration $[kg\ (kg\ dry\ matter)^{-1}]$
d	disturbance
j	class number
k	reaction rate $[s^{-1}]$
r	reaction components
t	time $[s]$
u	controlled input
x	process state
y	measurable outputs
z	non-measurable outputs of interest
Superscripts:	
a	assisting
c	constraints
ref	reference
m	main
Subscripts:	
d	direct environment
i	indirect environment
m	measurement
n	non-reactive
p	primary
q	quality
r	reactive
z	reconstruction from measurements

Chapter 7

General discussion

7.1 Objectives

The objectives of this thesis were:

- the development of a model-based Product Quality Control methodology that enables the design of controllers that are safe, energy efficient, constrain quality variation and maximise product quality to increase the overall objectives of increased productivity and flexibility in operations,

- the improvement of the application of more advanced control techniques in industrial environments,

- the improvement of understanding and exchange of knowledge between the product specialists and the control and climate specialists.

The realisation of these objectives will be discussed in this chapter. This chapter ends by mentioning some directions and topics for future research.

7.2 Control methodology

In this thesis a model-based product quality control methodology is presented for a class of climate controlled operations that process agro-material. To describe the dynamics of the product with its quality and the environments of the product in processing agro-material, a separation is made into three sub-states. Considering product quality a model structure for the relevant quality attributes was presented. This model structure is based on some often occurring reactions that are to a large extend responsible for the dynamic behaviour of the quality attributes. Examples of processing agro-material were given that could be modelled using the proposed model structure. Furthermore, the model structure was extended to include constraints and variation in one or more state variables. The model for the product and its quality is included in a more general modelling structure for the class of climate controlled operations that process agro-material. The modelling distinguishes between primary state variables of the quality attributes, and the direct environment and indirect environment state variables that may be deduced from the conservation laws. This leads not only to more insight in the process, but also to localised information that is useful for time scale decomposition. Time scale decomposition allows for (goal-based) controllers with improved economic performance. Mirroring the model structure resulted in the presented control structure that is mainly characterised by the decoupled time-scales involved in the process. Therefore, the control structure was separated into slow, intermediate and fast time scale controllers.

The Model Predictive Controller on the intermediate time scale was closely linked with the (existing) local fast time scale controllers. Control of product quality by means of the product responses was directly incorporated, while the fast time scale aims at energy efficient operation. It was shown that allowing (controlled) high-frequent climate fluctuations results in significant energy-savings as long as they do not harm the product. Restrictions for these fluctuations result from both the time scale analysis and physical product constraints.
Operating on the highest control level, the slowest time scale, product quality is optimised against operation cost. It was shown that mechanistic models describing the relevant product dynamics and product quality can be used to improve process operations involving agro-material. The relation between product quality and product price enables the explicit trade-off between profits and cost of operation thereby meeting the overall objectives of increased productivity and product quality. Furthermore, product variation is included in the economic optimisation on the highest control level.
The control methodology presented in this thesis allows for the design of specific controllers that fit in the hierarchical control structure as illustrated in the several case studies. From the results one may conclude that the presented control methodology, when applied to climate controlled operations involving agro-material, will contribute to the required improvements in process operations with respect to product quality, environmental regulation and energy efficient operation. It will enable the maximum use of knowledge about process and product (quality) to design controllers that are safe, energy efficient, reduce quality variation and maximise product quality.

7.3 Application of control techniques

The control methodology presented in this thesis was applied to industrial case studies on potato storage and transport of apples. Models were validated using data directly taken from the storage and container application. Control components were designed on the appropriate time scales taking into account the specific properties of the operation of interest. The control components were tested in simulation studies and then implemented in industrial applications on both small-scale and full-scale facilities. Results did not only show the applicability of the methodology, but did also show the benefits. These benefits are:

- reduction of variation (shown in storage) and
- energy consumption (more than 50 % in the transport operation).

These benefits are achieved by the use of the control methodology for climate controlled operations involving agro-material that was presented in this thesis. It combines and makes use of several control techniques like optimising control and model predictive control. Through the implementation and testing of these techniques a contribution was made to close the gap that exists between control theory and implementation of modern control technology in industrial applications.

7.4 Understanding and exchange of knowledge

As the control methodology explicitly requires combination of knowledge from both the product and the process, at least for the commercial operations considered in this thesis, understanding and exchange of knowledge between the product specialists and the control and climate specialists is essential for improving operations.
Often, product specialists think in terms of reaction mechanisms that take place inside the product. These reaction mechanisms provide the product with energy necessary to stay alive. Modelling means describing the reaction mechanisms qualitatively or by the reaction kinetics. Climate conditions are mostly considered constant. This enables the use of algebraic relations that describe the time evolution at constant climate conditions.
Often, control and climate specialists consider air flow distributions and spatial distributions of climate variables like temperature. Dynamics of these variables are studied in detail including partial differential equations that are solved numerically. Risks for product loss and damage are minimised by keeping climate variables as close as possible to the fixed settings. Problems with product quality are often answered by increasing ventilation rates and cooling power whilst product dynamics are not considered.
In this thesis an attempt is made to close the existing gap between both worlds. Therefore, mechanistic models were used as they improve understanding in the process operation. Dynamic product models provide the product specialists with insight in the dynamic behaviour of the product to changing climate conditions. Modelling product dynamics enables the control and climate specialists to consider these dynamics directly in control and design of operations. These models are, more than data-driven models, useful for discussion of the relevant mechanisms that need to be modelled and would improve understanding of the entire process operation. In this thesis the relevance of this improved understanding and exchange of knowledge was illustrated. Hopefully, this contribution will continue to have a lasting effect.

7.5 Future research

Often, research raises more questions than it answers. This thesis is no exception. Questions raised typically include the application field of the presented control

methodology and its individual control components. They are not only applicable in storage and container transport, but also in other climate controlled operations like drying operations. Furthermore, as in process industries (like food and pharmaceutical) more operations exhibit similar characteristics with respect to time scale separation and the property of controlling the slowly-reacting product with a fast-reacting environment, the presented control methodology may also be useful in improving these operations.
Besides questions related to the fields of application, the research presented in this thesis triggered several new and additional questions that future research may solve. These include:

- How may the restrictions for control separation into a hierarchical control structure be defined?
- How may information about seasonal variation and pre-harvest conditions be incorporated and contribute to the improvement of product models describing the quality evolution?
- How to extend the control methodology to allow for spatial distributions that may be described using e.g. CFD-techniques?

Finally, by the incorporation and application of product knowledge and quality measurements directly in the control components of the presented control methodology, this may enhance research on new measurement techniques.

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Samenvatting

De verwerking van agrarische producten wordt geconfronteerd met alsmaar toenemende eisen op het gebied van productiviteit en product kwaliteit. Binnen deze verwerking kan een speciale groep van klimaat geregelde processen worden onderscheiden, zoals transport, opslag en drogen. Momenteel worden deze processen geregeld op basis van meestal vooraf vastgestelde klimaatinstellingen. Voldoen aan de steeds hoger wordende eisen vereist een meer integrale aanpak waarin direct rekening wordt gehouden met het product en de bijbehorende kwaliteit. De doelstelling van dit onderzoek is dan ook de ontwikkeling van een modelgebaseerde regelmethodiek op basis van product kwaliteit voor de groep van klimaat geregelde processen.
In een klimaat geregeld proces kunnen diverse sub-processen worden onderscheiden. De typische overeenkomst tussen deze sub-processen is dat de interactie tussen het product en de omgeving-(en) gezien kan worden als een concentrische schakeling van de sub-processen. Bijzonder is dat deze functionele onderverdeling in sub-processen overeen komt met een verdeling aan de hand van verschillende tijdschalen. De primary sub-state met langzame dynamica van b.v. reactieve massa concentraties in het produkt. De direct environment sub-state met medium dynamica van b.v. produkt- and luchttemperaturen. De indirect environment sub-state met snelle dynamica van b.v. luchttemperaturen in luchttoevoerkanalen. Elk sub-process kan dan ook afzonderlijk (wiskundig) beschreven worden op zijn eigen tijdschaal. Dit leidt tot modellen van het product gedrag en de kwaliteit op de langzame tijdschaal, en de directe en indirecte omgevingen op respectievelijk de medium en snelle tijdschaal.
Bij de beschrijving van het product gedrag wordt rekening gehouden met het nominale gedrag, maar ook met de daaraan verbonden variatie. Het nominale gedrag wordt beschreven met een beperkt aantal basis reacties. Voor de variatie wordt gebruik gemaakt van een gediscretiseerd model.
Het model concept wordt aangevuld met meet- en uitgangsvergelijkingen. Direct hierop gebaseerd is de regelaarstructuur. Dit leidt tot een hierarchische regelaarstructuur. Door het product gedrag expliciet in de regelaars in rekening te brengen kan hierop rechtstreeks worden geregeld.

Op de middelste tijdschaal wordt gebruik gemaakt van een voorspellende regelaar (MPC). Deze regelaar houdt rekening met product kwaliteit door de activiteit van het product te regelen (respiratie en fermentatie). Om, naast een goed product, ook een laag energiegebruik (kosten) na te streven zijn de regelaars van de middelste en de (bestaande) regelaars op de snelste tijdschaal sterk gekoppeld. Energiebesparing wordt gerealiseerd door gecontroleerde hoog-frequente klimaatschommelingen toe te staan.

Op het hoogste regelniveau met de langzaamste tijdschaal wordt een economische optimalisatie procedure voorgesteld. Deze is onderdeel van de totale (hierarchische) regelaarstructuur en maakt gebruik van het ontwikkelde model concept. De optimalisatie maakt het mogelijk om een afweging te maken tussen kosten en kwaliteit met inbegrip van variatie in product.

De ontwikkelde regelmethodiek is geïmplementeerd en getest in industriële operaties met opslag van aardappels en CA-transport van appels in zeecontainers. Hiermee worden de toepasbaarheid en de mogelijkheden van de methodiek aangetoond. De methodiek maakt het mogelijk de kennis van product en proces maximaal te benutten voor een brede groep verwerkingsprocessen. Hiermee kunnen regelaars worden ontworpen die veilig en energiezuinig zijn, kwaliteitsverlies en variatie beperken, om daarmee de doelstellingen van productiviteit en kwaliteit te realiseren.

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Curriculum Vitae

Gerwald Verdijck werd geboren op 4 maart 1973. Na het behalen van het VWO-diploma op het Elzendaal College in Boxmeer in 1991 begon hij zijn studie Werktuigbouwkunde aan de Technische Universiteit in Eindhoven. Opdrachten bij Stork Brabant voor optimalisatie van het stoomproces bij het bedrukken van textiel en AVEBE voor het optimaliseren van het drogen van zetmeel, wekten zijn interesse voor proces operaties en dan met name in de voedingsindustrie. In januari 1997 studeerde hij af binnen de Systeem- en Regeltechniek groep. In februari 1997 begon hij als onderzoeker bij het agro-technologisch onderzoeksinstituut ATO B.V. Hij combineerde zijn werk voor de industrie met het onderzoeksproject dat uiteindelijk heeft geresulteerd in dit proefschrift.
Vanaf augustus 2002 werkt hij als senior proces engineer voor RBV-Leaf (Red Band, Sportlife, Venco, King en Xylifresh).

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