Towards Model Based Adaptive Control for the Watergy Greenhouse

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Design and Implementation

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Preface

This thesis is the final work of the my PhD study at the Systems and Control Group of Wageningen university. This PhD study was part of the Watergy project that aims at the development of a technology platform for decentralized supply of energy, water and food. The Watergy project is funded by the European Union under contract number NNE5/2001/683. The partners in the project were the Technical university in Berlin (TUB), research station Las Palmerillas, Almeria, Spain and two groups of Wageningen University and Research Center; Wageningen UR greenhouse horticulture and the Systems and Control Group.

This thesis consists of six chapters including introduction and conclusions. Three of the four main chapters are accepted for publication by international journals. These chapters describe the methodic design of a measurement and control system, a lumped parameter greenhouse model, a way to adapt the parameters online and the optimal control applied to the Watergy greenhouse system.

Wageningen, May 2008

Bas Speetjens

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1

Introduction

The research described in this thesis is part of the Watergy project that aims at the development of a technology platform for decentralized supply of energy, water and food. The Watergy project consists of two parts; one is to study possibilities of local energy savings and waste water treatment in an urban environment. The second part of the project studies a closed greenhouse where year round plant production is combined with water desalination. The primary focus of our research is on the second part. The Watergy greenhouse has the potential to improve water use efficiency in agriculture considerably as will be demonstrated in this thesis. The importance of increasing water use efficiency in agriculture is first emphasized in this chapter. Following that, the second part of this chapter describes the Watergy project in more detail and it explains the overall functioning of the two prototypes that were built in Spain and Germany. A brief overview of alternative systems with the same goals as the Watergy greenhouse is presented in the third section. This chapter ends with a motivation for the control system that was developed for the Watergy greenhouse (which lies at the heart of our studies), followed by a brief outline of the thesis.

1.1 Scope and motivation

A human-being needs 2-4 liters of drinking water per day. Much more water is needed to produce a persons daily food, depending on his/her diet in the range of 1000 to over 5400 liters per day (Renault and Wallender, 2000). Many areas in the world have a limited amount of water available. Figure 1.1 shows a world map that depicts the water stress calculated with a global water model. The figure depicts the water consumption compared to the minimum river discharge per region, the so called consumption-to-Q90 ratio[1] (Alcamo et al., 2007).

From figure 1.1 it can be observed that there are large areas with severe water stress and according to many studies this problem will get worse in the future due to population growth and climate change. Alcamo and Henrichs (2002) studied the effects of global climate change to water stress in the world

[1]Consumption is the average monthly volume of water that is withdrawn, used, evaporated and not directly available for downstream users, and Q90 is a measure of the monthly river discharge that occurs under dry conditions (monthly discharge is higher than the Q90 value 90% of the time).

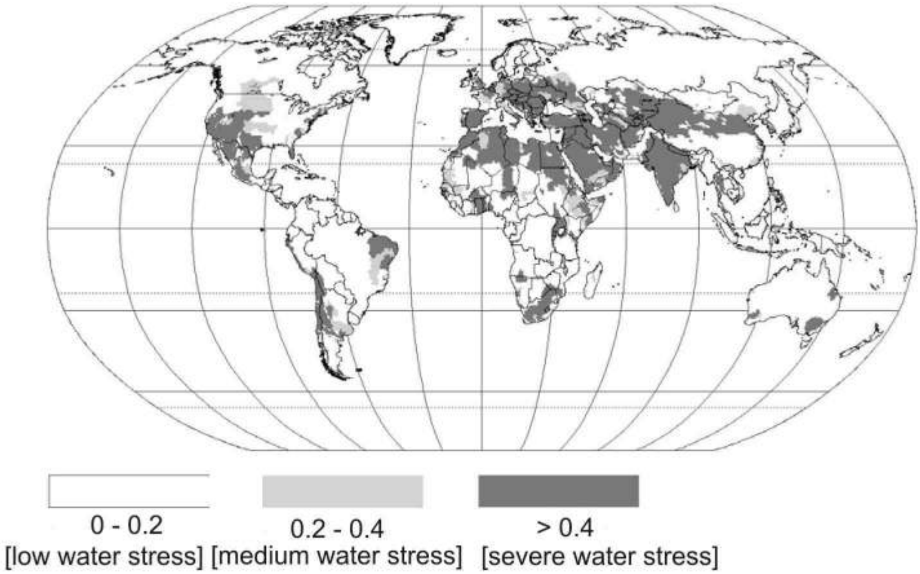


Figure 1.1: Water stress in the world (based on consumption-to-Q90 ratio (Alcamo et al., 2007))

by looking at changes in water availability and water withdrawals (due to for example population growth, changes in precipitation, etc). Different scenarios were simulated; in the worst case scenario, 13% of the worlds watershed surface and approximately $2.6{\cdot}10^9$ people show a higher sensitivity to global climate change than others. In the best case scenario, still 7.4% (and about $1.4{\cdot}10^9$ people) is affected. Another study (Vörösmarty et al., 2000) shows that the population that lives under severe water stress will rise from $1.2{\cdot}10^9$ (1985) to over $2{\cdot}10^9$ (2025). In addition, the number of people that are dependent on irrigation for agriculture will rise from $1.9{\cdot}10^9$ to over $3{\cdot}10^9$. The mildest conclusion that can be drawn from these figures is that there is a tendency for the water related problems to increase.

One of the consequences of a decreasing water availability is an increase of water related conflicts and wars. Gleick (2006) gives an extensive overview of water related wars and conflicts over the past 5000 years. Although his study does not only focus on wars on water supply but also on hydro-energy (amongst other matters), it becomes clear that the number of conflicts is bound to increase steadily. Examples include local conflicts over wells and rivers as well as international conflicts over water sources like rivers and lakes. Since the water stress will increase in the future, it is therefore likely that the number of conflicts over water sources also increases.

Productive agriculture in areas with severe water stress is not possible without irrigation. Agriculture accounts for approximately 70% of the water use (and even up to 80% in developing countries) (FAO, 2007a). Since 1960, the irrigated area in the world has gone up from under $150 \cdot 10^6$ hectares to almost $300 \cdot 10^6$. Figure 1.2 shows a map of all irrigated areas in the world. The water withdrawals for agriculture as a fraction of the total available amount of water is depicted in figure 1.3. Water withdrawals are especially high in the Middle East, parts of Asia and Northern Africa. To decrease the water demand in agriculture the water use efficiency[2] clearly should be substantially enhanced (Postel, 1998, 2000; Gleick, 2003; Rijsberman, 2006; Renault and Wallender, 2000). Technical solutions such as drip irrigation have great potential for water savings (Postel et al., 2001).

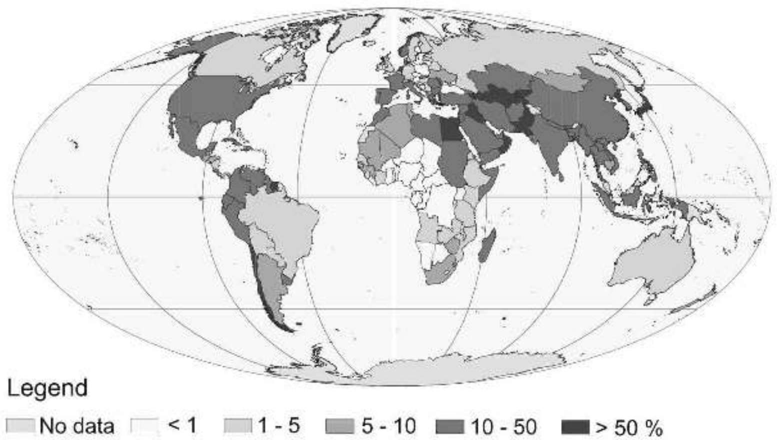


Figure 1.2: Area equipped with irrigation equipment as a percentage of cultivated land (2003)(FAO, 2007b)

Apart from reducing our water use, desalination is also a possibility to alleviate fresh water shortage. The production of desalinated water is rising

[2]water use efficiency is the ratio of dry matter gained to water lost by evapotranspiration.

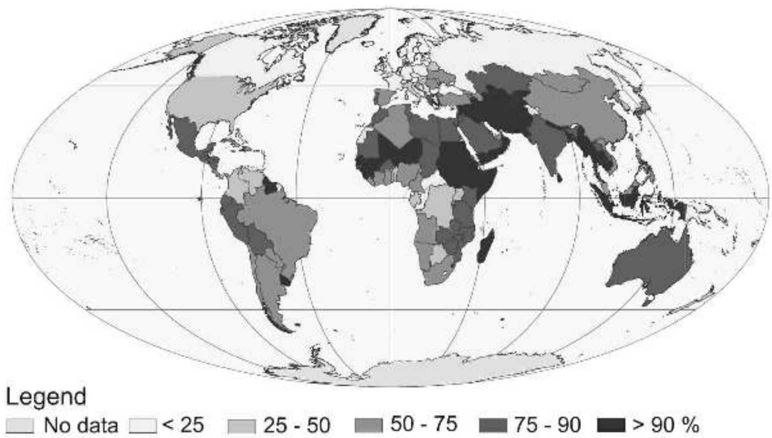


Figure 1.3: Agricultural water withdrawals as a percentage of total renewable water resources (2003) (FAO, 2007b)

fast (figure 1.4). At the end of 2004, the total desalination capacity was estimated to be $35.6 \cdot 10^9$ l fresh water day^{-1}, produced by a total amount of 10402 desalination plants. On January 1st 2005, new plants with a total capacity of $21.4 \cdot 10^9$ l day^{-1} were either ordered or already under construction (Wangnick, 2005). This clearly shows that the methods for desalination have a promising future ahead.

With the picture as sketched in the above in mind, it is clear that something should be done to improve the current water situation in many parts of the world and to reduce future risks of water shortage. Since agriculture is one of the major water consumers, much is to be gained when water use efficiency is improved upon. The FAO made an assesment to the applicability of greenhouses for vegetable production (Zabeltitz, 1999), and concluded that greenhouses have important advantages over open-field vegetable production:

- protection from excessive strong rainfall, high global radiation and wind
- collection and storage of rainwater
- water-saving by drip-irrigation
- water-saving due to lower radiation and wind levels
- yield improvement; clean crops

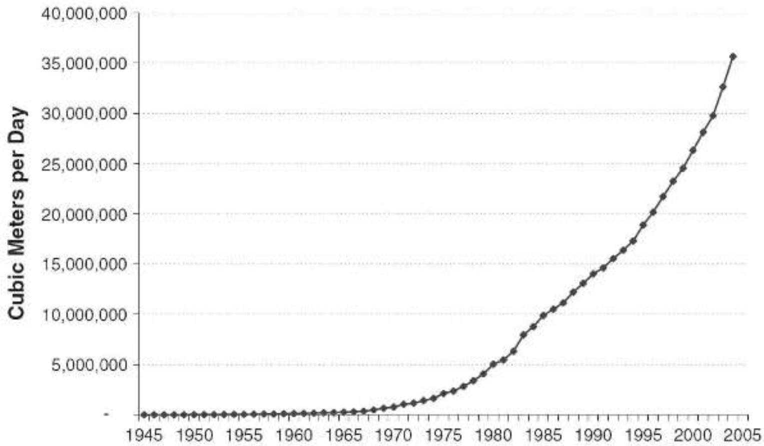


Figure 1.4: Cumulative capacity of desalination plants in the world. (Wangnick, 2005)

- erosion is reduced by shielding the soil from strong rain
- plant protection is easier as pesticides are not washed of by strong rain
- work with the crop is (mostly) independent from weather influences

Especially in dry climates, additional advantages are:

- Increased humidities inside the greenhouse reduce water use
- Protection from sandstorms
- Water collection and storage reduces water shortage in dry periods
- Large temperature variations between day and night are leveled out

Also the report recognizes that often brackish (ground) water is available that can be desalinated by solar energy.

The major disadvantage of using greenhouses in warm, semi-arid regions is the temperature inside that easily exceeds the outside temperature. This limits the growing season to autumn, winter, spring, as it gets too hot inside the greenhouse in summer to grow plants. The Watergy project is an initiative to improve water use efficiency in horticulture as well as extending the growing season by applying greenhouse cooling. This thesis is part of the project, which is summarized in the next section.

1.2 The Watergy Project

The Watergy project aims at integrating decentralized functions for supply of energy, food and water. The integration of these functions should result in systems that make the best possible use of natural resources. The concept was first described by (Buchholz, 2000). In the Watergy project, two prototypes have been designed and built: a greenhouse in Southern Spain, and an energy preserving building with an integrated glasshouse compartment built in Germany.

1.2.1 Watergy greenhouse in Spain

An experimental greenhouse with a ground area of 14×14 m was built in Almeria, Spain (see photograph in figure 1.7(a)). Figures 1.5 and 1.6 give a cross-section diagrams of the greenhouse and its functionality during day and night. The photographes in figures 1.13 to and 1.17 give a visual impression of the inside of the greenhouse and the equipment used to control it.

The most remarkable feature is the double walled tower (4) with a height of 10 m. During the day, the sun heats the (humid) air inside the plant compartment (1). The heated air rises through the inner roof compartment (2), into the outer duct of the tower where it is further heated by the sun (3). As the tower is closed at the top, the air does not leave the greenhouse but is cooled with a heat exchanger in the central duct of the tower (4). The coolant is stored in a heat buffer (7). The cooled air flows back into the warm greenhouse (5), closing the cycle. During the night, the heat exchanger heats the air and the air movement reverses; hot air rises through the heat exchanger to the top of the tower (9, 10) and flows down through the outer duct (11). The cooled cooling-water returns to the storage for later use (12). Since the air cycle in the greenhouse is closed, water evaporated by plants stays inside. During the day, warm, moist air flows into the tower, where the moisture condenses against the cold surface of the heat exchanger. To facilitate water desalination it is possible to spray water on the a so-called inner roof (6). The inner roof has been constructed in such a way that the water that evaporates from the inner roof follows the air flow and condensates in the heat exchanger. If this facility is used, clean water is collected from the bottom of the tower.

The crop (first green bean, later followed by okra) was grown in soil with a balanced texture of about 20-30 cm deep. A sand bed with a thickness of about 10 cm was placed on top of the soil. Drip irrigation was used, controlled by an autonomous fertigation system. The drain water was recovered and recycled. For more information see Buchholz and Zaragoza (2004), Zaragoza et al. (2007) and www.watergy.info for a general description and Jochum and Buchholz (2005) for a detailed, static model of the system.

The condensate coming from the heat exchanger and from the roof is recovered, the quantity is measured automatically and it is used again for irrigation. Temperature and humidity are measured at all vital places inside and outside the greenhouse and technical installation. Other quantities that are measured are outside global radiation, wind speed and -direction and the CO_2 concentration. The control inputs for the system are:

- pump speed for the coolant (continuous control)

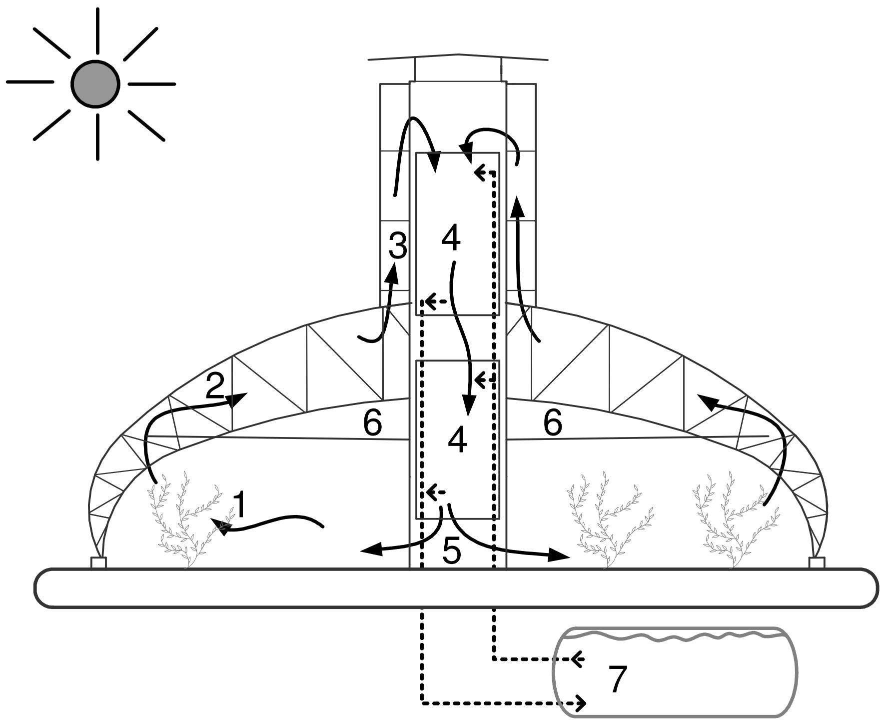


Figure 1.5: Functioning of the Watergy greenhouse during the day

- ventilator to circulate the air through the system (on/off control)
- sprinklers in the inner roof compartment (on/off)
- in/outlet positions for the cold storage

All pumps and valves are controlled by data loggers that are connected to a personal computer on which a database runs. This enables implementation of controllers in several software packages, including Matlab and Labview. See Janssen et al. (2004) and chapter 2 of this thesis for a detailed description of the control systems layout and equipment.

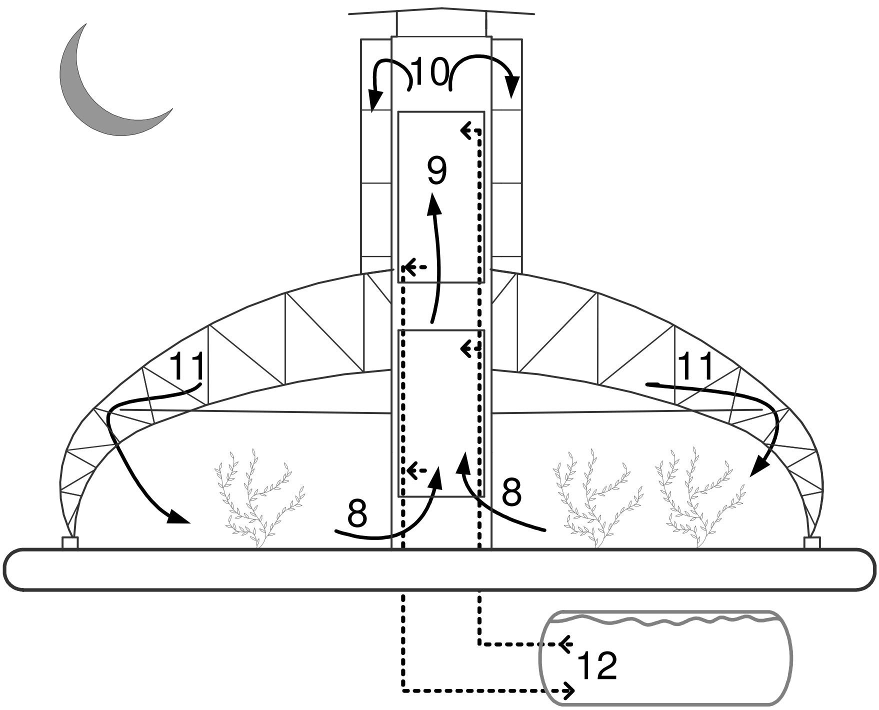


Figure 1.6: Functioning of the Watergy greenhouse during the night

1.2.2 Watergy house in Germany

The aim of the Watergy building in Berlin is to study ways of making buildings self sufficient with respect to energy and water use. The control of this house has not been part of this thesis, although the methods described in this thesis offer perspectives for use in the Watergy house. As the house is part of the Watergy project a short introduction is given here.

The building has been constructed based on the known concepts of passive house insulation standards and solar based near distance heating systems from seasonal heat storages. A greenhouse is placed in front of a transparent wall at the southern side of a building and acts as a modified double facade. A solar heat collector is placed on the roof and inside the house a heat exchanger and heat storage are installed to meet energy demands over the seasons. A picture of the house is shown in figure 1.18(a). The appendix shows some of the sensor and actuators used in the house.

Compared to collector systems using just dry air, the heat transfer from the collector to the air and from the air to a heat exchanger is increased by the process of water evaporation and condensation. The greenhouse is part of the energy collector and offers advantages as a supplementary living space and for integrated food production. Grey water[3] from the building is used for irrigation in the greenhouse. By using evaporation and condensation processes, the water is purified and could be re-used in the building. Together with the collection of rainwater, this is a basis for a self sufficient system that does not need connections to water supply and a sewage system. The house is build such that the air and energy can flow through it in many ways, which are selected by switching valves and air flaps. The appendix gives an overview of all operation states.

[3]"Grey water" is the term for all the water that has been used in the home, except water from toilets.

(a) Watergy greenhouse, spring 2004.

(b) Watergy house, spring 2005.

Figure 1.7: The two Watergy prototypes

1.3 Systems with similar goals as the Watergy greenhouse

The Watergy greenhouse has two major functions, being growing of plants and desalination of water. Both functions have a long history as separate systems, but also attempts have been made in the past to integrate both functions into one system. Some systems that focus on greenhouse cooling can potentially be used for desalination too. In this section examples of systems for desalination and/or cooling are presented.

1.3.1 Desalination systems

The least advanced way of water desalination with solar energy is the single effect still basin (Fath, 1998a), illustrated in figure 1.8. It consists of a water basin covered by a transparent cover. The basin is filled with salt or brackish water, which is heated by the solar radiation. The water evaporates from the basin and condensates on the cover. After condensation, the water flows along the cover surface and is collected on the sides.

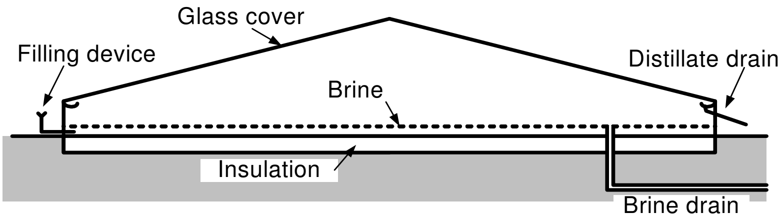
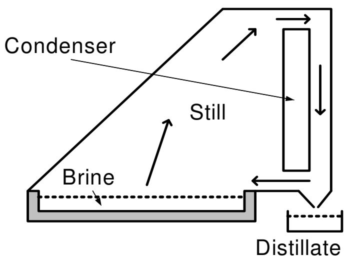


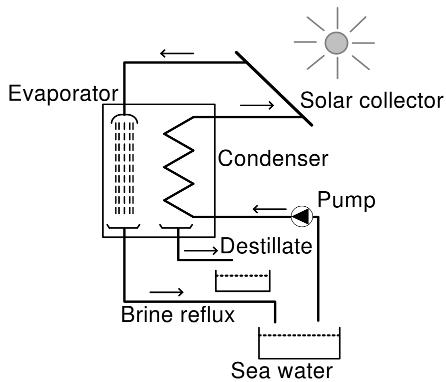
Figure 1.8: Single effect solar still (Fath, 1998a)

The efficiency of a single effect basin is not very high. Examples of improvements are (Fath, 1998a): (1) Cooling of the cover (to increase the amount of condensation). (2) Treatment of cover surface (to increase condensation yield by avoiding formation of droplets). (3) Use of dye in the water (to improve the absorbance of solar heat into the water). (4) Adding an additional condenser to the solar still (see figure 1.9(a)). When an additional condenser is added to the solar still, the system works similarly to the Watergy greenhouse (apart from the plants): hot, humid air is transported upward, to the additional condenser (by natural convection or by fan). In this condenser the air is cooled, so the water vapor condenses and the air falls back, down into the still. A review of water desalination systems with humidifying-dehumidifying is given by Bourouni et al. (2001). They argue that this type of desalination system is well suited for smaller installations, especially when heat is available at low cost. The combination of the desalination system with a greenhouse could be a good way to increase the economic viability.

Muller-Holst et al. (1998, 1999) describe an optimized distillation system that consists of one box with both evaporator as well as condenser in it (figure 1.9(b)). This results in a robust system that runs with only three days of maintenance per year.



(a) Solar still with additional condenser (Fath, 1998a)



(b) Low Tech Desalination system (Muller-Holst et al., 1998, 1999)

Figure 1.9: Two examples of solar stills

A way of cleaning polluted water with the use of solar energy and membranes is described by Zwijnenberg et al. (2005). They study a system that contains tubes of a membrane. Solar energy heats the water in the tubes and creates the driving force for water evaporation through the membrane. This system is capable of filtering polluted water from oil industries as well as sea or brackish water.

1.3.2 Combined desalination and greenhouse cooling

The classical way to cool greenhouses in practice is with the pad and fan system. The cooling effect of these systems is based on evaporation of water, which makes this system particularly useful in regions with low relative air humidities. However, this requires large amounts of water, which is often scarce in regions where cooling is needed. A combination of air cooling and water recovery (and/or desalination) would improve the current practice tremendously.

Davies (2005) describes an addition to the normal pad and fan cooling systems; before the outside air is led through the evaporation pad, it is dried by a salt solution. In this way, the cooling effect of humidifying the air is enhanced. Compared to traditional greenhouses with fan and pad, the maximum temperature is lowered by 5 $^\circ$C. It is possible to produce the desiccant (hygroscopic salt solution) from sea water (Davies and Knowles, 2006).

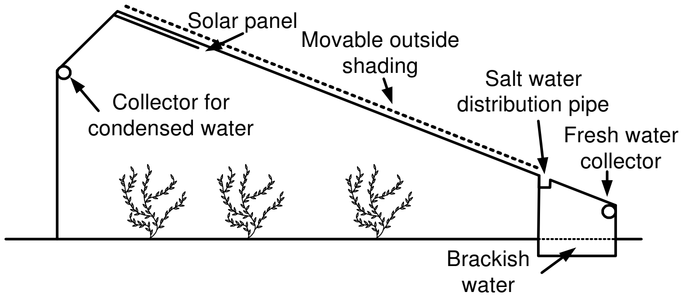
A more direct way of cooling is the use of cold water that is stored in the sub-soil. In the Netherlands, efforts are made to 'harvest' the energy that enters the greenhouse in summer, store it in aquifers and to use the energy during the cold winter. Several prototypes have been built and the first systems are commercially available (www.innogrow.nl, www.kasalsenergiebron.nl). Ooteghem (2007) found that energy consumption in a similar type of 'solar greenhouse' will be half of that in traditional greenhouses and that crop production will rise with approximately 40%. Although it is not the primary aim, these systems recover most of the transpired water in the coolers.

The idea to combine a solar still with a greenhouse is not new. Already in 1961 Trombe and Foex (1961) described such a system. Although it is an old idea, the concept has not yet gone beyond the experimental phase (Chaibi, 2000b). A closed greenhouse with integrated solar water desalination was developed and evaluated by Strauch (1985), and (Baytorun et al., 1989). Experiments showed a water productivity of 2 to 2.5 l $m^{-2}_{greenhouse}$ d^{-1}.

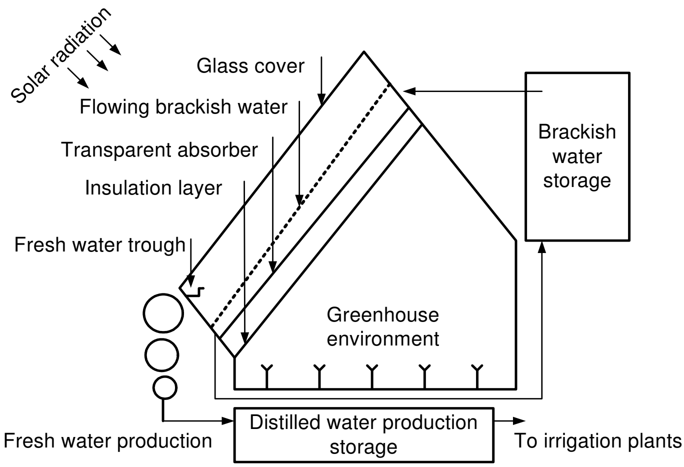
Fath (1998b) described a naturally ventilated greenhouse solar still with waste heat and mass recovery. The concept consists of a greenhouse with a chimney on top of it. Water basins are positioned between the roof and the plants. Water in these basins is heated by solar radiation (the basins are transparent for PAR, but absorb other wavelengths). From the basins, moist air flows upward, through the chimney. In the chimney the air is cooled, so the water condenses. The heat of air is partially recovered by the heat exchanger in the chimney, where the inlet water is heated.

To recover water in a pad and fan cooling system, it can be combined with a condenser. The 'Seawater Greenhouse' follows this principle (Davies and Paton, 2005a; Sablani et al., 2003; Davies and Paton, 2005b; Goosen et al., 2003; Dawoud et al., 2006; Perret et al., 2005) . At one side of the greenhouse, evaporative pads are installed (number 1 in figure 1.12). Air is drawn through the pads into the greenhouse by fans (5). In the middle of the greenhouse, a second evaporative pad (3) is installed to humidify the air further. The condenser (4) is located behind this pad and uses cold seawater to condensate the water out of the wet greenhouse air. To reduce solar radiation loads on the greenhouse, the roof is equipped with filters to remove non-PAR light (2). Davies and Paton (2005b) describe how the seawater greenhouse is improved by placing pipes in the greenhouse roof. Through these pipes, the seawater for the evaporator in the middle of the greenhouse is heated, so that evaporation is increased. Also, this layer of pipes provides shading in the greenhouse. CFD model calculation predict a water production in the range of 14.5 to 31.5 kg water $m^{-2}day^{-1}$) (Goosen et al., 2003).

The main disadvantage of the seawater greenhouse is that large (outside) air volumes are required for cooling, making it impossible to supply the plants with extra CO2 to increase crop growth. The commercially available closed greenhouse systems are complicated and require (in the Netherlands) seasonal heat storage, which is expensive and not possible in many regions. The Watergy project makes an attempt to combine the advantages of low-tech, open cooling systems with the advantages of closed greenhouses into one new design.



(a) Cross section of the desert greenhouse designed by ITG in 1987 at the University of Adana, Turkey. Both plant transpiration and evaporation of the solar still are collected. (picture from Chaibi (2000b))



(b) Solar still built in a greenhouse roof. The plant transpiration is not recovered. (Chaibi, 2000a)

Figure 1.10: Two examples of greenhouses combined with solar stills

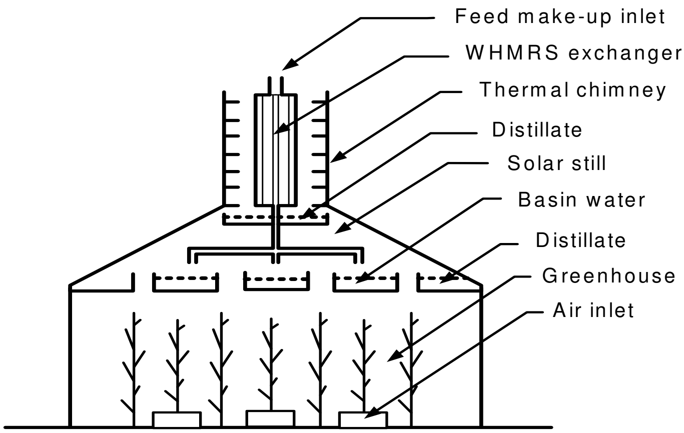


Figure 1.11: A solar still combined with a naturally ventilated greenhouse (Fath, 1998b)

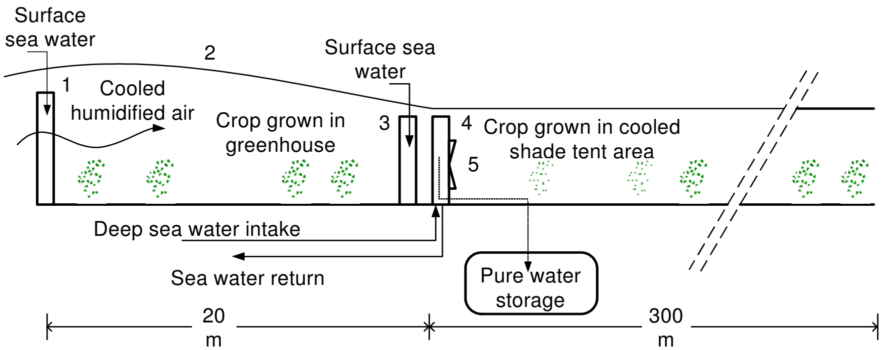


Figure 1.12: The seawater greenhouse as it is built in Oman. (after: www.seawatergreenhouse.com)

1.4 Watergy greenhouse control methodology

The previous section shows that much effort has been invested in designing new systems for (combined) greenhouse cooling and water recovery (and/or water production). Control of these (often complicated) systems has not been studied extensively, however, although it is expected that an advanced control method will increase the performance substantially. Control methods that are currently often used in normal greenhouse practice, such as the use of low-level PID controllers that draw their setpoints from heuristic rules inspired by 'normal' use of the greenhouse, are not sufficiently able to deal with multi criteria goals and couplings between the dynamics of the system. In addition, the consequences of the various couplings between state variables may have large effects on the goal for which the system has been developed, while conventional methods do not take accurate predictions of possible future revenues into account. For example, it is easy to see that high temperatures and humidity levels could improve water production (which may be our primary goal), but we know that these requirements for optimal water production are potentially harmful for plants. Another example for the case of the Watergy greenhouse in Spain is the possibly limited amount of cooling liquid that is available for air-cooling of the system. Of course, the cooling liquid should be used in the best possible way as to maximize water production whilst guaranteeing a good climate for the plants in the greenhouse. In fact, these plants are an important part of the dynamic climate behavior in the greenhouse because of their evapotranspiration and growth, thereby further complicating the control task.

Let us further emphasize that model based dynamic control of the Watergy greenhouse is not an easy task. The climate model developed in this thesis has some 26 states, a number that is mainly due to the many compartments that have to be taken into account to facilitate a fairly accurate prediction of the greenhouse climate. Although one might argue that perhaps simpler models could have been used, our findings substantiate the minimality of the proposed model. To include this model, then, into a model predictive controller that respects all the constraints of actuators, humidity levels, coolant levels, etc, is quite a daunting task that might explain the limited amount of literature that can be found on the subject.

With these considerations in mind, it was nevertheless decided to develop a model based controller for optimal control of the climate inside the Watergy greenhouse that provides new setpoints for the actuators at a rate of approximately once every 15 minutes. As argued, the use of a model enables the controller to explicitly take the couplings and multi criteria goals into account, which leads to a better performance of the system (more water production in combination with a better environment for the plants). Unfortunately, this method has a downside, which is the inevitable limited accuracy of the model that is embedded in the algorithm. If the predictions of the model are not accurate enough, then, of course, the control actions that are calculated are not the best possible. Also, the model must be simple enough as to allow for fast computation times so that new management strategies can be evaluated quickly. These requirements put heavy constraints on the applicability of model predictive control (MPC) in practice, especially in changing environments such as a greenhouse climate that can vary considerably over the course of one day.

One way to enhance the model fit of the possibly inaccurate model prediction (and therefor the applicability of MPC in general) is to make some of the lumped parameters in the model adaptive. This accommodates the possibility for the model to adapt itself to changing circumstances (like pollution of the greenhouse cover, and plant growth). Since changes can occur on various timescales (seconds, minutes, hours, days, weeks, etc), a choice was made for the Watergy case to adapt to seasonal variations of certain plant parameters that seem to affect the humidity balance, and thus the fresh-water production of the greenhouse unit, most. Systems theory provides useful tools, such as the well-known extended Kalman filter (Gelb (1974), for example), that allow on-line 'observation' of the system, thereby interpreting the continuous data stream from the temperature, humidity, and possibly other sensors into *changes* of the model's state and parameter values. Such an approach has to our knowledge hardly been applied in greenhouse climate control and certainly not for the case of the Watergy greenhouse in Spain that was built as part of the project. Admittedly, proper use and tuning of these sophisticated types of algorithms may be difficult indeed and have in the past shown to be rather subjective due to initialization errors, such as the improper specification of the various noise-levels that are assumed to underly the dynamic climate behavior in the greenhouse (such as spatial inaccuracies) and, also, the errors in the sensor readings that are corrupted by measurement noise.

Nevertheless, we feel that the advantages of the adaptive approach taken here are certainly worthwhile the research we are about to undertake in this thesis. In addition, there is a certain elegance in our approach to the problem due to its flexibility and inclusion of intelligence into the management decisions that have to be taken for an optimal performance of the greenhouse unit.

Finally it must be mentioned that to point to a rather sophisticated solution for optimal greenhouse climate control of the Watergy greenhouse is one thing, to *build* such an advanced control scheme is a completely different thing and a very challenging task indeed. When consulting with various companies on hardware that would be capable to achieve model-based optimal control for the Watergy greenhouse unit in Spain, we found at a very early stage in the project that these kind of systems simply do not exist on the market. It was therefore decided to build an advanced control system (that is also accessible over the internet) ourselves. Much, if not most, of the time in this project was spend on design, implementation, and testing of the hardware – both in situ and also from Wageningen University where most of the research was conducted.

This introductory characterization of the challenges we have been facing in the Watergy project and also the motivation behind the design of the two buildings, have dominated our research agenda over the past four years. Clearly, greenhouse design, management, and climate control has many challenging aspects that need to be addressed – not only in this thesis, of course, but also in future (international) projects that will be initiated on these subjects.

Research questions

The main aim of this thesis is *"to study a complete model-based control-design and to move forward towards an experimental setup for adaptive, receding horizon optimal control in the Watergy greenhouse"*. Sub-questions related to this aim are:

- Given the high computational demands of dynamic optimization, how can the dynamic behavior of the climate in the Watergy greenhouse be modeled with a relatively small number of states so that receding-horizon optimal control becomes feasible for a practitioner?

- Into what extend does the currently available commercial hardware for greenhouse climate and irrigation control facilitate adaptive receding horizon control and, if it does not facilitate our demands, how can we address this problem in the best possible way?
- Into what extend are the (lumped) parameters in the greenhouse model changing over the seasons and what influence does this have on the model fit?
- Given a choice for the goal function in the receding-horizon optimal controller (which will be studied separately), what does the optimal control pattern for the Watergy greenhouse look like?
- How does the optimal control pattern change if the model parameters are changed online?
- What do we really gain if online parameter adaptation in receding horizon optimal control is included?

1.5 Outline of the thesis

This thesis describes the development and application of a model based, adaptive control system for the Watergy greenhouse. The hardware (sensors, actuators and computer equipment) that was installed in the greenhouse and the functionality of the control system are described in chapter 1. The combination of hardware and software that is chosen enables flexible use of the greenhouse, required for the research in the Watergy project.

The second chapter describes the development of a physics based model that mimics the climate in the greenhouse. The model contains some lumped parameters to avoid laborious modeling of the smallest details, so called 'minimal information modeling'. Of course, the values of these lumped parameters are situation specific, hence they must be calibrated carefully. Calibration is done with a controlled random search (CRS) algorithm that is used on partial models, a method we will call 'estimation in parts'.

The lumped parameters change over time. To deal with that, an extended Kalman filter (EKF) was introduced to estimate the time-varying parameters over the year, as described in chapter 3. From the figures of the parameter variation shown there, events can be deduced, for example the moment that the plants were pruned, and the moment that the greenhouse roof was whitened to reduce solar radiation loads on the greenhouse.

With the model and the adaptive mechanism in place, all requirements are met to develop a model based controller. This process is described in chapter 4. The gradient method is used to calculate the best possible control actions to maintain the optimal climate inside the greenhouse. Goal functions were varied, and the effect of this on the greenhouse climate is shown in this chapter.

The final chapter contains the conclusions that can be drawn from this study. The implications for horticultural practice and horticulture in semi-arid regions are discussed.

Appendix 1: pictures of the Watergy greenhouse built in Almeria

Figure 1.13: Front of the Watergy greenhouse, spring 2004

(a) Backside of the greenhouse; the heat storage tanks are positioned left shielded from the sun by a cloth

(b) interior of the Watergy greenhouse, seen from above

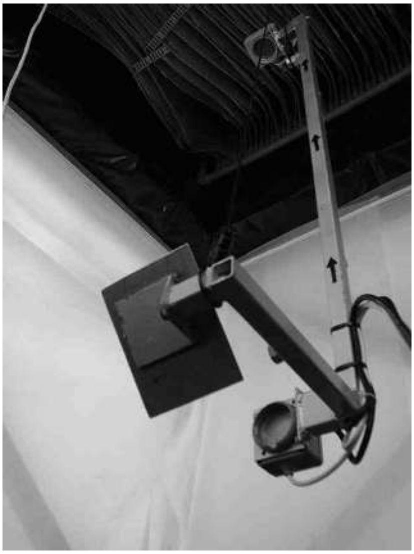
Figure 1.14: Watergy greenhouse, spring 2004

(a) View on the inner roof

(b) Interior of the Watergy greenhouse

(c) The heat exchanger in the tower, before the tower was closed

Figure 1.15: Interior of the Watergy greenhouse

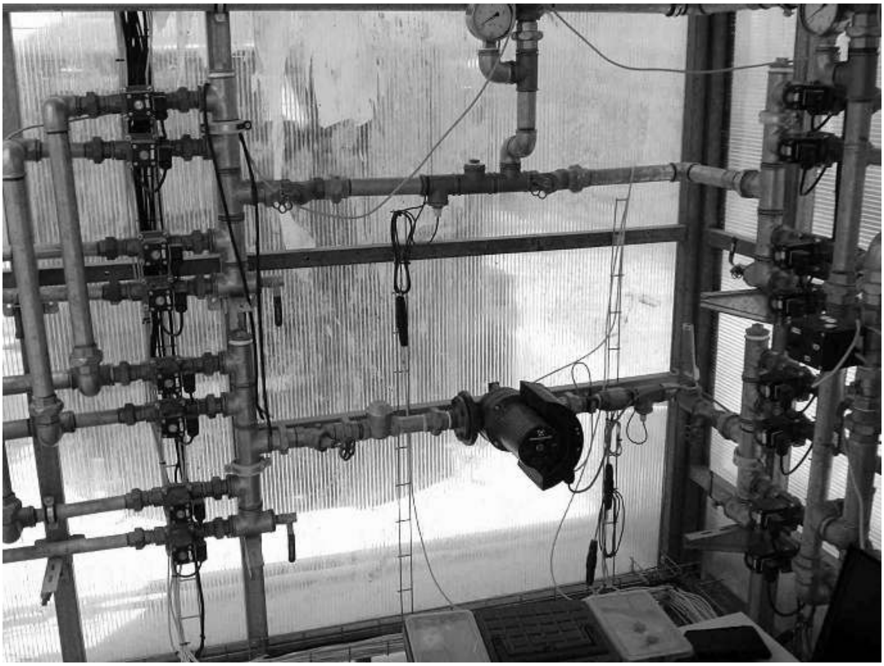


(a) The air velocity sensor in the tower

(b) The local weather conditions were measured on the roof of shed where the control equipment was located

(c) Temperature and humidity sensor under the heat exchanger

Figure 1.16: Equipment in the Watergy greenhouse



(a) The valves and sensors of the cooling and heating system

(b) A web cam was used to monitor the crop remotely

(c) Measurement of the condensation from the walls and roof

Figure 1.17: Equipment in the Watergy greenhouse

Appendix 2: pictures of the Watergy house built in Berlin

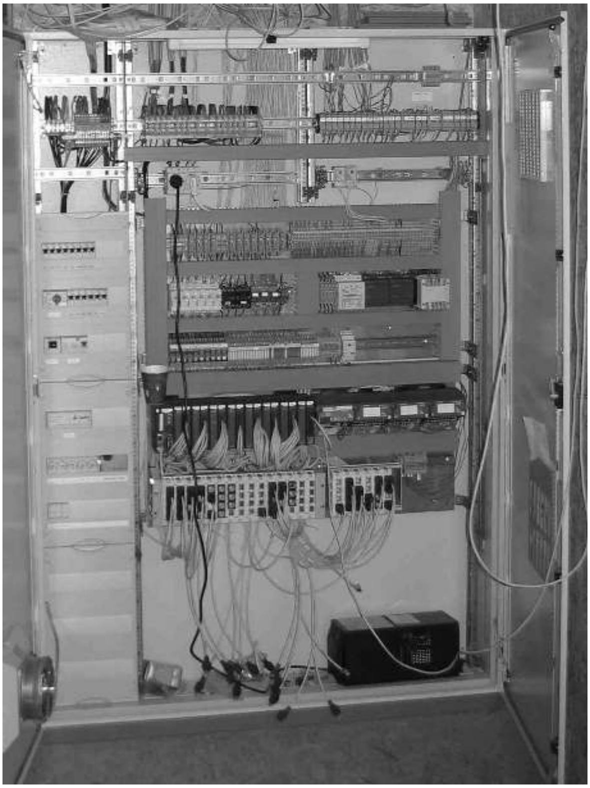
(a) Exterior of the Watergy house

(b) Swamp in the greenhouse; white boxes contain sensors

Figure 1.18: Watergy house, spring 2005

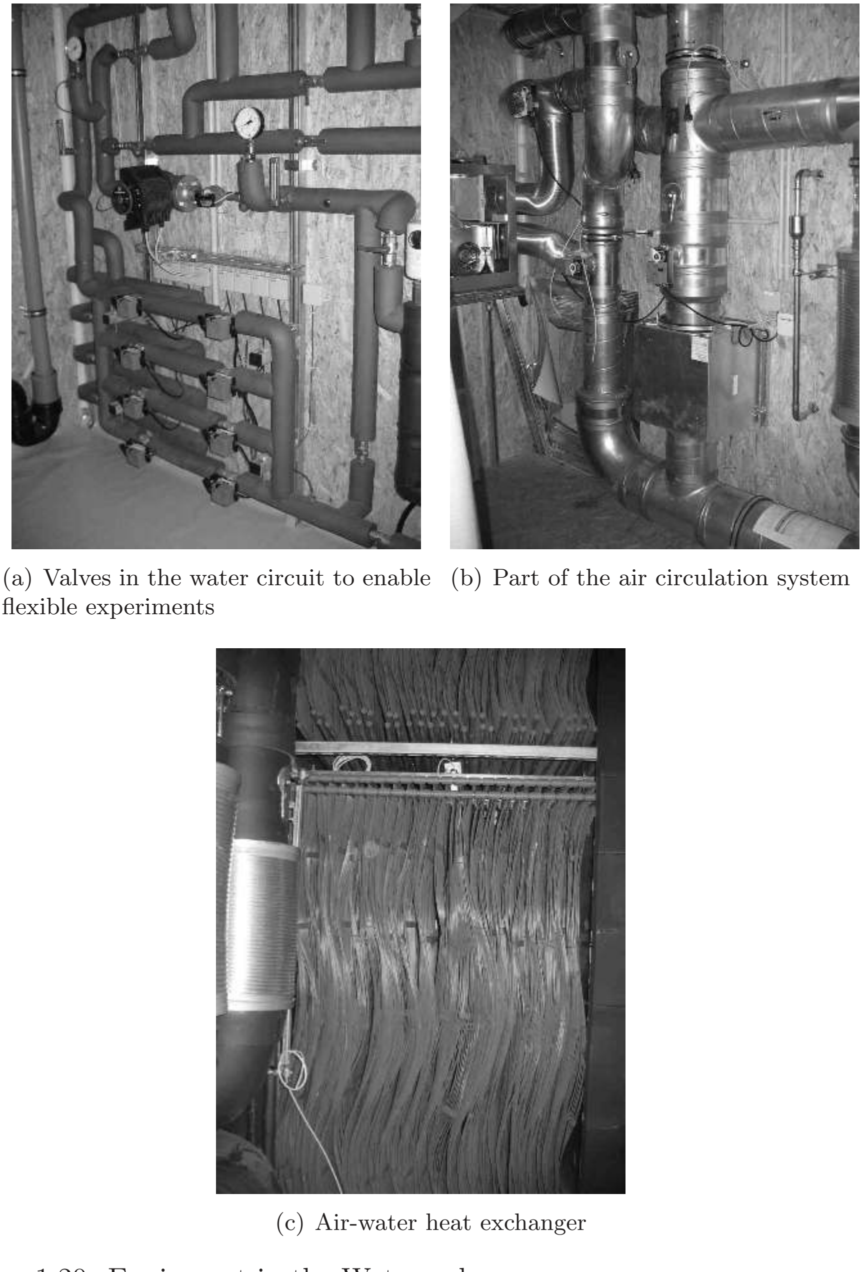
(a) Condensate flow sensor

(b) Air temperature sensor installed in the greenhouse



(c) Cabinet with data loggers and relay technique

Figure 1.19: Interior of the Watergy house



(a) Valves in the water circuit to enable flexible experiments

(b) Part of the air circulation system

(c) Air-water heat exchanger

Figure 1.20: Equipment in the Watergy house

(a) View from the house into the greenhouse

(b) Inside of the solar heat collector

Figure 1.21: Equipment in the Watergy house

Appendix 3: The Watergy house in Berlin

Although the study described in this thesis focusses on the Watergy greenhouse (Spain), also a basic control system for the Watergy house (Germany) has been developed. The setup of this control system is similar to the control system of the greenhouse (as described in chapter 2).

The Watergy house is equipped with many air channels to guide the air through the house in various ways (figure 1.22). This facilitates adjustment of the airflow to circumstances; during the summer, heat gained in the greenhouse is stored into the heat buffer. During winter, the house is heated from this tank. The building consists of two main areas, the greenhouse (GH) and

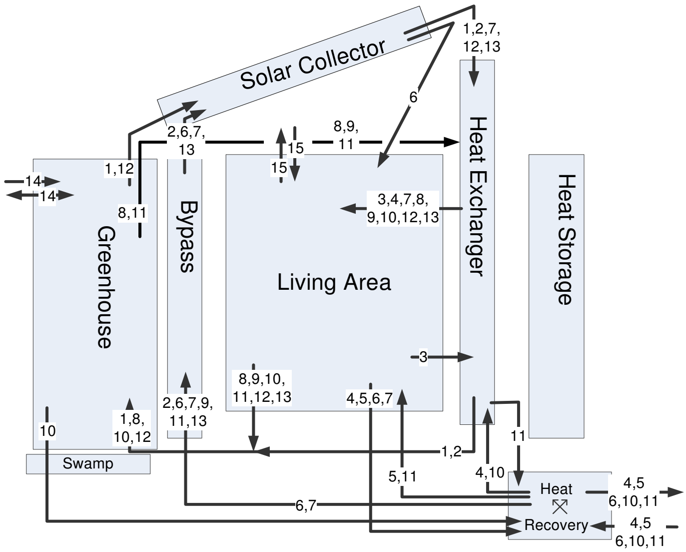


Figure 1.22: Possible air flows in the Watergy house as it is built in Berlin.

the living area (LA). Both areas can be cooled and heated with the central heat exchanger (hex), which is connected with a heat buffer (HB). To avoid heat loss by ventilation, a heat recovery unit (HR) is installed. An extensive control system makes it possible to achieve airflows through the building in many different ways. The possible air circuits are listed here (the numbers correspond to the numbers in figure 1.22):

1. fill the heat storage with heat from greenhouse and solar heat collec-

tor or heat the greenhouse

2. fill the heat storage with heat from the solar heat collector

3. heat/cool the air from the living area with the heat exchanger

4. heat the air in the living area with the heat exchanger and refresh it with the HR

5. refresh the air in the living area with the heat recovery unit

6. heat the air in the living area with the solar heat collector and refresh it with the HR

7. heat the air in the living area with the solar heat collector and the heat exchanger and refresh it with the HR

8. heat the air in the greenhouse with the exhaust air of the house, fresh air to LA via HR

9. same as 8, but instead of the greenhouse, the bypass is used to heat the air

10. heat/cool the air in the greenhouse and heat/cool the air in the LA with hex

11. use the bypass to heat the air for the living area. Refresh the air with the heat recovery

12. use the greenhouse and solar air collector to heat the air

13. same as 12, but instead of the greenhouse, the bypass is used to heat the air

14. open the greenhouse windows

15. Open the living area windows

The control system is capable of selecting all these operation modes. To facilitate this, many air (figure 1.20(b)) and water valves (figure 1.20(a)) are installed, including the accompanying I/O channels. The software (written in Labview) enables the users to experiment with the operation modes and to optimize the systems performance.

The sensors that were used are mostly similar to the ones used in the greenhouse. Temperature was measured with PT100 sensors (figure 1.19(b)), humidity with capacitive sensors. Enotemp supplied the air velocity sensors and the amount of condensation in the heat exchanger was measured with a custom made sensor (figure 1.19(a)). The data logger was a Compact Field-point which was built into a control cabinet together with the relays and power supplies (figure 1.19(c)).

2

Hardware

This chapter is based on:

S.L. Speetjens, H.J.J. Janssen, G. van Straten, Th.H. Gieling and J.D. Stigter. Methodic Design of a Measurement and Control System for Climate Control in Horticulture. Computers and Electronics in Agriculture (2008). In Press, doi:10.1016/j.compag.2008.04.010

Abstract

In the literature many papers describe various applications of advanced controllers in greenhouses. As the control literature focusses on control algorithms, the layout of the measurement and control system is usually underexposed. Unfortunately, commercially available greenhouse climate control systems do not have the necessary flexibility to accommodate these types of controllers. This paper describes a systematic approach to the design of a flexible measurement and control system, that can be adjusted to suit most control research in horticulture. Individual functions within a measurement and control system are identified and alternative solutions are given. The design methodology is applied to the design of the measurement and control system for the Watergy greenhouse. The controllers (in software) are versatile and setpoints can be generated by an easy-to-use user interface as well as by external software (like Matlab). Data is centrally stored and the system is easy to expand. It has been shown that the system has functioned robustly for the past three years. The flexible control system has the capability to serve as a basis for research and testing of various advanced control strategies in the Watergy system with with adaptive model based control as a final goal.

2.1 Introduction

Many research projects study possibilities for improvement of existing greenhouses and/or control systems in these greenhouses. Often, it is necessary to develop an enhanced measurement and control system to facilitate these studies, since commercially available systems do not provide the necessary flexibility for this type of research. For example, it often happens that new control laws cannot be implemented in the available software, or that the number of measurements is limited. For instance, in many advanced control studies it it necessary to have access to the low-level manipulators directly. This is often not possible.

Apart from developing a completely new control system, one way to handle the limitations of commercially available systems is to connect a PC to the commercial climate computer. This PC runs advanced algorithms that generate setpoints, which are send to the climate computer. An example is the study of Sigrimis et al. (2000), who developed a framework to interface between a decision support system and the greenhouse management system. Another example is the thorough research by Aaslyng et al. (2003) describing a climate control system that functions as an addition to a generic climate control computer. Setpoints are generated by mathematical models in their software tool, IntelliGrow, and send to the climate computer that controls the actuators. The control system consists of individual components that each handle a biological, physical or environmental task (like temperature or CO2 control). The communication between PC and climate computer was handled with a systems integration interface called BipsArch (Aaslyng et al., 2005).

When developing the Watergy greenhouse, the limitations of commercially available hardware lead to the decision to design a new measurement and control system that has the required versatility. Surprisingly, only few studies are found in the literature describing all aspects of an advanced, flexible measurement and control system for climate and irrigation control in horticulture. Most studies that describe the application of advanced control in horticulture touch upon the measurement and control system only very briefly (Young et al., 1994; Chalabi et al., 1996; Blasco et al., 2007). This is the motivation to describe a generic design for a measurement and control system that serves the need of horticultural research.

The setting in which the Watergy project was initiated is the general concern about the limited availability of fresh water in semi arid regions. Improvement of water use efficiency is of prominent importance in these regions and in agriculture a large contribution to sustainable water use can still be achieved by introducing new ways of growing crops (Postel, 2000; Gleick, 2003; Renault and Wallender, 2000). In horticulture advanced water-saving methods are possible, such as desalination of (brackish or salt) water and closing water cycles in the greenhouse. The aim of the Watergy project is to study these possibilities by constructing an experimental greenhouse, designed for (semi)-arid climates (built in Almeria, Southern Spain). The main objectives of the project are water recycling and air cooling inside a potentially commercial greenhouse.

From a control point of view integrating several functions such as crop growth, water re-use, and energy conservation pose additional challenges due to the many interactions and restrictions. Therefore, to exploit the possibilities of such greenhouses, many more sensors than usual are required and Watergy is no exception. With the available sensors and actuators it is possible to operate the greenhouse in many different ways and make it a multi-functional place for both plant physiological, control theoretical and physics based experiments. As commercially available measurement and control systems for horticulture are not suitable for this task, this is another reason for the design of a new measurement and control system.

A measurement and control system is a complicated system to design, especially when the number of inputs and outputs is large. It is important to design the system in a methodic way, such that the system will fulfil the expectations of the users. Three topics are discussed in this paper: (1) the design of the hardware, like actuators, computers and sensors, (2) the way these components are connected and how they communicate, and finally (3) the functionality of the controllers (mostly software).

The Watergy greenhouse

To understand the requirements set out for the measurement and control system, a short introduction into the functioning of the Watergy greenhouse is now presented. More extensive information on the project can be found on the website www.watergy.info and in the references (Buchholz and Zaragoza, 2004) and (Zaragoza et al., 2007).

The most remarkable feature of the Watergy greenhouse is the double walled tower (see figure 2.1). The sun heats the (humid) air inside (1), which rises into the outer duct of the tower (2) where it is further heated by the sun (3). The tower is closed at the top, so the air does not leave the greenhouse. Instead the air is cooled with a heat exchanger in the central duct of the tower (4). The cooled air falls and flows back into the warm greenhouse (5), closing the cycle. During night, the heat exchanger heats the air and the air movement reverses. Hot air raises through the heat exchanger (8) to the top of the tower (9) and falls back into the greenhouse (10+11) due to cooling at the greenhouse roof . The water used as coolant in the heat exchanger is heated during the day and cooled during the night, using a tank (7) as storage buffer.

Because the greenhouse is completely closed, the water evaporated by the plants stays inside. During daytime, warm and moist air flows into the tower, where the water condenses against the cold surface of the heat exchanger. Surplus heat load can be reduced by desalination of sea water, which is achieved by spraying salt water over the inner roof (6) during the day. The water evaporates here, follows the air stream into the tower and condenses inside the heat exchanger. At night, when the heat exchanger is used to heat the air, salt water is evaporated inside the heat exchanger (9) and condenses against the (outer) roof. In both cases the condensate is collected for use as irrigation water or is exported out. This improves the overall water use efficiency of the greenhouse.

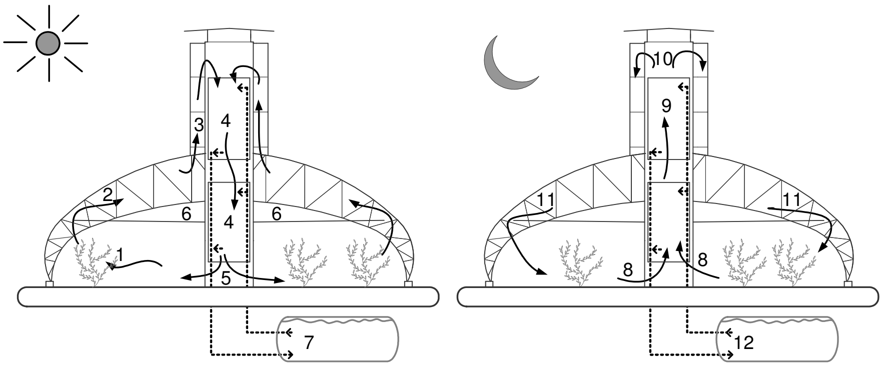


Figure 2.1: Air flow in the Watergy greenhouse at day-time (left) and at night-time (right)

2.2 Method

In this section some theory on the design method is introduced, followed by a short background on the layout of measurements and control systems. Second, the design methodology is described in detail for the Watergy hardware and software.

2.2.1 Hardware design – theory

A phase model is used to design the control system hardware. This means that different phases in the design process are distinguished, each phase with its own level of abstraction (Kroonenberg and Siers, 1998). The advantage of this approach is that a wide range of options is considered, thereby minimizing the chance of overlooking something, without loosing track of the main objectives. This design procedure has been used for the design of sophisticated machinery (see for example Krick (1969) or Bakker et al. (2004)), but its application is for the design of a measurement and control system is new to the best of our knowledge.

The design process is performed in four steps (see figure 2.2):

1. Objective. First, an objective for the system is defined.

2. Problem definition phase. With this objective in mind, the *problem definition phase* starts, in which the first step is to define fixed and variable requirements for the system. Fixed requirements must be fulfilled in any case. Variable requirements determine how good the design is; the better the variable requirements are met, the better the design is. The second step in the problem definition phase is to identify all functions of the system and to represent them in a scheme, the *function structure* (a function is defined as an action taken by the system to reach a specific goal).

3. Alternative definition phase. Once both the requirements and the functions are defined, for each individual function *alternative principles* are identified. In this phase, the designers need to be creative to avoid exclusion of potential solutions. Brainstorming methods (Osborn, 1957) can help with this, for example brain writing (Rohrbach, 1969) and synectics (Gordon, 1961). After identifying a wide range of optional solutions for all individual functions, several overall concept solutions are chosen. An overall solution is a set of combined solutions that fulfill all functions in the system.

4. Construction phase. A rating procedure is used to select the best over-all concept solution. This solution is put to practice in the *construction phase*, resulting in a *prototype*.

2.2.2 Hierarchy and architecture of control systems – theory

Apart from choices for hardware, the way hardware is linked together is an important consideration in the design of a measurement and control system. Two concepts are important here: hierarchy and architecture. The hierarchy describes the layers in the system and their functions and requirements (Kirmann, 2006). The first layer concerns primary technology (see figure 2.3); the hardware of a system (e.g. pumps, valves, vessels). The second layer

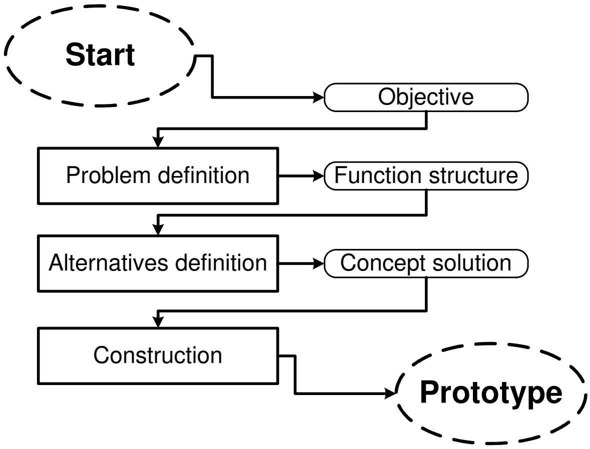


Figure 2.2: The design process (Kroonenberg and Siers, 1998)

consists of sensors and actuators. The third layer contains the control of individual actuators (low level control; e.g. pump speed control). The fourth layer (group control) consists of the control of a well defined part of a system (e.g. a heating system). The fifth layer supervises the whole system; more sophisticated tasks are performed here (such as optimization). The sixth and seventh layers are applicable in large plants and deal with strategies, planning of resources etc.

Timescales in the hierarchy are increasing from bottom to top; low level controllers have a much smaller time constant than the supervision layer. The amount of data decreases from bottom to top; lower levels process more (raw) data than the upper levels. The man-machine-interface is located at the supervision layer (layer 5 in figure 2.3) and sometimes at group control level (layer 4). Two main types of architecture of a measurement and control system exist, both extensively described in the literature (Doebelin, 1990; Johnson, 1993; Rijnsdorp, 1991). The first is a centralized control system; a system where one central computer monitors the system and sends commands to the low level controllers. Second is the decentralized control system, where all low level controllers can communicate with each other, without interference of a central computer at supervisory level.

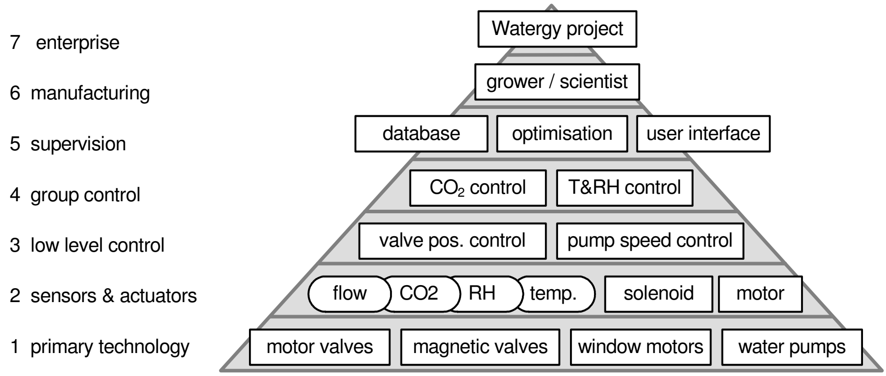


Figure 2.3: Control hierarchy of the Watergy project. On the left are general names of the layers, the pyramid on the right gives the implementation for the Watergy project (adopted from Kirrmann (2006)).

2.3 Application of the method

The theoretical steps outlined in section 2.2.1 were applied to the Watergy case, resulting in the following design procedure:

1. Objective. The objective of the Watergy measurement and control system is "To measure variables that allow the reconstruction of all relevant states and to be able to control all actuators in the experimental greenhouse with advanced control methods".

2. Problem definition phase. In our case, six fixed requirements have been defined:

- All variables that are judged relevant for modeling and control of the greenhouse must be measured automatically (temperature, moisture content, radiation, flows, etc).
- All actuators (pumps, valves) must be software controllable.
- It must be possible to calculate new settings for the actuators in the system itself as well as by external software, and to apply both cascade and direct control.
- All information relevant for modeling and control must be stored for later analysis.

- The system must be accessible from the intra- and internet with adequate authorization and security levels.

The variable requirements are defined as follows:

- The system must be flexible in all the points above.
- Testing and troubleshooting should be easy to perform.
- The system should be easy to operate (both software and hardware).
- The system interface should be easy to understand for outsiders.
- Maintenance should be low; the system should be robust.
- The system should use as much as possible standard components and protocols.

Next, individual functions within the system were identified and grouped into five tasks; measure, actuate, control, store data and interact with the user. All groups contain several functions that together perform a task. Table 1 to table 5 give details on the functions; for example table 1 gives all the tasks needed to fulfill the function measuring.

3. Alternative definition phase. After identifying the individual functions for the system, alternative solutions were defined for each function. This process resulted in a matrix of alternative solutions as shown in tables 1 - 5. The design for the whole system, the *concept solution*, has been chosen from tables 1 - 5 by selecting different possible solutions and weighting them against each other with the variable requirements mentioned before. The choices for the Watergy measurement and control system are motivated in the next section and shown in the tables by bold text.

2.4 Design choices

This section elaborates on the functions, tasks and alternative solutions. Considerations for choosing the hardware used to build the measurement and control system are presented here.

2.4.1 Functions of the control system

Function: measure

One of the most important tasks of the measurement and control system is to measure all data needed to study the behavior of the greenhouse and to gain enough information for modeling of the greenhouse climate and validation of these models. The sensors installed in the greenhouse and considerations taken into account when choosing these sensors are given here.

Temperature is measured outside, in the greenhouse, in the soil and in the water circuits at various locations. For comparable data the same type of sensors is used at all locations. Pt-100 sensors were selected, since, at the same level of accuracy, these sensors offer better reliability and long term stability than alternatives like thermocouples and thermistors.

Moisture content can be measured very accurately with the principle of wet/dry bulb temperatures. In our case however most RH sensors are difficult to reach, which complicates filling the water container of the wet bulb sensor. Therefor electronic humidity sensors were selected. After calibration their accuracy is good enough for greenhouse experiments and they are more reliable than other options since no frequent maintenance is required. Most dominant drawback is that electronic RH sensors do not function when condensation occurs on the sensor. To avoid these problems, measurement of dew point temperature is used at points where condensation is expected.

CO_2-concentration is measured with a commercially available CO_2 sensor that works according to the infra red measurement principle. These sensors are small, do not have a long response time (as some centrally placed analyzers) and do not require frequent maintenance.

Air velocity is measured both inside the heat exchanger as well as outdoors (wind speed). The latter is easy to measure with commercially available wind sensors (rotating turbine wheel). The air velocity inside the central heat exchanger is very low (0-0.5 ms^{-1}), and is more difficult to measure. A hot wire anemometer is a good option, although it is not very robust. An acoustic, custom built sensor proved to be a better solution (the sensor is water tight, has a resolution of 1 mms^{-1} and a good robustness (Enotemp)).

Water flow is measured with commercially available turbine wheels. These proved to be more accurate than other options at a lower cost level.

Solar radiation is measured with a Kipp solari meter (CM10). A stack of thermocouples measures the global solar radiation in Wm^{-2}.

The temperature, CO_2 and humidity sensors are mounted in mechanically ventilated boxes to ensure low time constants when measuring and to limit the influence of solar radiation on the sensors.

Signal conditioning and A/D conversion. Data is measured with industrial, embedded processors and I/O modules of the compact Field Point series (National Instruments). These data loggers are a good compromise between multi purpose data loggers for laboratory use, with high flexibility and accuracy but low robustness and side industrial data loggers with lower flexibility and accuracy but higher robustness. The data loggers are connected to sensors and actuators via a standard computer network patch panel. Standard computer network cables (UTP CAT5) and standard connectors (RJ45) connect all sensors and actuators to this patch panel. The advantages of using these components are high connection density, fast mounting (strip and crimp), reliable contacts and cost effectiveness. A test box connects easily to every sensor, actuator and I/O channel to allow for individual testing. The I/O modules, power supplies, patch panel and network equipment have been built together in a steel cabinet and form a compact process control unit (PCU). A built-in un-interruptible power supply improves the continuous availability and quality of the electric power supply.

Convert raw values to SI units. Measured variables, like ohms, voltage, etc., are converted to data in SI units by software running on the data loggers. For reliability, both raw as well as the calculated values are stored in the database, so re-calibration of sensors is possible.

Function: actuate

Settings are generated on the central computer and the data loggers convert them to analog signals. Relays are connected to the data loggers that switch high power currents to drive actuators.

Read settings for actuators is a function performed in the software that runs in the embedded processors.

D/A convert The compact Field Point embedded processor performs the D/A conversion. All actuators use either standard 24 V relay technique or 0-20 mA.

Convert low voltage to high power Relay boxes and hard-wired circuits are located though the whole greenhouse. This brings them close to the appliances, thus reducing cabling and giving more flexibility during experiments.

Table 2.1: Alternative solutions for the function "measure states"

Function	Alternative solutions				
Sensors					
Temperature	Analogue	**PT100**	Thermistor	Thermocouple	Acoustic
Moisture content	Hair hygrometer	**Dew point temp.**	Wet & dry bulb temp.	**Electronic RH sensor**	Acoustic
CO_2 concentration	**infrared**	Gas chromatography			
Air velocity (anemometer)	Hot wire	**Measuring fan/turbine**	**Ultrasonic**	Pitot tube	
Water flow	Mass flow (inductive)	Weighing	**Ultrasonic**	Volumetric	**Rotating wheel**
Solar radiation	**Solari meter 300- 3000 nm**	PAR sensor; 300-900 nm	Light Depending Resistor	LUX meter	
Signal conditioning and A/D convert	Hand measurement	PCI card computer	Stand alone data logger, mp.[1]	**Stand alone data logger, ind.**[2]	Dedicated ind. computer
Convert raw value to SI units	Software in PC	Software in data logger mp.	**Software in data logger ind.**	Software in ind. computer	

[1] mp.=multi purpose; [2]ind.=industrial

Function: control

Settings for the actuators are calculated in the PC that contains the database. These settings are generated in real time from the measured data and user requirements. The rules used for this can be changed from a simple time clock to more sophisticated trajectory settings. Also external programs, such as Matlab, can be used to provide settings. Section 2.4.2 gives more a detailed description of the available types of settings and how they are communicated through the system.

Table 2.2: Alternative solutions for the function “actuate”

Function	**Alternative solutions**			
Read settingsfor actuators	Software in PC	Software in data logger, mp.	**Software in data logger, ind.**	Software in ind. computer
D/A convert	Data logger, PCI card computer	Data logger, Stand alone, mp.	**Data logger, Stand alone, ind.**	Dedicated ind. computer
Convert low voltage to high power	Central relay technique	**Distributed relays**	Actuators with bus communication	

[1] mp.=multi purpose; [2]ind.=industrial

Function: store and exchange data

The embedded processor in the PCU makes the measured data available for clients on the local computer network. The database, located on the central computer, reads the data and checks if anything has changed. If so, the new data point is stored, together with a time tag. In this way considerable computer storage is saved in periods with little activity.

Table 2.3: Alternative solutions for the function “control”

Function	**Alternative solutions**			
Read measured data into software	**Software in PC**	Software in data logger mp.	Software in data logger ind.	Software in ind. computer
Read requirements set by user	**Software in PC**	Software in data logger mp.	Software in data logger ind.	Software in ind. computer
Calculate setpoints	**Software in PC**	Software in data logger mp.	Software in data logger ind.	Software in ind. computer
Location	**Computer**	Data logger	PLC	
Software	**Labview**	Matlab Simulink xPC	dll’s (e.g. C code)	Complete SCADA package

[1] mp.=multi purpose; [2]ind.=industrial

Function: Interact with the user

To *present current data* to the users of system, real time data are shown in an on-screen graphical user interface (GUI), showing the greenhouse in a schematic drawing (see figure 2.4.1). Other details, like valve positions, pump rates, flow rates etc. are shown in different parts of the GUI. To *present* *historical data*, a standard software tool is used enabling the user to access current and historical data from the database and to export data to text files. *User setpoints* for controlled states in the greenhouse (e.g. temperature, humidity, air velocity, CO_2-concentration, etc.) can be changed in the graphical user interface, and sent to the central database after confirmation by the user.

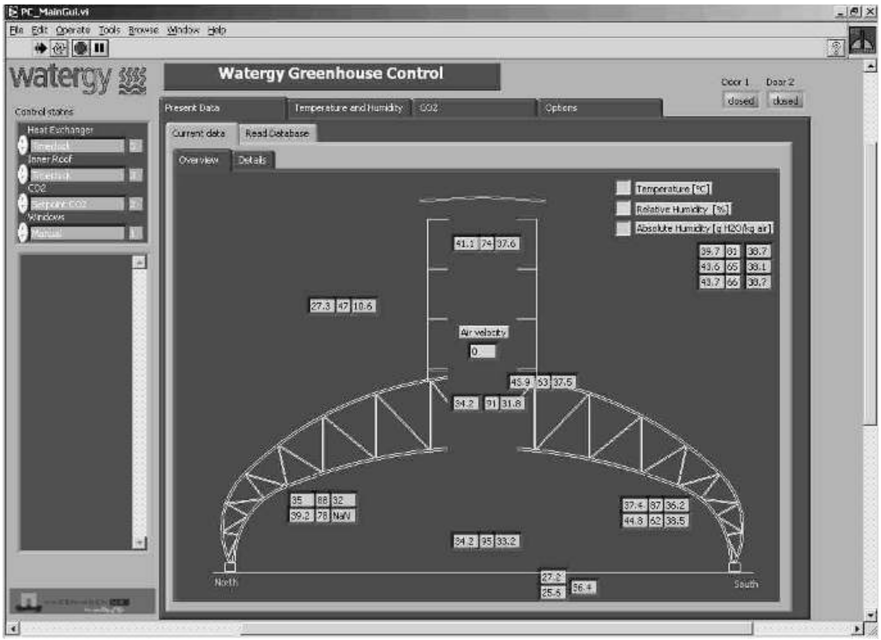


Figure 2.4: Graphical user interface of the control system; measured data is shown at places where it is measured

Table 2.4: Alternative solutions for the function "store data"

Function	Alternative solutions			
Read data	**Software in PC**	Software in data logger mp.	Software in data logger ind.	Software in ind. computer
Store data	Text files	**database**		
Location	**Computer**	Data logger		

[1] mp.=multi purpose; [2]ind.=industrial

Table 2.5: Alternative solutions for the function "user interaction"

Function	Alternative solutions			
Present current data on a screen	**GUI on computer**	Text based interface on computer	Touch screen	Input screen on data logger
Present historical data on a screen	**GUI on computer**	Text based interface on computer	Touch screen	Input screen on data logger
Read user setpoints	**Software in PC**	Software in data logger mp.	Software in data logger ind.	Software in ind. computer

[1] mp.=multi purpose; [2]ind.=industrial

2.4.2 Hierarchy and architecture in the Watergy control system

The layout of the hardware and software in the Watergy control system follows the hierarchy rules described earlier (see section 2.2.2). Lower layers contain sensors and actuators. On the hardware level, the functionality of low level control (level 3) and group control (level 4) are bundled into one embedded system combined in the PCU. The supervisory level (level 5) is implemented on the central PC. The top levels in the hierarchy, which deal with strategy and planning, are not implemented since these levels are not needed in a medium sized scientific measurement system. To keep the measurement system flexible with respect to requirements of future controllers, it is possible to bypass the central database and communicate directly from the supervisory level to the level of the sensors and actuators.

The architecture of our control system is a centralized control system; the central PC interacts with the user and sends settings to the PCU's. However as opposed to a purely centralized system, it is possible for the low level controllers to communicate over the network with other process control units. For some control schemes this 'bypass' of the central computer can prove useful, for example if the central PC stops functioning, the low level control can still steer the whole system. This set up combines the structure of a centralized system with the flexibility of a decentralized architecture.

A local area network connects the server with the embedded processors and the internet. Ethernet is a non deterministic network, so it is in principle not suitable for real time applications. Ethernet can be enhanced to meet real-time requirements of industry (Decotignie, 2005). If the network load is low and the real time definition is not too high (e.g. 100 ms) standard ethernet can still be used for supervisory control tasks. In the Watergy greenhouse, this is the case as time constants in the system are relatively large. Small delays in the communication between supervisory and group control level are allowed in this system design. The central personal computer is accessible through the internet, meaning that settings can be changed, data can be viewed and new control algorithms uploaded over the internet. The process control unit does not communicate over internet, to make sure the controllers are not affected by delay times (Yang et al., 2002).

2.4.3 Controllers in the software

The generation of settings for the actuators can be done in many ways. First, there is the possibility for manual control, which allows the user to set all actuators individually. Second, there is time control, which allows users to control settings of individual actuators over time. This is especially useful in the first steps of research because individual actuators can be easily tested. Third, there is basic automatic control, which allows users to specify setpoint profiles for output variables of the greenhouse (like temperature and humidity). Elementary automatic control uses well defined, basic controllers (like PID). Last, there is the possibility to control the greenhouse with advanced control methods. In this mode external programs (for example Matlab) calculate actuator commands for the system.

The software of the control system is distributed over the same levels as the hardware. In summary, the system consists of low level, group level and supervision controllers, each with their own specific task, inputs and outputs. Typically a control action would look like this: the supervision level calculates a desired greenhouse temperature, the group level controls the windows and the heating system with setpoints for window aperture or pump speed. The low level controller controls the actuators with these setpoints. In this case, the supervisory level does not influence the actuators directly; *cascade control*. However, in some control applications it is required that controllers at higher levels can directly influence the actuators; *direct control*. Optimal control is an example where direct control is applied (Van Straten et al., 2000a; Van Henten, 2003a). In this framework there is only one controller that calculates (low level) setpoints for all actuators. In contrast to commercially available systems, the control system for the Watergy greenhouse is able to handle both cascade and direct control strategies.

Low level control

Normally, low level controllers operate in cascade control; single actuators are controlled according to a setpoint coming from the group control layer. For example pump speed and window opening are controlled by low level controllers. Low level controllers realize setpoints in fast control loops without involving the higher level controllers. Control strategies are typically quite basic (e.g. proportional position control). In direct control mode the low level controller accepts setpoints directly from the supervisory level, to facilitate the direct control mode. In this case, the group control is bypassed.

Another important task of the low level controllers is the security of the system. When the controllers in the software at higher levels fail, the low level control detects this and steers systems to a safe situation (e.g. an acceptable climate for the plants). For extra safety, a hardware security has been built into the greenhouse; if the temperature becomes too high, the greenhouse windows and the top of the tower are opened to avoid damage to the crop.

Group control

Group control is implemented on the decentralized process control units and communicates over the network to the supervisory level. In cascade control mode, controllers in the group control layer realize settings for states of the system. For example the CO_2 level in the greenhouse is controlled by a group controller that gets its setpoint (required concentration of carbon dioxide) from the supervisory level. The group controller sends a setpoint (in this case a valve position [%]) to one or more low level controller(s). In the direct control mode, the group level does not play a role. It just passes on the setpoints from the supervisory level directly to the low level controllers.

Supervisory level

On the supervisory level, settings are generated for either group level (cascade control) or low level controllers (direct control). Interaction with the user takes place at the supervisory level through graphical user interfaces that allow users to supervise the system, change settings, view historical data, etc.

Most of the measured data is presented to users in schemes that represent the physical system (see figure 2.4.1). This way of representing the data is the preferred way according to literature on man-machine interfaces (Shneiderman, 1997; Wittenberg, 2003) as it allows non-experienced user to understand and interpret the data.

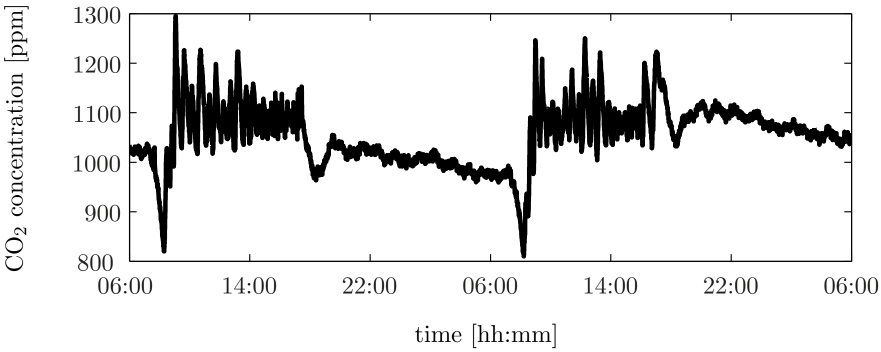
2.5 Results

After the measurement and control system was built, it was used to control the Watergy greenhouse. First, relatively simple controllers were used; setpoint control for the cooling/heating system and a PID control for CO_2 concentration inside the greenhouse. At a later stage, models were developed to be used for control purposes. In this paper, some results of the basic controllers are shown to illustrate the functionality of the measurement and control system. The more advanced controllers will be described in future papers.

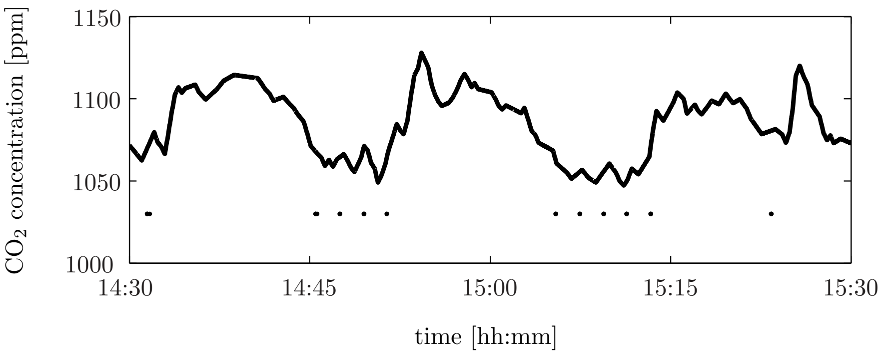
Figure 2.5(a) shows the CO_2 concentration inside the greenhouse for a period of two days. The concentration was controlled during daytime, at night the controller was switched off and the concentration was allowed to vary freely. To study the behavior of the controller, figure 2.5(b) is useful. It shows the concentration during one hour at daytime. The dots represent times at which the CO_2 dosing valve was opened for a short period (max 60 s). The measured concentration raises some minutes after a dosing and slowly decreases afterwards.

The temperature of the coolant, pump operation and the greenhouse temperature are depicted in figure 2.6. The temperature of the plant area in the greenhouse raises during the day, mostly because of solar radiation. The returning coolant (from the heat exchanger in the tower) follows this temperature, whereas the incoming water temperature remains more stable. At night, the water flow reverses (to maintain counterflow in the heat exchanger) and the water is cooled in the heat exchanger. The next morning, the temperature of water entering the heat exchanger is almost back to its original value, meaning that the regeneration of the coolant works well (at the time of measuring; early spring).

The combination of the data logger, power supply, patch panel and net-



(a) CO_2 concentration inside the Watergy greenhouse in the period from the 5^{th} to the 7^{th} of October 2006



(b) CO_2 concentration on the 5^{th} of October 2006, 14:30h until 15:30h. The dots depict times when the CO_2 valve was opened by the controller .

Figure 2.5: CO_2 control in the greenhouse

work equipment in one process control unit (PCU) proved to be quite robust. The measurement and control system has been running for the last 3 years to gather data on experiments with control and plant physiology and to control the climate inside the greenhouse. Results on the cooling and water recycling capabilities of the greenhouse are described by Buchholz et al. (2006) and Zaragoza et al. (2007). With the data gathered by this measurement and control system a greenhouse model was developed that is calibrated with measured data of a time-period of one year (Speetjens et al., 2008b, 2007).

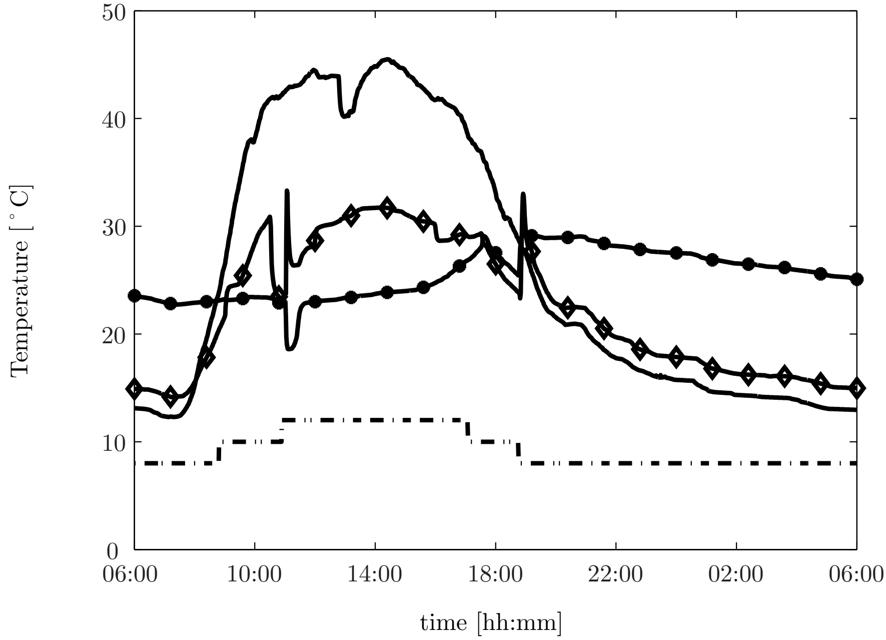


Figure 2.6: Temperature in the greenhouse (–), water supply (∘) and water return temperature (⋄) for one day (11^{th} of March 2006). The pump direction is given by (·–); 10: pump off, <10 and >10: pump on with different flow direction

2.6 Conclusions

A measurement and control system suitable for advanced control research and implementation in non-standard greenhouse environments was designed. The system has the required flexibility and versatility, in contrast to commercial greenhouse climate computers. The hardware of the presented system is flexible because of the generally available components that are connected in a modular way. The system was designed with methodic design, a method normally used for design of machinery. The main advantage of this approach is that the objective of the system is clearly defined and all functions are systematically reviewed. This makes it easy to discuss the design with a group of persons without misunderstandings, resulting in a much shorter construction phase than in an ad-hoc approach.

All relevant data are stored in a central database, new setpoints can be calculated and send to the actuators and the system is accessible through the internet. The combination of the data logger, power supply, patch panel and network equipment in one process control unit (PCU) proved to be robust. Since all sensors are connected to the PCU with standard plugs they can easily be disconnected, moved and replaced, making the system very flexible. The low level technical equipment like motor control, relays, etc. are distributed over the greenhouse. This considerably reduces the cabling and the system remains more flexible than when all the hardware installation would have been centralized.

The measurement and control system, the graphical user interfaces and the data storage in a database are programmed in Labview. The programs that were developed for the group and low level controllers run in embedded processors, the software at supervisory level (GUI and database) runs on a personal computer. It is possible to operate the system both in direct as in cascade control. In the direct control mode, set points for the low level controllers are generated at the supervisory level, e.g. when model predictive controllers are used. In the cascade control mode, setpoints for the group level are generated at the supervisory level and setpoints for low level controllers are generated at the group level.

Finally, it must be mentioned that compared to commercially available greenhouse control systems, the system at hand is very much suited for the research done with the Watergy greenhouse. Several model based control strategies are studied based on data gathered with this system. The final goal of the project is to come to an adaptive model based control.

Acknowledgements

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3

Greenhouse Model

This chapter is based on:

S. L. Speetjens, G. van Straten and J.D. Stigter. Physics Based Model for a Water-Saving Greenhouse. Biosystems Engineering. Accepted for publication, 2008

Abstract

A new greenhouse type is designed to study ways of decreasing horticultural water use in semi-arid regions. To control the greenhouse a model based control design will be applied. To this end a model is needed to predict the systems behavior (1 day ahead), without much computational effort. A physics-based model is developed, based on enthalpy and mass balances. The (lumped) key parameters of the model are identified with a controlled random search algorithm. To increase estimation accuracy and reduce computation time, estimation in parts was applied, meaning that only a part of the whole model was used in combination with measured data for state values of neighboring compartments. This method results in parameter estimates that converge well. In order to keep the model information needs limited, it was a deliberate choice to aggregate underlying process details into the lumped parameter description, at the expense of time-varying parameters over the seasons. The parameter fluctuation over the year was studied by repeated parameter estimation for each month. Since parameters fluctuate significantly, further research will focus on the use of adaptive mechanisms to facilitate model based control.

3.1 Introduction

Water use efficiency is of prominent importance in regions where fresh water is scarce. The Watergy project studies possibilities to increase water use efficiency in horticulture by combining plant production with water desalination, water recycling and space cooling. An innovative new greenhouse was designed and built in Almeria (Southern Spain). The greenhouse contains a plant compartment, a (salt) water evaporation compartment, condensation compartments and a central heating and cooling system. It is completely closed, regains 70 % of the irrigation water (as first tests show) and has a low energy demand.

The envisaged way to control the greenhouse climate is adaptive model based predictive control. The reason for this advanced method is the fact that the Watergy greenhouse is a complicated system to control. There are constraints in the control equipment and the combined goal of producing *both* crops *and* water causes contradictions in control actions. A model predictive controller can take these considerations into account and calculate the optimal control trajectory with respect to various criteria for the output.

The proposed control system needs a model that describes the climate inside the greenhouse and the functionality of the control equipment. This model is used intensively, so a model is needed with a limited number of states to keep computational loads acceptable. To enhance practical applicability it is also important to keep the information needs of the model as low as possible. This paper describes the development of this model and the procedure to estimate the parameters in the model.

Models that describe the climate in traditional greenhouses are well known from literature (see for example (Ooteghem et al., 2005; Chalabi et al., 1996; Tap and Willigenburg, 1996; Seginer, 2000). However, since the Watergy greenhouse is the first of its kind, new challenges have to be addressed. The model that is developed is physics based with a limited number of states. It contains lumped parameters that need to be calibrated on measured data. In a large model, parameter estimation can be laborious due to local minima or computational inefficient estimation algorithms. In this paper the controlled random search (CRS) algorithm is used on the parts of the model that contain the parameters to be estimated; *estimation in parts*. The data used for this calibration is collected during a two year period of experiments with the prototype.

The paper is organized as follows. First, the Watergy greenhouse and the technical equipment are described. Then the greenhouse climate model equations are given, together with a discussion on the main assumptions. The parameters in the model are estimated with the controlled random search method, using the estimation in parts' methodology, described in the third part of the paper. Finally, results are shown and conclusions on the model and the parameter estimation are given.

3.2 Watergy greenhouse

An experimental greenhouse with a ground area of 14x14 m was built in Almeria, Spain. Figure 3.1 gives a cross-section diagram of the greenhouse. The most remarkable feature is the double walled tower (4) with a height of 10 m. During the day, the sun heats the (humid) air inside the plant compartment (1). The heated air rises through the inner roof compartment (2), into the outer duct of the tower where it is further heated by the sun (3). As the tower is closed at the top, the air does not leave the greenhouse but is cooled with a heat exchanger in the central duct of the tower (4). The coolant is stored in a heat buffer (7). The cooled air flows back into the warm greenhouse (5), closing the cycle. During the night, the heat exchanger heats the air and the air movement reverses; hot air raises through the heat exchanger to the top of the tower and flows down through the outer duct. The cooled cooling-water returns to the storage for later use. Since the air cycle in the greenhouse is closed, the water evaporated by the plants stays inside. During the day, warm, moist air flows into the tower, where the moisture condenses against the cold surface of the heat exchanger. To facilitate water desalination, a so-called inner roof (6) is used over which (salt) water is sprayed. The water that evaporates here follows the air flow and condensates in the heat exchanger.

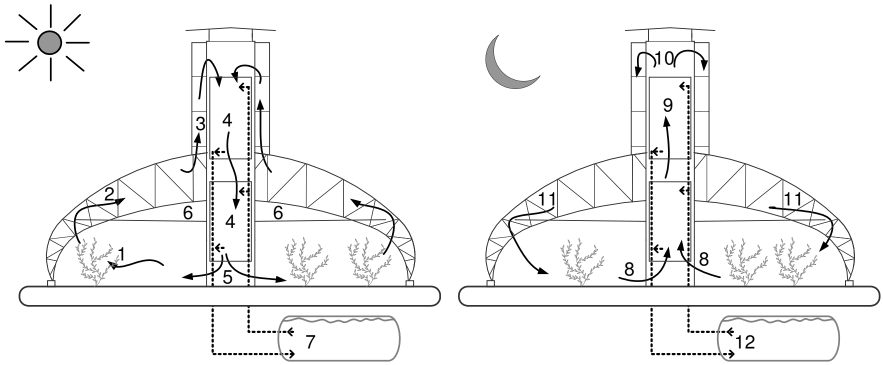


Figure 3.1: Function of the Watergy greenhouse during the day (left) and the night (right)

3.3 Watergy climate model

The crop (first green bean, later followed by Okra) is grown in soil with a balanced texture of about 20-30 cm deep. A sand bed with a thickness of about 10 cm is placed on top of the soil. Drip irrigation is used, controlled by an autonomous fertigation system. The drain water is recovered and recycled. For more information see (Buchholz and Zaragoza, 2004) and www.watergy.info for a general description.

The condensate coming from the heat exchanger and from the roof is recovered, the quantity is measured automatically and it is used again for irrigation. Temperature and humidity are measured at all vital places inside and outside the greenhouse and technical installation. Other quantities that are measured are outside global radiation, wind speed and -direction and the CO_2 concentration. All pumps and valves are controlled by data loggers that are connected to a personal computer on which a database runs. This enables implementation of controllers in several software packages, including Matlab and LabVIEW. See Janssen et al. (2004) for a detailed description of the control systems layout and equipment.

Many greenhouse models have been made in the past by various authors. One of the first to describe the greenhouse climate using physics-based models was (Bot, 1983). Later others followed, see for example (Jolliet et al., 1991; Tchamitchian et al., 1992; Jolliet, 1994; Chalabi et al., 1996; Zwart, 1996; Tap, 2000). The model needed for the Watergy greenhouse should contain a limited number of states (to reduce calculation times) and should only contain the key-dynamics of the system. Minor effects are accounted for in lumped parameters. The main differences to traditional greenhouse models are the presence of the central heat exchanger to cool and heat the air in the greenhouse (1) and the absence of air exchange with the outside air (2). The greenhouse is divided into six compartments, namely the plant compartment, the inner roof compartment, the solids (meaning soil and greenhouse construction parts) in both the plant compartment and the inner roof compartment, the heat exchanger and the heat storage (see figure 3.2). The first four are assumed to be homogenous, the heat exchanger and the heat storage are divided into sub compartments to model the spatial behavior.

The state vector of the model is given by:

$$\begin{bmatrix} T_p & T_i & x_p & x_i & x_{s_p} & x_{s_i} & T_{h_a}(n) & x_h(n) & T_{h_w}(n) & T_{hs}(m) \end{bmatrix} \tag{3.1}$$

where the temperature is denoted by T and the moisture content by x. Subscripts give the compartments of the greenhouse: p for the plant compartment, i for the inner roof compartment, s for the solids in both plant as well as the inner roof compartment, h for the heat exchanger and hs denotes the heat storage.

The *air velocity* inside the greenhouse is coupled to the operation of the heating/cooling system; if the pump in the heat exchanger works, the air

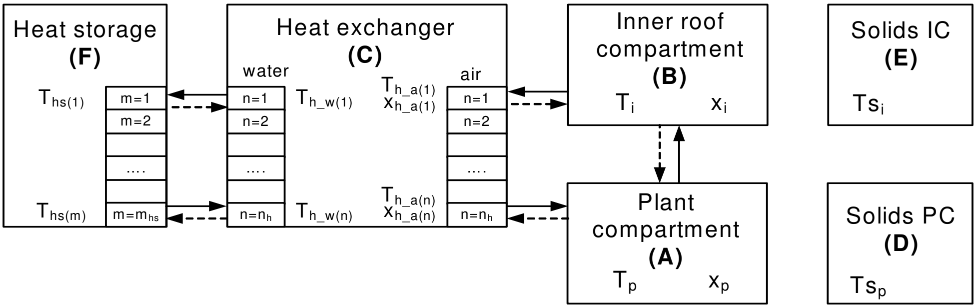


Figure 3.2: The greenhouse model. The arrows represent the air flow and the water flow during the day (–) and during the night (– –)

velocity in the heat exchanger is assumed to be constant at 0.5 m s^{-1}, if the pump is stopped, the airflow is zero. The direction of the airflow in the heat exchanger is top-bottom during the day and bottom-top during the night (figure 3.2). The change in air flow direction makes the model switch between different sets of equations. Since the model equations for day and night are equal if the air velocity is zero, the behavior of the model is smooth if the airflow is set to zero during switching.

Condensation is a process that does not occur constantly. The model structure changes in case of condensation, since an additional moisture sink is introduced. Condensation occurs when the saturated moisture content at surface temperature ($x_{sat}\left(T_{surface}\right)$) is smaller than the moisture content of the air (x). To describe the changes in model structure, the Heaviside unit step function is used to create a virtual control parameter (u^{con}) that describes whether the condensation terms are present (T_{r_p} denotes the temperature of the roof in the plant compartment (similar for the others)):

$$u_{r_p}^{con} = \begin{cases} 0 & \big(x_p - x_{sat}(T_{r_p})\big) \leq 0 \\ 1 & \big(x_p - x_{sat}(T_{r_p})\big) > 0 \end{cases} \tag{3.2}$$

$$u_{r_i}^{con} = \begin{cases} 0 & (x_i - x_{sat}(T_{r_i})) \leq 0 \\ 1 & (x_i - x_{sat}(T_{r_i})) > 0 \end{cases} \tag{3.3}$$

$$u_{h(n)}^{con} = \begin{cases} 0 & (x_{h_a}(n) - x_{sat}(T_{s_h}(n))) \leq 0 \\ 1 & (x_{h_a}(n) - x_{sat}(T_{s_h}(n))) > 0 \end{cases} \tag{3.4}$$

The sprinklers in the inner roof compartment can be switched on or off, which changes the model equations for the air temperature and moisture content in the inner roof compartment:

$$u_i = \begin{cases} 0 & \text{if sprinklers are off} \\ 1 & \text{if sprinklers are on} \end{cases} \tag{3.5}$$

3.3.1 Plant compartment

The energy balance of the plant compartment incorporates only the main energy flows in the greenhouse, i.e. solar radiation, convection, conduction and evapotranspiration.

The *solar radiation* received by the air in the plant compartment is given by $\eta_p G_o$, where G_o [$\mathrm{W\,m^{-2}}$] is the global radiation solar energy input and $\eta_p < 1$ an efficiency parameter (that must be calibrated). This description was preferred over detailed modeling of (long- and shortwave) radiation terms, to keep the number of states small and because the sky temperature was not measured ('minimal information modeling').

The driving force for *condensation* is the difference in moisture content between air (x_p, [kg kg^{-1}]) and the saturated moisture content at roof temperature ($x_{sat}(T_{r_p})$). To calculate $x_{sat}(T_{r_p})$, the temperature of the roof (T_{r_p}) must be known. To keep the model simple, T_{r_p} is not a state, but is estimated analytically. Since the roof is made of plastic foil it has almost no heat storage capacity, so its temperature mostly dependents on the temperature on both sides of the roof (T_p and T_o) and the heat transfer coefficients of the air boundary layers around it (R_{tot} and R_p):

$$T_{r_p} = T_p - \frac{R_p}{R_{tot}} (T_p - T_o) \tag{3.6}$$

With the estimated roof temperature, the condensation flux from the air to the roof is given by:

$$\begin{aligned} \Phi_p^{con} &= k_{po}\, \rho_a\, A_{po} \left(x_p - x_{sat}(T_{r_p})\right) \\ &\text{if } \left(x_p - x_{sat}(T_{r_p})\right) > 0 \end{aligned} \tag{3.7}$$

The mass transfer coefficient (k [m s^{-1}]) determines the rate of condensation. It is derived from the following relation:

$$k = \frac{\alpha_h}{\rho\, cp\, (a/D_c)^{2/3}} \tag{3.8}$$

where α_h is the heat transfer coefficient [Wm^{-2}K] and a/D_c the Lewis number [-] (a=thermal diffusivity and D_c the mass diffusivity).

The latent heat released due to condensation ($l_e \cdot \Phi_p^{con}$) is assumed to be transferred outside. The surface of the roof is not heated by this energy release; an assumption that holds if the heat conduction through the roof is large. Water that condenses against walls and windows is directly removed and therefore not available for evaporation again.

Evapotranspiration is described with the Penman-Monteith equation (Monteith, 1973). This empiric formula states that evapotranspiration (E [kg s^{-1}m^{-2}]) depends on incoming solar radiation (G_o [Wm^{-2}]) and vapor pressure deficit (D [Pa]; see appendix 1). The parameters α_p and β_p are calibration parameters:

$$E_p = \alpha_p\, G_o + \beta_p\, D_p \tag{3.9}$$

During the experiments, the amount of biomass was kept constant by interplanting (replacing only a fraction of the plants at the time) so that α_p and β_p will not change because of changes in leaf area.

The total energy balance of the plant compartment is given by:

$$
\begin{aligned}
m_p\, cp_a \frac{dT_p}{dt} =& \eta_p\, A_p\, G_o + \Phi_{p,T}^{conv} + U_{po}\, A_{po}\,(T_o - T_p) + \ldots \\
& U_{ps_p}\, A_{ps_p}\left(T_{s_p} - T_p\right) + U_{pi}\, A_{pi}(T_i - T_p) - \ldots \\
& l_e\, A_p\,(\alpha_p G_o + \beta_p D_p) \qquad (3.10) \\
\text{day: } \Phi_{p,T}^{conv} =& \phi_a\, cp_a\,(T_{h,out} - T_p) \\
\text{night: } \Phi_{p,T}^{conv} =& \phi_a\, cp_a\,(T_i - T_p)
\end{aligned}
$$

The total moisture balance of the plant compartment is described by the following function:

$$
\begin{aligned}
m_p \frac{dx_p}{dt} =& \Phi_{p,x}^{conv} + A_p\,(\alpha_p G_o + \beta_p D_p) - \ldots \\
& u_{r_p}^{con}\, k_{pr}\, \rho_a\, A_{pr}\,(x_p - x_{sat}(T_{r,p})) \qquad (3.11) \\
\text{day: } \Phi_{p,x}^{conv} =& \phi_a\,(x_{h,out} - x_p) \\
\text{night: } \Phi_{p,x}^{conv} =& \phi_a\,(x_i - x_p)
\end{aligned}
$$

3.3.2 Inner roof compartment

The structures of the energy and moisture balances of the inner roof compartment are similar to plant compartment. The amount of evaporation caused by this installation (E_i) if the sprinklers are on ($u_i = 1$) is modeled in the same way as the plant evapotranspiration, but with different parameters:

$$
E_i = \alpha_i\, G_o + \beta_i\, D_i \qquad (3.12)
$$

The temperature of the air in the inner roof compartment is denoted by T_i. The heat balance in given by:

$$
\begin{aligned}
m_i\, cp_a \frac{dT_i}{dt} =& \eta_i\, A_i\, G_o + \Phi_{i,T}^{conv} + \ldots \\
& U_{io}\, A_{io}\,(T_o - T_i) + U_{is_i}\, A_{is_i}\,(T_{s_i} - T_i) \ldots \\
& U_{pi}\, A_{pi}\,(T_p - T_i) - u_i\; l_e\, A_{po}\,(\alpha_i G_o + \beta_i D_i) \qquad (3.13) \\
\text{day: } \Phi_{i,T}^{conv} =& \phi_a\, cp_a\,(T_p - T_i) \\
\text{night: } \Phi_{i,T}^{conv} =& \phi_a\, cp_a\,(T_{h,out} - T_i)
\end{aligned}
$$

The moisture balance of the inner roof is given by:

$$
\begin{aligned}
m_i \frac{dx_i}{dt} &= \Phi_{i,x}^{conv} + u_i \; A_{po} \left(\alpha_i G_o + \beta_i D_i \right) - \ldots \\
&\quad u_{r_i}^{con} \, k_{ir} \, \rho_a \, A_{ir} \left(x_i - x_{sat}(T_{r,i}) \right) \qquad (3.14) \\
\text{day: } \Phi_{i,x}^{conv} &= \phi_a \left(x_p - x_i \right) \\
\text{night: } \Phi_{i,x}^{conv} &= \phi_a \left(x_{h,out} - x_i \right)
\end{aligned}
$$

3.3.3 Heat exchanger

A spatially distributed model is needed to model the heat and moisture transfer in the heat exchanger accurately. The heat exchanger is divided into a number of compartments (n) for which the air temperature, moisture content and water temperature are described. The heat exchanger always works in counter flow. Condensation in the heat exchanger is calculated in the same way as the condensation on the roof. To keep the heat exchanger model simple, the wall temperature is assumed to be equal to the water temperature in the same compartment. This is a valid assumption since the heat resistance of the air boundary layer in the heat exchanger is orders of magnitude higher than the heat resistance of both the boundary layer on the water side and the resistance of the wall material. The latent heat released due to condensation is assumed to be transferred directly into the water and not to heat the surface.

The heat balance of the air in a heat exchanger compartment is given by:

$$
\begin{aligned}
m_{h_a,n} \, cp_a \frac{dT_{h_a,n}}{dt} &= \Phi_{h,T}^{conv} - U_{h_a-w} \, A_{h(n)} \left(T_{h_a(n)} - T_{h_w(n)} \right) \qquad (3.15) \\
\text{day: } \Phi_{h,T}^{conv} &= \phi_a \, cp_a \left(T_{h_a(n-1)} - T_{h_a(n)} \right) \\
&\quad \text{for n=1} : T_{h_a(n-1)} = T_i \\
\text{night: } \Phi_{h,T}^{conv} &= \phi_a \, cp_a \left(T_{h_a(n+1)} - T_{h_a(n)} \right) \\
&\quad \text{for } n = n_h \; : \; T_{h_a(n+1)} = T_p
\end{aligned}
$$

The moisture balance of a compartment in the heat exchanger is given by:

$$
\begin{aligned}
m_{h_a,n}\frac{dx_{h_a(n)}}{dt} &= \Phi^{conv}_{h,x} - u_{con,h,n}\, k_{a-s}\, \rho_a\, A_{h,n}\left(x_{h_a(n)} - x_{h_{w,sat}(n)}\right)\\
\text{day: } \Phi^{conv}_{h,x} &= \phi_a\left(x_{h_a(n-1)} - x_{h_a(n)}\right)\\
&\quad \text{for } n = 1\ :\ x_{h_a(n-1)} = x_i\\
\text{night: } \Phi^{conv}_{h,x} &= \phi_a\left(x_{h_a(n+1)} - x_{h_a(n)}\right)\\
&\quad \text{for } n = n_h\ :\ x_{h_a(n+1)} = x_p
\end{aligned}
\tag{3.16}
$$

The heat balance of the water in a compartment in the heat exchanger is given by:

$$
\begin{aligned}
m_{h_w,n} cp_w \frac{dT_{h_w(n)}}{dt} &= \Phi^{conv}_{h,w} + U_{h_{a-w}} A_{h(n)}\left(T_{h_a(n)} - T_{h_w(n)}\right) + \ldots\\
&\quad u_{con,h,n}\, l_e\, k_{a-s}\, \rho_a\, A_{h(n)}\left(x_{h_a(n)} - x_{h_{a,s}(n)}\right)\\
\text{day: } \Phi^{conv}_{h,w} &= \phi_w cp_w\left(T_{h_w(n+1)} - T_{h_w(n)}\right)\\
&\quad \text{for } n = n_{max}\ :\ T_{h_w(n+1)} = T_{hs_w out}\\
\text{night: } \Phi^{conv}_{i,x} &= \phi_w cp_w\left(T_{h_w(n-1)} - T_{h_w(n)}\right)\\
&\quad \text{for } n = n_{min}\ :\ T_{h_w(n-1)} = T_{hs_w out}
\end{aligned}
\tag{3.17}
$$

3.3.4 Solids

The solid materials in the plant compartment and the inner roof compartment are both modeled as one body with a certain heat capacity (cp_{s_p} or cp_{s_i}) that exchanges energy with the air through an overall heat transfer coefficient (U_{ps_p} or U_{is_i}). For the plant compartment this means that the influence of the soil and the greenhouse construction parts are combined.

Long wave radiation is not explicitly taken into account, but incorporated in U_{ps_p} and U_{is_i} – which is another example of 'minimal information modeling'. Given these approximations it may be better to view the solids as virtual components. The heat balance of the virtual solids in the plant compartment is given by:

$$
m_{s_p}\, cp_{s_p}\frac{dT_{s_p}}{dt} = \eta_{s_p}\, A_{s_p}\, G_o + U_{s_p}\, A_{s_p}\left(T_p - T_{s_p}\right) \tag{3.18}
$$

The heat balance of the solids in the inner roof compartment is given by:

$$m_{s_i}\, cp_{s_i} \frac{dT_{s_i}}{dt} = \eta_{s_i}\, A_{s_i}\, G_o + U_{s_i}\, A_{s_i}\, (T_i - T_{s_i}) \tag{3.19}$$

3.3.5 Heat storage

The main assumption for the model of the heat storage is that no mixing between water layers occurs. Or, in other words, free convection in tank can be neglected with respect to forced convection. The number of compartments in the heat storage model is chosen according to empiric rules by Kleinbach et al. (1993); the minimum number of compartments (m) to reach enough accuracy in a one-dimensional multi-compartment model is given by: $m = 45.8\ tu^{-1.218}$ (where tu is the mean number of tank turnovers in one day). This relation is valid for fixed in/outlets in the tank and keeps relative errors in the estimated amount of energy in the tank within 5%. In the Watergy system, the number of tank turnovers is estimated around three, so that the number of compartments in the heat storage model is set to 12.

The flow direction through the tanks is top-down during the day and bottom-up during the night (to keep the stratification in the tanks). The compartment number is noted by m, the numbering convention is according to figure 3.2 (i.e. m=1 is the top compartment):

$$m_{hs,n}\, cp_w \frac{dT_{hs(m)}}{dt} = \Phi_{hs}^{conv} + U_{hs\,o}\, A_{hs(m)} \left(T_{hs(m)} - T_o\right) + \eta_{hs}\, A_{rad_{hs}(m)}\, G_o \tag{3.20}$$

$$\begin{aligned}
\text{day: } \Phi_{hs}^{conv} &= \phi_w\, cp_w \left(T_{hs(m-1)} - T_{hs(m)}\right) \\
&\quad \text{for } m = 1 : T_{hs(m-1)} = T_{h_{out}} = T_{h(1)} \\
\text{night: } \Phi_{hs}^{conv} &= \phi_w\, cp_w \left(T_{hs(m-1)} - T_{hs(m)}\right) \\
&\quad \text{for } m = m_{hs} : T_{hs(m+1)} = T_{h_{out}} = T_{h(m_{min})}
\end{aligned}$$

3.4 Parameter estimation

All parameters in the model have physical meanings and most of them can be given values from literature. Values for some lumped parameters cannot be taken from literature, since they encompass aggregated sub-processes that are specific for our situation. These parameters are U_{s_p}, U_{s_i}, cp_{s_p}, cp_{s_i}, ϕ_a,

η_p, η_i, η_{s_p}, η_{s_i} and (evapo)transpiration parameters α_p, α_i, β_p and β_i. To estimate values for these parameters, a controlled random search algorithm (CRS) was used (Price, 1976).

The controlled random search first randomly chooses a number (N) of values for the parameters (n) from the search domain (V). A goal function (f_p) is calculated for all trial points and stored in a matrix (A). Then, the search starts by choosing each iteration a new trial point (P) from the set (A), and calculating the goal function (f_p) for this point. When f_p is smaller than the trial point with the maximum goal function (M), P replaces M. This process continues until the set in A has converged.

The search domain is determined by an educated guess based on literature values and trial runs with the model. There are many ways to choose the new trial point P. Price chooses to take P as the centroid of $n + 1$ values from matrix A. Because the CRS scans through the whole parameter space the risk of local optima is low. The major drawback of the method is the long calculation time required compared to other parameter estimation methods. In our case, the goal function was chosen to be the sum of squared errors between measurements (y_{meas}) and simulated data (y_{sim}). The choice of outputs is explored in section 3.4.2.

$$f_p = \frac{1}{N} \sum_{t=1}^{t=t_{end}} (y_{sim} - y_{meas})^2 \tag{3.21}$$

3.4.1 Data

The prototype greenhouse was operational at the end of the summer of 2004 and was operated by manual control at that time. Data was collected in the period autumn 2004 to winter 2006. The available data includes measurements of temperature and humidity inside and outside the greenhouse (at various locations). Also air, water and condensation flows were measured in the heat exchanger and in the inner roof system. See Speetjens et al. (2008a) for more details on the measurement system and the measured data.

Most data sets for the parameter estimation are generated during the manual experimentation period. During this period, many ways of operating the greenhouse were tested, so data of many different situations is available. This is favorable as it gives rich excitation for the parameter estimation.

The parameters are estimated with data sets that are independent from the validation data sets. For the estimation of the heat transfer coefficient of the heat exchanger special experiments were performed to make the estimate more accurate.

The accuracy of the data is an important consideration when they are used for parameter estimation and validation. The measurements of temperature and humidity inside the greenhouse are quite accurate (± 0.1 K or ± 2% RH). The relative humidity is translated into moisture content [kg kg^{-1}] to compare the model with the data. The measurements of the air velocity and water flow in the heat exchanger have accuracies of ± 0.02 m s^{-1} and ± 50 m^{3}h^{-1}. The measurements of the condensation on the roof and in the heat exchanger are less accurate. The accuracy is estimated at ± 5%, which is approximately ± 6 l day^{-1}. Care was taken to place the sensors such that the measured values represent the average value in the compartments as well as possible.

3.4.2 Parameter estimation in parts

The CRS algorithm is computational intensive. To reduce the complexity of the problem it is possible to use only the compartment of the model that contains the parameters to be estimated (see figure 3.3). Measured values are used to replace the inputs at the boundaries of the compartment.

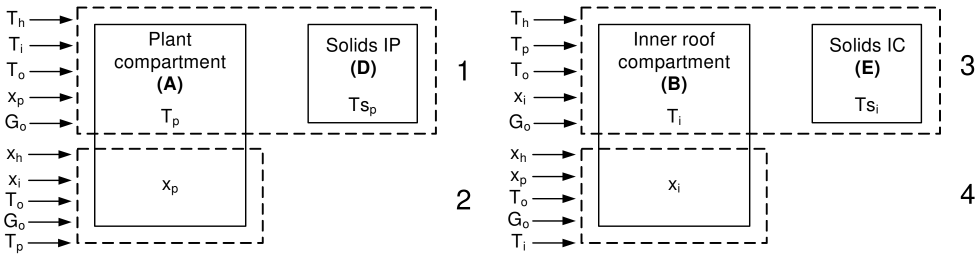


Figure 3.3: Principle of estimation in parts; the four partial models that are used to estimate the parameters are numbered 1 to 4.

The main advantage of estimation in parts is that inaccuracies in other compartments of the model do not influence the parameter estimation. In addition, computational load decreases.

Four partial models (as numbered in figure 3.3) are used to estimate twelve parameters, namely (the context dependent inputs are denoted by u and the output is denoted by y):

1. Temperature plant comp.:	η_p	$y = T_p$
	$\theta_1 = cp_{s_p}\, m_{s_p}$	$u = [T_i, T_h, x_p, x_i, x_h]$
	$\theta_2 = \eta_{s_p}\, A_{s_p}$	
	$\theta_3 = U_{ps_p}\, A_{ps_p}$	
2. Moisture content plant comp.:	α_p	$y = x_p$
	β_p	$u = [T_p, x_i, x_h]$
3. Temperature inner roof comp.:	η_i	$y = T_i$
	$\theta_5 = cp_{s_i}\, m_{s_i}$	$u = [T_p, T_h, x_i, x_p, x_h]$
	$\theta_6 = \eta_{s_i}\, A_{s_i}$	
	$\theta_7 = U_{ps_i}\, A_{ps_i}$	
4. Moisture content inner roof comp.:	α_i	$y = x_i$ $u = [T_i, x_p, x_h]$
	β_i	

ad 1. The temperature of the air and the solids in the plant compartment cannot be simulated separately because they influence each other and cannot be separated due to the lack of measurements of the solids temperature. Since the plant evapotranspiration has an important influence on the air temperature, parameters α_p and β_p were estimated first (alternatively, it is possible to estimate the parameters with experiments in an empty greenhouse). The fraction of solar energy received by the air is given by η_p. The heat capacity of the solids is given by θ_1. (it is not necessary to estimate the unknown mass (m_{s_p}) and specific heat (cp_{s_p}) of the solids separately). The surface of the solids (A_{s_p}) is also unknown, so it is estimated in combination with the conversion factor for solar radiation (η_{s_p}) in the new parameter θ_2, and combined with the heat exchange coefficient U_{ps_p} in θ_3.

ad 2. Both parameters in the evapotranspiration model are crop and situation specific. To estimate these parameters, only the model equation for the moisture content for the plant compartment was used. The inputs (air temperature and incoming moisture content) as well as the disturbances (solar radiation) were taken from the measured data.

ad 3. The parameters in the model for inner roof compartment temperature were estimated in exactly the same way as the parameters in the plant compartment model.

ad 4. The parameters in that describe the water evaporation on the inner roof (α_i and β_i) are estimated similar to α_p and β_p.

Apart from the twelve parameters that were estimated with the CRS algorithm, two parameters were estimated in special experiments using least squares, namely the heat transfer coefficient in the heat exchanger (U_{tot}) and the air velocity in the heat exchanger (v_{air})

3.5 Results and discussion

The search process of the CRS for α_p and β_p is depicted in figure 3.4 (for a data set of 1 day with measurement interval of 1 minute, obtained in April 2006). The figure shows the parameter values and the accompanying goal function (f_p) that were added to the set stored in matrix A every iteration. The search converges to the final value of $\alpha_p = 0.012$ and $\beta_p = 0.034$.

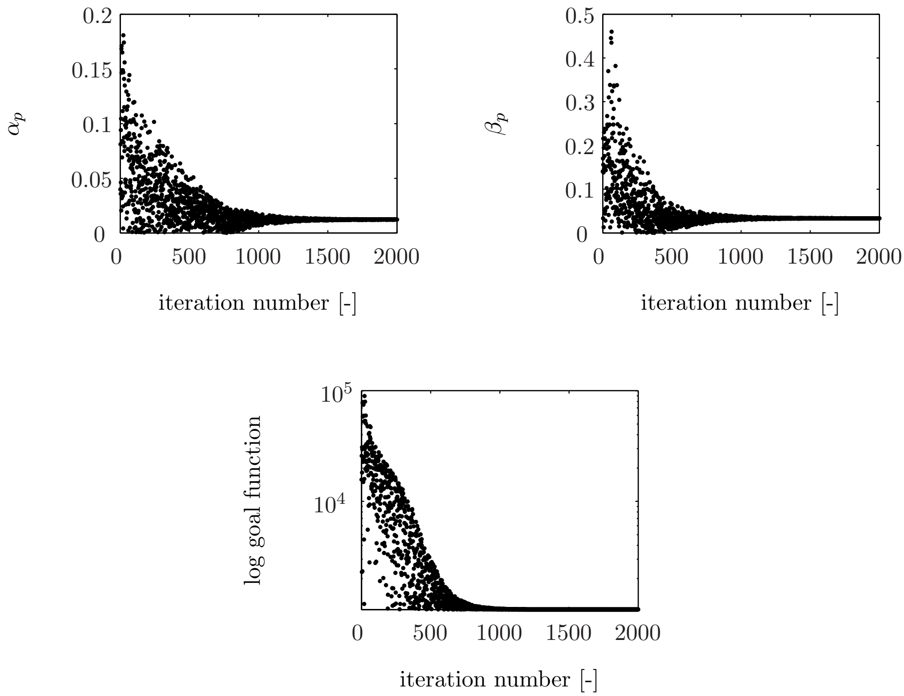


Figure 3.4: Example of the controlled random search history for α_p and β_p. The dots represent the sample point that were added to the set A (data from 13^{th} and 14^{th} of April 2006)

When the search is finished (if the goal function does not improve anymore), histograms are plotted of the parameter set (A). The price algorithm does not provide information about the confidence interval of the estimates, but the histograms of the distribution have been used to check the unimodality of the estimates (figure 3.5). The same procedure was followed for all twelve parameters.

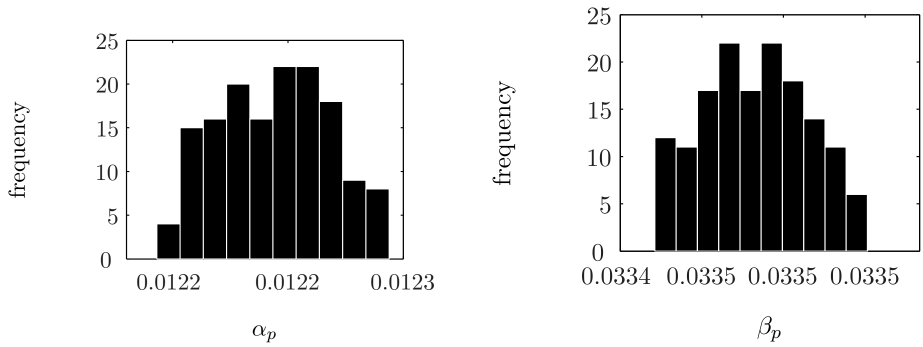
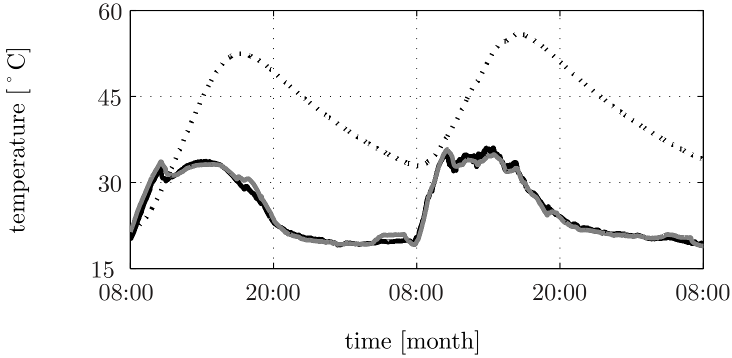


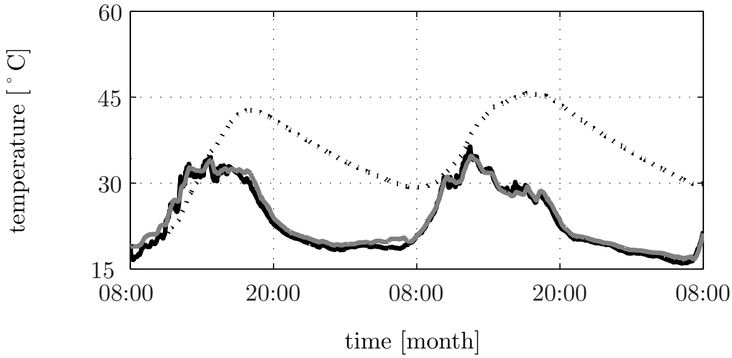
Figure 3.5: Histograms of final values for α_p and β_p (data from 13^{th} and 14^{th} of April 2006)

As said before, the parameter values were estimated with partial models. The results for the partial models were studied; an example is shown in figure 3.6. The figure shows the output of the partial model for the plant compartment temperature using the calibration data (13^{th} and 14^{th} of April 2006) and the validation data (15^{th} and 16^{th} of April 2006). The model fits the validation data quite well, despite the fact that the solar pattern on the validation day was very different from the calibration day.

After the parameter estimation with the partial models, the whole model is run with the same data set (13^{th} to 16^{th} of April 2006) that was used to estimate the parameters. This is shown in figure 3.7 and figure 3.8. As expected, the fit is quite good at the same date as was used to calibrate the model (13^{th} and 14^{th}), only the moisture content of the air in the inner roof compartment is somewhat underestimated. To test the model further, validation data is used from the same period, but with a very different solar radiation pattern (15^{th} and 16^{th} of April 2006; see the same figures). At



(a) calibration (13^{th} and 14^{th} of April 2006)

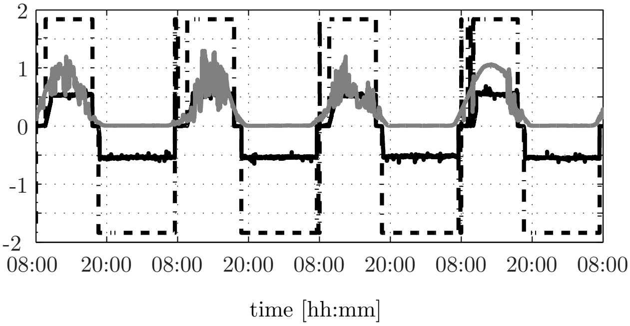


(b) validation (15^{th} and 16^{th} of April 2006)

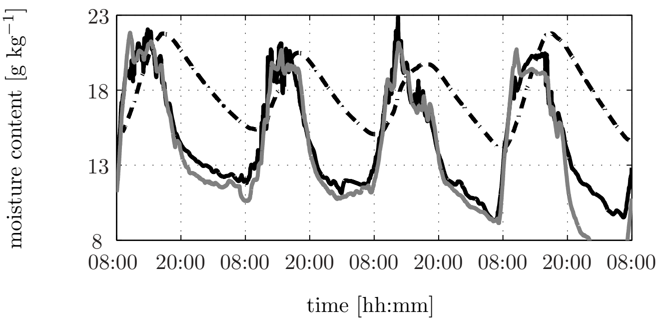
Figure 3.6: Temperature of the air and the solids in the plant compartment, (legend: $T_p$measured value (gray), $T_p$simulated value (–), T_{s_p}simulated value (...))

these times, the model predicts both the temperatures as well as the air moisture content well (as with the 13^{th} of April 2006 data set), the moisture content of the inner roof compartment is again slightly underestimated. The model predicts fast fluctuations in the plant compartment and inner roof compartment temperature due to the fast dynamics in solar radiation input. In the measured data, these fast fluctuations cannot be seen (at a sample interval of 1 minute). Probably the fast changes in the model output are caused by the fact that the solar radiation is added mostly to the air instead of the solids (adding the solar energy to the solids is more physically sound, but simulations showed a worse over-all model fit). These results suggest that the calibrated model gives a fair description of the system behavior on other days nearby the day used for the calibration.

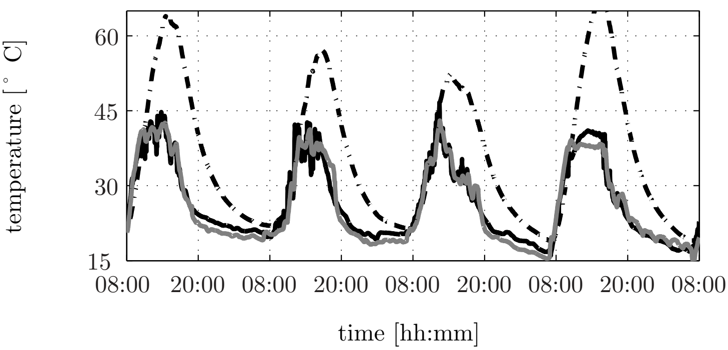
When the model was tested on data sets obtained in other seasons, the fit was not too good. This lead to the conclusion that the model parameters must be fluctuating over the year. To test this, the CRS algorithm was used to estimate parameter values on data sets of each month (on the 15^{th} and 16^{th} day). The parameter values fluctuate from month to month, as is shown in figures 3.9 and 3.10. The fluctuations are caused by changes in circumstances (like transmissivity of the roof due to whitening and pollution, plant stage (Jemaa et al. (1995), etc). When the simulation was run for the 5^{th} and 6^{th} day of each month, similar values were obtained.



(a) exogenous signals legend: (.)air velocity in the chimney, (m s^{-1}); (–) water flow, (l s^{-1}); (gray) solar radiation, (kWm^{-2})

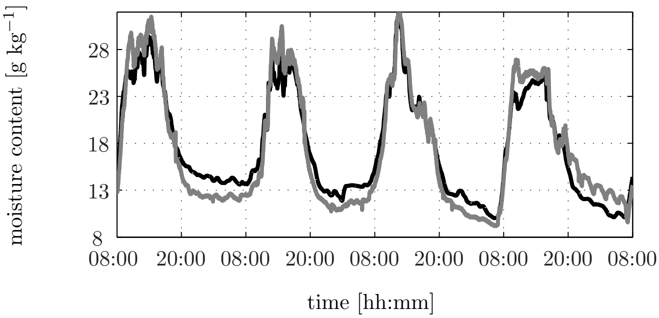


(b) Temperature in the plant compartment legend: (gray) T_p, measured; (–) T_p, simulated; (-.) T_{s_p}, simulated

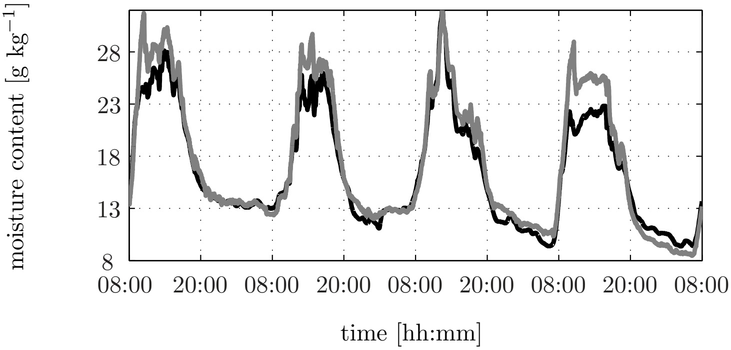


(c) Temperature in the inner roof compartment legend: (gray) T_i, measured; (–) T_i, simulated; (-.) T_{s_i}, simulated

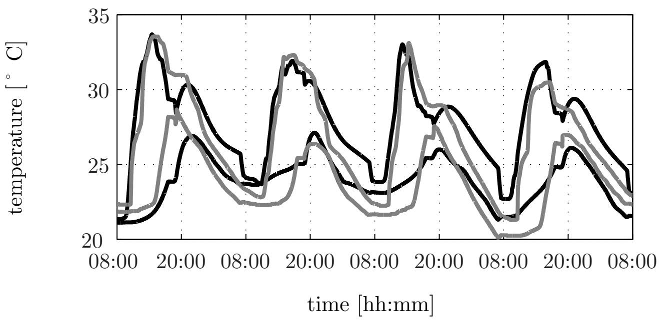
Figure 3.7: Validation of the model (data of 13^{th} to 16^{th} of April 2006)



(a) Moisture content in the plant compartment legend: (gray) x_p, measured; (–)x_p, simulated

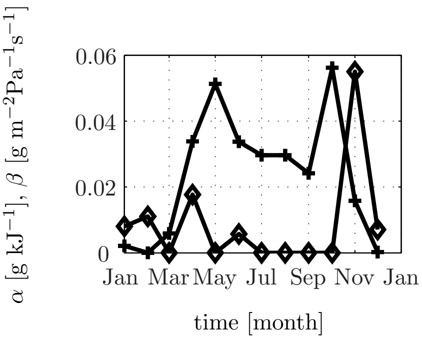


(b) Moisture content in the inner roof compartment legend: (gray) x_i, measured; (–) x_i, simulated

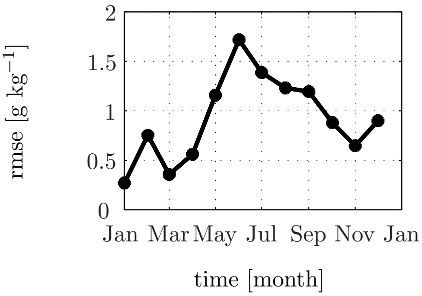


(c) Temperature in the heat storage tank legend: (gray) T_{hs}, measured; (–) T_{hs}, simulated

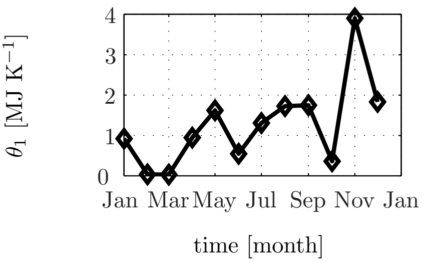
Figure 3.8: Validation of the model (data of 13^{th} to 16^{th} of April 2006)



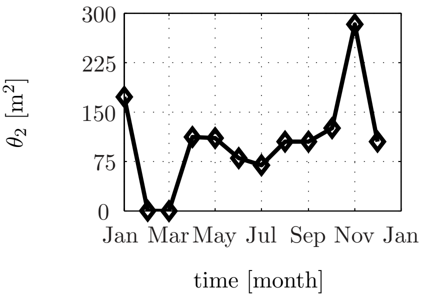
(a) Parameter α ($\diamond$; (g kJ^{-1})) and parameter β (+; (g m^{-2}Pa^{-1}s^{-1}))



(b) Root mean square error of the evaporation model ($\sqrt{(}f_p)$; (g kg^{-1}))

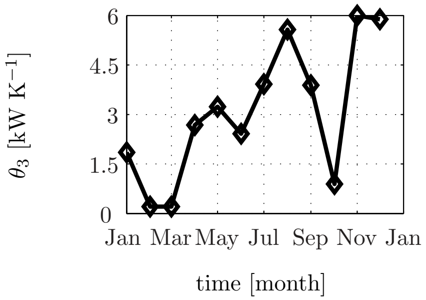


(c) Parameter θ_1 (MJ K^{-1})

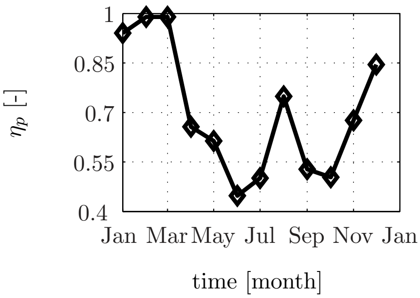


(d) Parameter θ_2 (m^2)

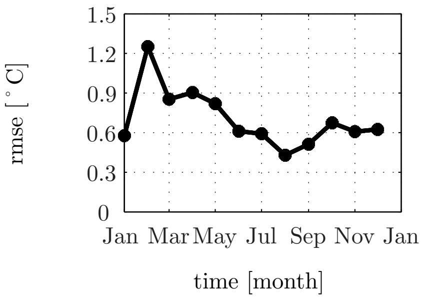
Figure 3.9: Parameter value estimates, estimated every 5^{th} and 6^{th} day of each month



(a) Parameter θ_3 (kW k^{-1})



(b) Parameter η_p (-)



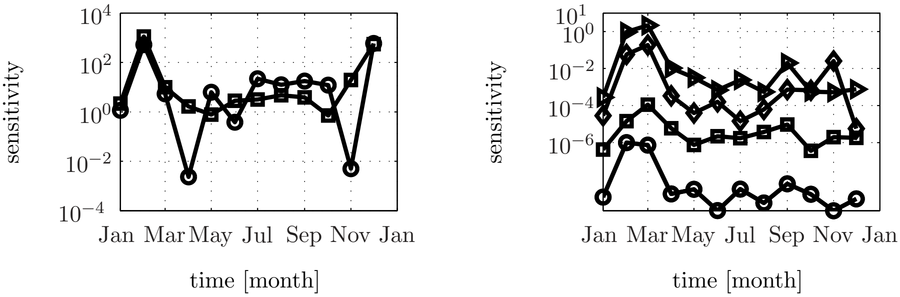
(c) Root mean square error of the temperature model ($^\circ$ C)

Figure 3.10: Parameter value estimates, estimated every 5^{th} and 6^{th} day of each month

The sensitivity (S) of the goal function (f_p as given in equation 3.21) for a change in parameter values (θ) provides a way to judge the quality of the estimated parameter values. It is given by:

$$S(N,\theta) = \left(\frac{\delta f_p(N,\theta)}{\delta\theta}\right) \tag{3.22}$$

A high sensitivity indicates that the estimated value is influential in the model. The sensitivity of the goal function for a change in parameter value is plotted in figure 3.11 (note the log scale). The fluctuation in sensitivity over the months is due to changing circumstances (like plant stage, radiation pattern, etc). The sensitivity of the moisture model that contains (α_p and β_p) is larger than the partial model of the temperature in the plant compartment. This is caused by the fact that there are more parameters in the latter model, that can partly compensate for each other (or, in other words, the model might be slightly over-parameterized).



(a) Parameter α ($\circ$) and parameter β ($\Box$)

(b) Parameter θ_1 ($\circ$), parameter θ_2 ($\Box$), parameter θ_3 ($\diamond$), parameter η_p ($\triangleright$)

Figure 3.11: Sensitivity of the goal function for changes in the parameters

The combination of the model and parameter estimation presented in this paper yield a suitable model for control applications. The model is relatively simple, yet does describes the dynamic behavior of the greenhouse well. As shown, the lumped parameters tend to change over the seasons, which in itself limits the applicability of the model for longer simulations. In our view, when the model is used in control, its parameters must be continuously adapted.

In this framework, the initial parameters are estimated with the method described here and are adapted with methods like an extended Kalman filter.

3.6 Conclusions

A relatively simple model is developed to be used in a model based control system for the Watergy greenhouse. The model describes the main dynamic behavior of the Watergy greenhouse with a limited number of states. Lumped parameters are used to describe less important physic processes to reduce the model's complexity. Also the complex biological processes of plant evapotranspiration are described in a simplified, lumped model. The key model parameters are identified with a controlled random search algorithm. This results in a model that mimics the real behavior of the greenhouse well on the short term (several days).

On the longer term, lumped parameters tend to change due to for example plant growth and pollution of the roof. Instead of expanding the model and demanding information inputs from the user it is more practical to cope with time varying parameters automatically via adaptive estimation techniques (as recursive estimation or extended Kalman filters. In chapter 4 online parameter estimation is described that is finally used in chapter 5 to build an adaptive receding horizon optimal controller.

The estimation of lumped parameters with the controlled random search algorithm only works well when the number of parameters to be varied is small and computing time to evaluate the model is short. It has been shown that (for this compartmental model) estimation in parts, meaning that only a part of the whole model is used in combination with measured input data for neighboring compartments, can serve the purpose. The method results in parameter estimates that converge well and computation time reduces significantly as compared to calibration of the full model.

Concluding, the model, with properly estimated parameters, is suitable for its intended use in a model predictive controller. Computation time (a main issue in model based controllers) is short because of the limited complexity of the model due to a limited number of states and lumped parameters.

Acknowledgements

The authors would like to thank Hans Janssen, Theo Gieling and Guillermo Zaragoza for their substantial contributions in both the discussions and the practical work that were part of this project. Furthermore, we would like to acknowledge the European Union for the financial support of the WATERGY project under contract number NNE5/2001/683.

Appendix 1: Vapor pressure deficit

The vapor pressure deficit (D_p [Pa]) calculated from the saturated vapor pressure (P_{sat}, [Pa]) and the actual vapor pressure of the air (P_{act}, [Pa]):

$$D = P_{sat}\left(T_a\right) - P_{act} \tag{3.23}$$

NB. T_a must be given in K in this formula.

The saturated vapor pressure is calculated from the empirical formula given below:

$$P_{sat} = 133.32 * e^{\frac{1.0887 * T_k - 276.4}{0.0583 * T_k - 2.1938}} \tag{3.24}$$

The actual vapor pressure is calculated from the moisture content (x, [kg kg^{-1}]):

$$P_{act} = \frac{pressure * x}{M_w/M_a + x} \tag{3.25}$$

where pressure is a constant of 101325 Pa, M_w is the molar mass of water (18.01528 g mol^{-1}) and M_a is the molar mass of air (28.9645 g mol^{-1}). Moisture content x must be given in [kg kg^{-1}].

4

Parameter Adaptation for a Greenhouse Climate Model

This chapter is based on:

S. L. Speetjens, G. van Straten and J.D. Stigter
Adaptive model for greenhouse control
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Abstract

Application of advanced controllers in horticultural practice requires detailed models. Even highly sophisticated models require regular attention from the user due to changing circumstances like plant growth, changing material properties and modifications in greenhouse design and layout. Moreover, their calibration is data demanding and laborious. This study explores the suitability of the extended Kalman filter (EKF) for automatic, on-line estimation and adaptation of parameters in a physics-based greenhouse model. The method was tested with measured data recorded over a period of one year, and with a model that describes the air temperature and moisture content in the Watergy greenhouse. In order to keep the parameters estimation problem tractable, and to improve the local accuracy of the parameters, separate EKFs are applied to sub-systems, using observation data at the sub-system boundaries. The filter adequately adjusts parameter values, thus significantly improving the model fit as compared to simulations with no-varying parameters. It appears that the filter is robust with respect to sudden changes in the system; when a disturbance occurs, such a pruning of plants or emergency opening of the windows, the EKF changes the parameter values accordingly. The result suggests that the extended Kalman filter is, indeed, a suitable method to provide the required automatic adaptation to time-varying phenomena for when modeling is impractical.

4.1 Introduction

Climate control in commercial greenhouses is mostly based on heuristic rules (Van Straten et al., 2000a). Many alternative control methods are known which show, in well described situations, a better performance than heuristic rules for typical horticultural applications. One of these alternatives is receding horizon optimal control (RHOC) (for example Ooteghem (2007); Tap (2000); Chalabi et al. (1996)). However, the application of RHOC in commercial greenhouses is hampered by the need for laborious calibration of the model that, essentially, is part of the initialization of the model-based control scheme. Careful calibration is needed to fit the model in the controller to the situation in which it is used. This means that for each individual greenhouse the models must be calibrated first. In addition, in practice, the greenhouse is a lively system that will almost never remain entirely the same as originally planned. For instance, the type of crop may vary over time, the crop is subject to manual action, such as pruning, and the greenhouse is a working place. Also design modifications occur frequently. A model whose parameter values adjust themselves automatically would be a large improvement since it reduces both the time needed for initial calibration and, in addition, the adjusted model increases the accuracy of the model-prediction resulting in an improved controller performance.

Currently, adaptive models and adaptive control are not commonly used in horticultural practice. This despite the fact that adaptive mechanisms are used in many industrial applications and are potentially quite promising for the design of models and controllers that really *work* in commercial greenhouse control. As an adaptive model can account for errors both in model structure as well as errors in the parameter estimates, the model does not have to mimic reality for 100 %. This may reduce the modeling effort for individual cases substantially. Also the model parameters are automatically adjusted for changes in layout, maintenance, wear, etc, and this is a significant benefit for the controller implementation in practice.

This paper utilizes the well-known extended Kalman filter for adaptation of the model parameters over time (seasons). It is applied to a special type of water-saving greenhouse, i.e. the Watergy greenhouse, which is described in the next section. This greenhouse has been built in Almeria, Spain, to study possibilities for extension of the growing season and increasing water use efficiency in horticulture by combining plant production with water desalination, water recycling and space cooling.

To optimize the operation of the Watergy greenhouse an adaptive model based controller is developed to take into account the complicated structure of the control system and the multi-criteria goals (production of both water and plants). The proposed control system uses a physics based model. For the sake of model simplicity and to reduce computational loads for the controller, the number of states is limited. Details of sub-processes are encapsulated in aggregated (lumped) parameters. However, these parameters tend to change over time, making an adaptation mechanism inevitable to keep the model fit accurate over a longer time period. The model should be capable of predicting the climate inside the greenhouse accurately over the prediction horizon of 1-2 days, during a whole year, without external adjustment of the model structure or parameter values.

This chapter consists of four parts; first a short description is given of the Watergy greenhouse and the climate model. Second, the extended Kalman filter and its application in the Watergy climate model are given. Third, the filter is applied to estimate parameters with real data from a one-year period in the Watergy greenhouse showing some interesting results. Forth, general conclusions concerning the adaptive model and its applicability for greenhouse climate control are drawn.

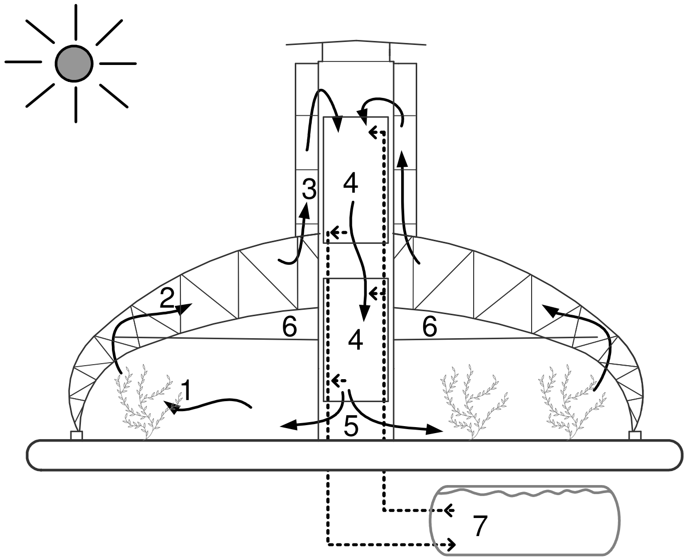


Figure 4.1: Model and functioning of the Watergy greenhouse. Five compartments are distinguished; plant compartment(A), inner roof compartment (B), heat exchanger (C), solids in the plant compartment (D), solids in the inner roof compartment (E) and the heat buffer (F). The numbers 1 to 7 refer to the functions as described in the text.

4.1.1 Function of the Watergy greenhouse

The Watergy project and the details of the prototype greenhouse are described in Buchholz and Zaragoza (2004) and Zaragoza et al. (2007). Here, only the basic idea of the greenhouse is briefly explained. The aim of the newly designed greenhouse is to provide a closed, cooled environment for the crop, so that the growing season can be extended. The excess heat is used to make fresh water from gray or salt water. The most remarkable feature of the experimental greenhouse is the double walled tower (see figure 4.1). During the day, the sun heats the (humid) air inside (1), which rises along the inner roof (2), into the outer duct of the tower where it is further heated by the sun (3). As the tower is closed at the top the air does not leave the greenhouse but is cooled with a heat exchanger in the central duct of the tower (4). The coolant is stored in a heat buffer (7). The cooled air flows back into the warm greenhouse (5), closing the cycle. During night, the heat exchanger heats the air and the air movement reverses; hot air rises through the heat exchanger to the top of the tower and flows down through the outer duct. The ground surface of the prototype greenhouse is 14x14 meters, the height of the tower 10 meters. Temperature and humidity are measured at all vital places inside and outside the greenhouse. Other measured quantities are outside global radiation, wind speed and -direction and the CO_2 concentration. See Janssen et al. (2004) and Speetjens et al. (2008a) for a detailed description of the control system.

4.1.2 Climate model of the Watergy greenhouse

A model is developed that describes the dynamic behavior of the Watergy greenhouse with a limited number of states. The greenhouse is divided into compartments A to F (see figure 4.1 and figure 4.2). The heat storage (F) and the heat exchanger (C) are divided into sub-compartments. For each compartment, energy and moisture balances are determined from the key (physical) processes. Lumped parameters are used to avoid laborious modeling of small details and to keep the model simple, which is required to keep computational loads for the controller low. The complete model is described in Speetjens et al. (2008b) and is not repeated here. For the sake of illustration of the adaptive mechanisms, the part of the model that describes the temperature and moisture content in the plant area is briefly explained.

The states of the model as a whole are given by:

$$\begin{bmatrix} T_p & T_i & x_p & x_i & x_{s_p} & x_{s_i} & T_{h_a}(n) & x_h(n) & T_{h_w}(n) & T_{hs}(m) \end{bmatrix} \tag{4.1}$$

where T and x are temperature and moisture content, respectively, and sub-

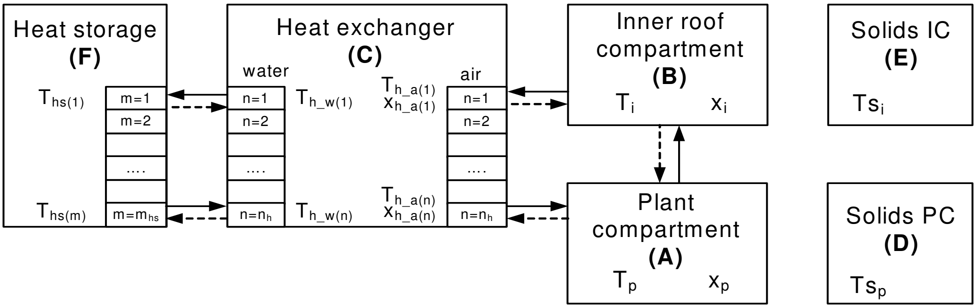


Figure 4.2: Layout of the greenhouse model. The arrows represent the airflow during the day (—) and during the night (– –).

scripts indicate plant compartment (p), inner roof compartment (i), and solids in the plant (s_p) and inner roof compartment (s_i). $T(n)$ is a vector denoting the temperature in the heat exchanger (on water (h_w) and air side (h_a)), and $\mathrm{x}_h(n)$ is the moisture content in the air in the heat exchanger. $T_{hs}(m)$ is a vector that denotes the temperature in the heat storage.

Plant evapo-transpiration is described by the Penman-Monteith equation (Monteith, 1973). This empiric formula states that evapo-transpiration (E [kg s^{-1}m^{-2}]) depends on incoming solar radiation (G_o [Wm^{-2}]) and vapor pressure deficit (D [Pa], given in the appendix of chapter 3). Parameters α_p and β_p are calibration parameters:

$$E_p = \alpha_p \, G_o + \beta_p \, D_p \tag{4.2}$$

The energy balance of the plant compartment (eq. 4.3) incorporates the main energy flows in the greenhouse, i.e. solar radiation, convection, conduction and evapo-transpiration. The solar radiation received by the air in the plant compartment is given by $\eta_p \, G_o$, where G_o [W m^{-2}] is the global radiation and $\eta_p < 1$ an efficiency parameter. As the airflow direction reverses at night, the convective term ($\Phi^{conv}_{p,T}$) in the equation changes. The total energy balance of the plant compartment is given by:

$$
\begin{aligned}
m_p\, cp_a \frac{dT_p}{dt} &= \eta_p\, A_p\, G_o + \Phi_{p,T}^{conv} + U_{po}\, A_{po}\, (T_o - T_p) + \ldots \\
&\quad U_{ps_p}\, A_{ps_p} \left(T_{s_p} - T_p\right) + U_{pi}\, A_{pi} (T_i - T_p) - \ldots \\
&\quad l_e\, A_p\, (\alpha_p G_o + \beta_p D_p) \qquad (4.3) \\
\text{day: } \Phi_{p,T}^{conv} &= \phi_a\, cp_a\, (T_{h,out} - T_p) \\
\text{night: } \Phi_{p,T}^{conv} &= \phi_a\, cp_a\, (T_i - T_p)
\end{aligned}
$$

Condensation is driven by the difference in moisture content between air (x_p, [kg kg^{-1}]) and the saturated moisture content at roof temperature ($x_{sat}(T_{r_p})$). Latent heat release due to condensation ($l_e \cdot \Phi_p^{con}$) is assumed to be transferred outside, so the surface of the roof is not heated by this energy release. The total moisture balance of the plant compartment is described by:

$$
\begin{aligned}
m_p \frac{dx_p}{dt} &= \Phi_{p,x}^{conv} + A_p\, (\alpha_p G_o + \beta_p D_p) - \ldots \\
&\quad u_{r_p}^{con}\, k_{pr}\, \rho_a\, A_{pr}\, (x_p - x_{sat}(T_{r,p})) \qquad (4.4) \\
\text{day: } \Phi_{p,x}^{conv} &= \phi_a\, (x_{h,out} - x_p) \\
\text{night: } \Phi_{p,x}^{conv} &= \phi_a\, (x_i - x_p)
\end{aligned}
$$

The solid materials in the plant compartment are modeled as one body with a certain heat capacity (cp_{s_p}) that exchanges energy with the air through an overall heat transfer coefficient (U_{ps_p}). As with the air, $\eta_{s_p}\, A_{s_p}\, G_o$ gives the total amount of solar energy received (eq. 4.5). The heat balance of the solids in the plant compartment is given by:

$$
m_{s_p}\, cp_{s_p} \frac{dT_{s_p}}{dt} = \eta_{s_p}\, A_{s_p}\, G_o + U_{s_p}\, A_{s_p} \left(T_p - T_{s_p}\right) \qquad (4.5)
$$

The initial values of the lumped parameters are identified with a controlled random search algorithm (Price, 1976). This results in a model that mimics the real life behavior of the greenhouse well, especially in the *same period* as was used for parameter estimation. In other periods, the model fit is less good, indicating that parameters change slowly (Speetjens et al., 2008b). This motivates the study described in this paper to adapt parameters with the extended Kalman filter (EKF).

4.2 Background and theory of the EKF

The lumped parameters in the greenhouse model vary over time, so they should be adjusted to keep the model fit accurate over time. One way to adjust parameters online is the use of an extended Kalman filter (EKF). This section first describes literature on application of adaptive parameter methods in horticulture, followed by the theoretical background of the EKF and the application to the Watergy greenhouse model.

4.2.1 Previous studies

The number of studies that investigate the use of adaptive mechanisms in greenhouse climate and plant models is fairly limited. In other fields of science the EKF is widely applied, both for state and parameter estimation and shows good results that suggest that application in horticulture could be fruitful.

An example of the use of the EKF as an observer for state estimation is described by Piñón et al. (2005). They use an EKF to estimate the leaf temperature (not measured directly) from other measurement data.

Of the few references that describe parameter adaptation in greenhouse models, Udink ten Cate and van de Vooren (1978) describe an early statistical climate model of which the parameters are estimated online. Later Davis (1984) describes the use of a control ARMAX model in combination with a Kalman filter. This control law was tested in practice against P and PI controllers, leading to the conclusion that the adaptive ARMAX controller yielded the better results.

Cunha et al. (1997) found that parameter values in their model changed due to variation in operational conditions. They found that the value of the solar efficiency of a greenhouse changes over the day as well as over a growing season due to changes in the optical properties of the transparent materials, the angle of incoming radiation, etc. Since it was difficult to derive a physics based model for these phenomena, they choose to develop a data based (ARX) model in combination with recursive parameter estimation, extended with a forgetting factor and windup protection.

Sigrimis et al. (1999) describe the use of multi-rate-output controllers in an adaptive framework to deal with changing, un-modeled, circumstances. The adaptive mechanism estimates three process parameters online, resulting in a globally stable control scheme.

Berenguel et al. (2003) describes the use of a recursive least squares (RLS) method to estimate parameters online in a simplified, physics based greenhouse model and parameters in a PI controller. Each time step, model parameters are estimated with a RLS scheme combined with a variable forgetting factor and a supervisory module. This module checks conditions under which identification has to be stopped, like saturation of the control signal, low excitation, etcetera. Also, the controller parameters are estimated each time step, after which the controller output is calculated, checked by the supervisory module and subsequently effectuated in the greenhouse by the actuators.

In summary, the available literature describes studies that use an EKF with statistical models and one study shows a RLS method with a physics based model. No studies in the greenhouse horticulture literature are known to the authors in which an EKF is combined with a complex, physics based greenhouse climate model for parameter adaptation.

4.2.2 Theoretical background

The extended Kalman filter is a popular state and parameter re-construction algorithm for (non)linear systems. It is described in many books and papers, for example Gelb (1974); Ljung and Söderström (1983); Lewis (1986). Although originally intended for state estimation it can also be used for parameter estimation by augmenting the states with the parameters:

$$\dot{x}(t) = f\left(x(t), u(t), \theta(t)\right) \tag{4.6}$$

$$\dot{\theta}(t) = 0 \tag{4.7}$$

$$\dot{x}_a(t) = \begin{bmatrix} \dot{x}(t) \\ \dot{\theta} \end{bmatrix} \tag{4.8}$$

This results in the following sampled data, continuous state model:

$$
\begin{aligned}
\dot{x}_a(t) &= f\left(x(t), u(t)\right) + \xi(t) && (4.9)\\
\xi(t) &\sim N(0, Q(t))\\
y_k &= h_k\left(x_a(t_k), u(t_k)\right) + \eta(t_k) \qquad k = 1, 2, \ldots && (4.10)\\
\nu_k &\sim N(0, R_k)
\end{aligned}
$$

The system noise ($\xi(t)$) and the measurement noise (η_k) are assumed to be white and independent. The spectral density matrix Q and the variance-covariance matrix R for system and measurement noise, respectively, first have to be guessed before the filter can actually be used. This, in fact, is one of the well-known drawbacks of the EKF, since it is especially difficult to obtain a good educated guess of the spectral density matrix Q 'a-priori' (Stigter JD, 1997). The EKF first obtains a prediction of the state by solving

$$
\hat{x}_k^- = \hat{x}_{k-1}^+ + \int_{t_{k-1}}^{t_k} f\left(x(t), u(t)\right) dt \tag{4.11}
$$

where $u(t)$ is a vector of all input signals and $\hat{x}_{k-1}^+$ is the estimate of the state vector from the previous time step. Subscript a is dropped to simplify the notations. Next, the state vector is corrected by the weighted error between model and measurements ($y_k - \hat{y}_k$):

$$
\hat{x}_k^+ = \hat{x}_k^- + K\ (y_k - \hat{y}_k) \tag{4.12}
$$

The Kalman gain K, that weights the error, is given by:

$$
K = P_k^- H_k \left[H_k P_k^- H_k^T + R_k\right]^{-1} \tag{4.13}
$$

where H_k is given by:

$$
H_k\left(\hat{x}_k^-\right) = \frac{\partial h_k(\hat{x}_k^-, u_k)}{\partial \hat{x}_k^-} \tag{4.14}
$$

Matrix P is the covariance matrix, estimated by:

$$P_k^- = \Phi_k P_{k-1}^+ \Phi_k^T + Q_k \tag{4.15}$$

where the state transition matrix Φ_k follows from the Jacobi matrix:

$$\Phi_k = \exp(F_k \Delta t) \tag{4.16}$$

$$F_k\left(\hat{x}_k^-\right) = \frac{\partial f\left(\hat{x}_k^-, u_k\right)}{\partial \hat{x}_k^-} \tag{4.17}$$

The final step is to update the error covariance matrix P (here in Joseph form to guarantee symmetry):

$$P_k^+ = \left(I - K_k H_k\right) P_k^- \left(I - K_k H_k\right)^T + K_k R_k K_k^T \tag{4.18}$$

4.3 Application of the EKF in the Watergy greenhouse model

The EKF is used to both reconstruct the states of the Watergy model and to estimate the (lumped) parameters online. Estimation of the parameters is performed on *sub-models*, meaning that only the subsystem that contains the parameter(s) of interest is simulated and observations are used on the subsystem boundaries (embedded in the large system). This process is explained in more detail in the next section.

4.3.1 Parameter estimation with sub-models

The use of the EKF for recursive parameter reconstruction in large models is computational intensive and the estimations do not necessary converge to the correct parameter values due to, for example, wrong ‘a priori’ noise assumptions. Under certain conditions it is possible to reduce the complexity of the problem by using only the part of the model that contains the parameters to be estimated. This is possible when accurate measurements are available at the boundaries of the sub-system that contains the parameters to be estimated. Figure 4.3 shows this principle: the partial model estimates the value of one or more parameters and the whole (deterministic) model is updated every time step.

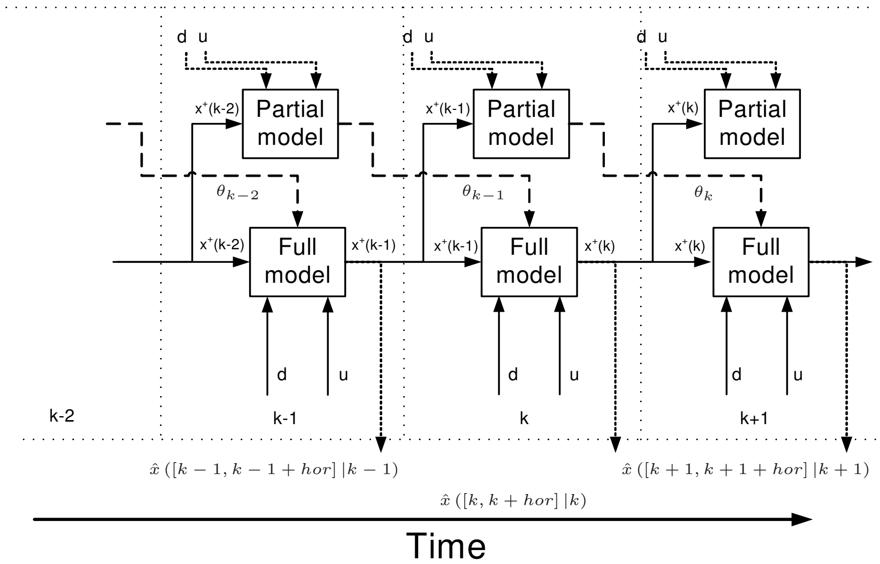


Figure 4.3: EKF for parameter estimation. (legend: x=state variables; u=input variables, d=disturbances, θ=parameters, hor=prediction horizon of the model)

The main advantage of estimation in parts in practical situations is that inaccuracies in other compartments of the model do not influence the parameter estimation. This improves the accuracy of the estimated values. In addition, computational load decreases.

In this study, four parameters are estimated that have a large influence on the fit of the model for the plant compartment; η_p, α_p, β_p and $\theta_2 = \eta_{s_p} A_{s_p}$. The part of the total greenhouse model that describes the energy balance of the air (eq. 4.3) and solids (eq. 4.5) in the plant compartment are used to estimate η_p (the parameter that describes the fraction of the solar energy that is added to the plant compartment air) and $\theta_2 = \eta_{c_p} A_{c_p}$ (the amount of solar energy added to the solids in the plant compartment). Since the surface of the solids that receives the solar radiation is unknown and could change due to plant growth, a new parameter (θ_2) is introduced that combines both solar energy efficiency (η_{c_p}) and surface (A_{c_p}). Apart from measured weather data, extra inputs for this sub-model are the temperature and moisture content of the air flowing into the plant compartment from the heat exchanger (T_h and x_h) or from the inner roof (T_i and x_i) and the moisture content in the plant compartment itself (x_p).

The parameters in the plant evapo-transpiration model (α_p and β_p) are estimated with the sub-model that describes the moisture balance of the plant compartment. Additional inputs for this model are the moisture content of the air flowing into the plant compartment from the heat exchanger (x_h) or from the inner roof (x_i) and the temperature in the plant compartment itself (x_p).

Table 4.1: Parameters estimated with the EKF, and the inputs (u) and outputs (y) used in the estimation procedure

1. Model of energy balance in plant compartment:		
parameters:	η_p	$y = T_p$
	$\theta_2 = \eta_{s_p} A_{s_p}$	$u = [T_i, T_h, x_p, x_i, x_h]$
2. Model of moisture balance in plant compartment:		
parameters:	α_p	$y = x_p$
	β_p	$u = [T_p, x_i, x_h]$

4.3.2 Tuning of measurement noise covariance matrix (R)

The matrix R in the extended Kalman filter is the measurement noise covariance matrix and is deduced from the accuracy of the sensors. A different value for R is given for each measured state, resulting in a m x m matrix, with the noise covariance on the diagonal and the off-diagonal elements equal to zero. Our sensors have accuracies of about ± 0.14 °C for the temperature sensors and ± 0.5 g kg^{-1} for the humidity sensors. This results in a R-matrix with (0.14^2=) 0.02 and 0.25 on the diagonal for the respective measurement data.

4.3.3 Tuning of spectral density matrix (Q)

The spectral density matrix (Q) contains the noise in the model. This noise is more difficult to quantify than the noise in the measurements, since it is a collection of factors like errors in model structure, errors in the parameter values, spatial distribution, etc. These factors change from one state to another resulting in a matrix Q that has different values on the diagonal. Off-diagonal elements relate to the correlation between state errors. As nothing is known about these error densities they are set to zero, hence Q has only elements on its diagonal.

Since Q cannot be directly deduced from the data, it must be tuned. It is clear from equation 4.9 that the system noise $\xi(t)$ has units of the rate of change of the associated estimation variable. Hence, the units of the elements of Q are ($^\circ$C s^{-1})^2 for temperature, (g kg^{-1} s^{-1}))^2 for moisture content and can similarly be derived for the augmented states representing the model parameters. By changing the values of Q model parameters can be forced to change faster (hours) or slower (days/weeks). In our case, the parameters should adapt slowly, so Q should be chosen small. As the structure of the greenhouse model for the Watergy greenhouse is reasonably trustworthy, Q is tuned such that more emphasize lays on parameter estimation than on state estimation. This is done by choosing the matrix elements of Q for the states fairly small compared to the matrix elements that correspond to the parameters. This forces the parameter estimates to react to the difference between model output and observations. A good compromise appeared to be the choice diag(Q)=[$1{\cdot}10^{-12}$ $1{\cdot}10^{-13}$ $1{\cdot}10^{-13}$] in the EKF for plant evapo-transpiration and diag(Q)=[0 0 $1{\cdot}10^{-10}$ $1{\cdot}10^{-6}$] in the sub-model for the energy balance of the plant compartment.

4.4 Results and discussion

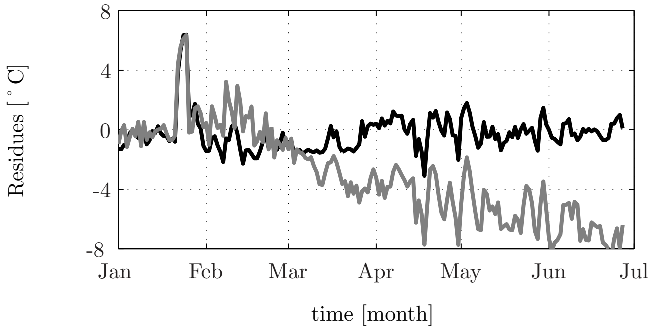
The sub-models for both moisture and temperature are simulated for a period of almost 1 year (1st of January 2006 - 18th of December 2006), both with the EKF to vary parameter values as well as a simulation without time-varying parameters. The EKF for estimation of η_p and θ_2 was tuned such that the fluctuations in the parameter values are relatively slow, since the parameter values are not expected to show high frequent behavior. To estimate α_p and β_p, the EKF was tuned on a shorter timescale, so that daily fluctuations are taken into account in the parameter adjustments.

The results are presented in figures 4.4 and 4.5 for the thermal sub-model and figures 4.6 and 4.7 for the moisture balance, split for reasons of readability

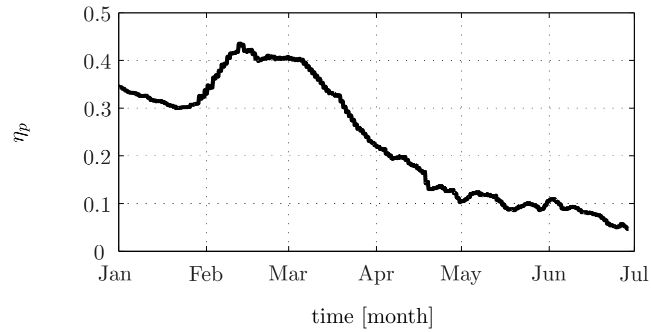
Table 4.2: Main events in the Watergy greenhouse that influenced the parameter values during the year 2006

Nr	Date	Event
1	14 March 2006	Whitening of the greenhouse roof and start of the experiment
2	7 April	Pruning of the plants (green bean)
3	12 April	Pruning of the plants (green bean)
4	21 April	Greenhouse windows open for 1 day
5	15 May	Greenhouse windows open for 1 day
6	31 May	Installation of internal shadow screen
7	1 June	Part of the plants removed
8	9 June	New plants sown (Okra)
9	14 June	Greenhouse windows open for 1 day
10	28 July	Internal shadow screen removed
11	31 July	Okra plants pruned
12	25 August	Greenhouse windows open for 1 day
13	13 September	Greenhouse windows open for 1 day
14	28 September	Whitening removed from greenhouse
15	21 November	Electrical problems in greenhouse
16	11 December	End of test; greenhouse is emptied

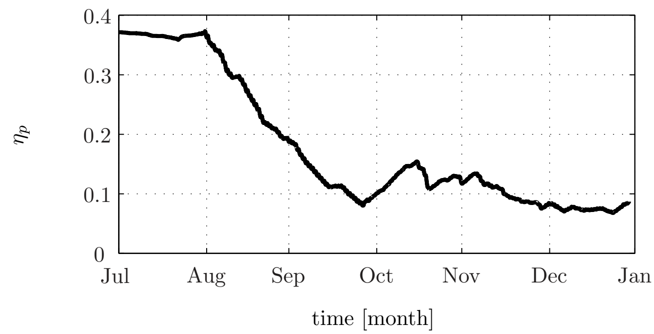
over the first and second half year.



(a) Daily mean residuals $(=\frac{1}{1440}\sum_{00:00h}^{24:00h}(y_m - y_{sim}))$. Legend: gray=fixed parameters, black=varying parameters

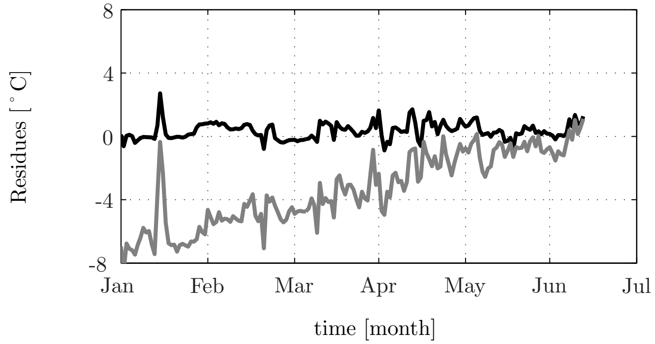


(b) Solar efficiency parameter plant compartment η_p

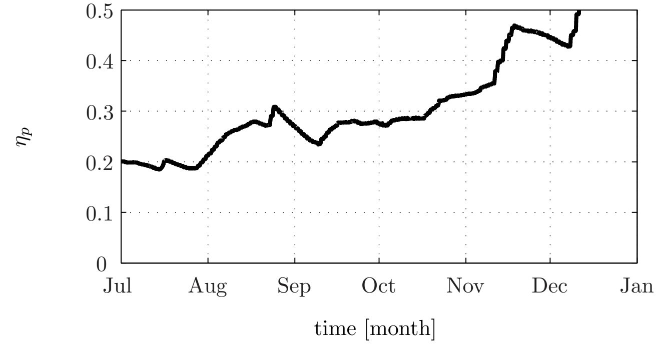


(c) Solar efficiency parameter solids θ_2

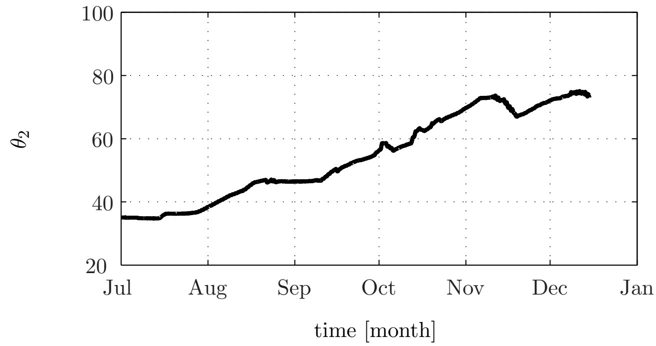
Figure 4.4: Parameter estimates for η_p (b) and θ_2 (c) and residuals (a) over the period 1 January – 1 July 2006, using the sub-model for temperature



(a) Daily mean residuals $(=\frac{1}{1440}\sum_{00:00h}^{24:00h}(y_m - y_{sim}))$. Legend: gray=fixed parameters, black=varying parameters



(b) Solar efficiency parameter plant compartment η_p



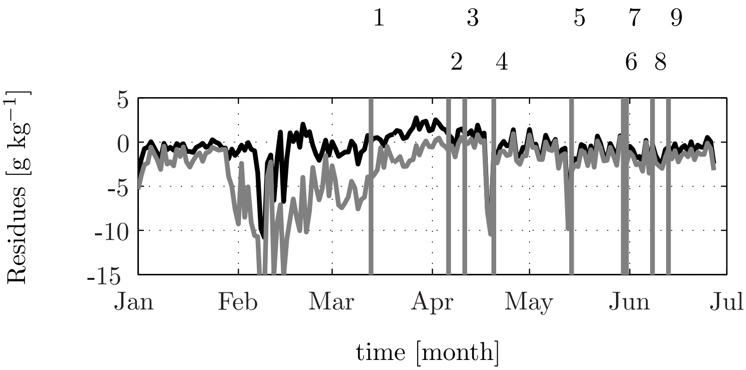
(c) Solar efficiency parameter solids θ_2

Figure 4.5: Parameter estimates for η_p (b) and θ_2 (c) and residuals (a) over the period 1 July – 18 December 2006, using the sub-model for temperature (legend: - time-varying parameters; -. fixed parameters)

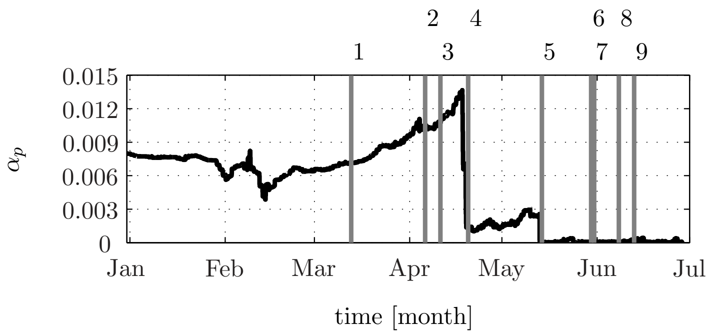
According to figures 4.4(b), 4.5(b), 4.4(c) and 4.5(c) the radiation effectiveness varies over the year. A physical explanation is the changing light transmissivity of the greenhouse cover, which changes due to pollution by dust, whitening for shading, etc. Table 4.2 gives an overview of the most important events that have large influence on the parameter estimates. The model residuals for η_p and θ_2 are shown in figures 4.4(a) (first half year) and 4.5(a) (second half of the year). The residuals are defined as the mean difference between measured and simulated data (with time-varying parameters), over the whole day $\frac{1}{1440}\sum_{00:00h}^{24:00h}(y_m - y_{sim})$. The residuals are plotted both for a simulation with fixed values for the parameters as well as for a simulation with time-varying parameters (as estimated by the EKF). When parameters η_p and θ_2 are varied, the model fits the data better than when a constant value is used for these parameters, especially during the first half of the year.

Figures 4.6(b) and 4.6(c) show the values of parameters α_p and β_p for the period of 1^{st} of January to 1^{st} of July. Figures 4.7(b) and 4.7(c) show the values for the period of 1^{st} of July to 18^{st} December 2006. The beans that were grown inside the greenhouse were planted in the second week of March (number 1 in the superscript of the graph). Before that time the greenhouse was empty. Some of the largest jumps in parameter values are explained by the opening of the greenhouse windows (numbers 4, 5, 12 and 13 in the graphs). This effect is not included in the greenhouse model, so the model structure fails in describing this situation (which can be noticed in the residuals plot, especially at numbers 4 and 12). It may be better not to continue the estimation process in these periods to avoid windup effects in the filter. However, after the windows were closed, the model residuals quickly recover so the EKF seems quite robust for major disturbances. The parameter estimate after these disturbances does not immediately return to the old value, which might point at an over-parameterized system. Number 11 shows pruning of the plants, where the values of α_p and β_p decrease due to reduced evapo-transpiration because of reduction of the leaf area. In the period after number 1 and after number 8, the plant growth is clearly seen in the increase of values for α_p and β_p. It is interesting that beta remains virtually zero until plants are put in the greenhouse, and then gradually increases until a plateau is reached. As beta is related to vapor pressure deficit, the increase of beta might indicate that the term represented by beta is largely determined by the evaporation from the soil and the base evapotranspiration of the growing plants associated with nutrient transport. This term seems less sensitive to pruning than the term represented by α, which is related to the evapotranspiration from the sun-lit leaves to cool the plant.

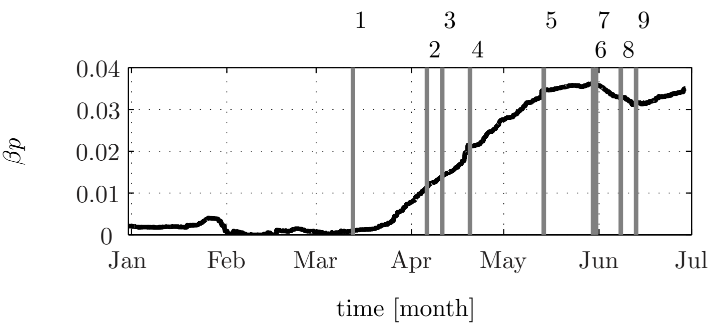
The model residuals for α_p and β_p are shown in figures 4.6(a) and 4.7(a). The model run with fixed parameters used values estimated with a controlled random search at the 15^{st} of April 2006 (Speetjens et al., 2008b). The model fit in the case with EKF is slightly better than the model fit without parameter adjustment by the EKF. When the EKF is tuned differently, the parameters were fluctuating faster, resulting in decreased model residual. However, these fast changing values are not useful for predictions (as they showed large fluctuations, even over 24 hours).



(a) Daily mean residuals $(=\frac{1}{1440}\sum_{00:00h}^{24:00h}(y_m - y_{sim}))$. Legend: gray = fixed parameters, black = varying parameters

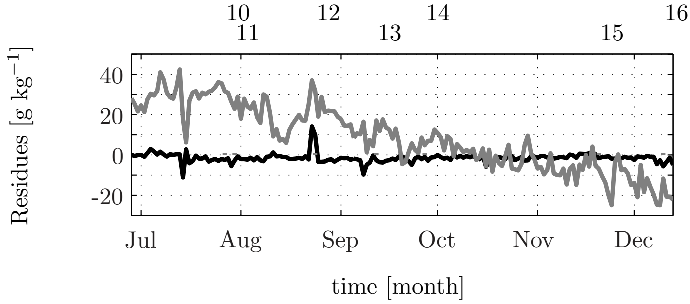


(b) Evaporation parameter α_p

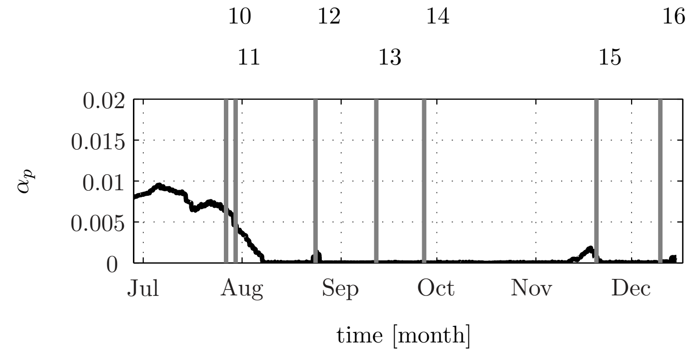


(c) Evaporation parameter β_p

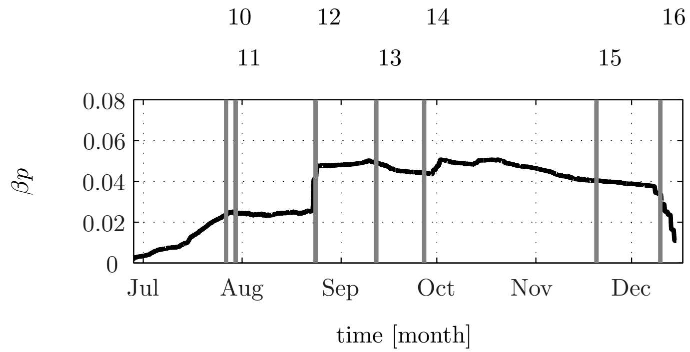
Figure 4.6: Parameter estimates for α_p and β_p over the period 1 January – 1 July 2006, using the sub-model for moisture content



(a) Daily mean residuals ($=\frac{1}{1440}\sum_{00:00h}^{24:00h}(y_m - y_{sim})$). Legend: gray = fixed parameters, black = varying parameters



(b) Evaporation parameter α_p



(c) Evaporation parameter β_p

Figure 4.7: Parameter estimates for α_p and β_p over the period 1 July – 18 December 2006, using the sub-model for moisture content

4.5 Conclusions

Compared to the model with fixed parameters, online parameter estimation with an EKF improves the model fit over a longer time period, especially in periods further away from the time of initial parameter estimation. After tuning of the filter, the parameters in the sub-models were adapted, so that changes in the system were dealt with. The estimation of parameters only works well if the number of parameters to be estimated is not too large compared to the available measurement data. Splitting a large compartment model in smaller pieces with the use of measurement data for the inputs at the boundary is a good way to deal with parameter estimation in practical situations.

The use of the EKF is a valuable addition to current greenhouse climate models to bridge the gap between current practice in commercial greenhouse control and more advanced control systems. In future work, the described EKF will be used in a model based adaptive control framework for control of the climate in the Watergy greenhouse.

Acknowledgements

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5

Adaptive Optimal Control for the Watergy Greenhouse

5.1 Introduction

The greenhouse developed in the Watergy project is a completely new design that needs a custom made control system to regulate the climate. As the Watergy greenhouse produces both water and plants, there are multi-criteria goals and mutual interactions that make the greenhouse climate difficult to control. The control methods used nowadays in horticultural practice are not able to deal with complications in an explicit way. Nor do they take predictions of the future (e.g. weather) into account. For example, it is easy to see that high temperatures and humidity levels could improve water production, but, obviously, these conditions are potentially harmful for plants. Another example is the limited amount of available cooling liquid, which must be used in the best possible way to accommodate an optimal operation of the greenhouse in terms of water production, energy use, and plant production. An advanced controller that takes into account weather predictions and the changing capacity of the cooling system (due to weather changes), could substantially improve the performance of the system and is therefore a valuable tool.

With these considerations in mind, it was decided to develop a receding horizon optimal controller (rhoc) to regulate the climate inside the Watergy greenhouse. The use of a greenhouse climate model enables the controller to explicitly take the couplings and multi-criteria goals into account, which should result in a better overall performance of the system (e.g. more water production in combination with a better environment for the plants).

The application of a receding horizon optimal controller in practice hinges on the fulfilment of two conditions. First, the model in the controller must be simple enough to allow for fast computation times as the optimal control trajectory is calculated every few minutes. Second, the model should have good prediction capabilities, since a model based controller is as good as the model it uses. Especially this second issue is troublesome, since a greenhouse is a lively system of which properties tend to change over time. Therefore a model needs to be re-calibrated continuously – especially if the underlying model structure, for reasons of fast computation and manageable data needs, does not include all the mechanisms that explain variations of temperature and humidity over time. Hence, in such models parameter values change over time. For example, the greenhouse cover light-transparency will change as a result of pollution (by dust), which is a process that is not easy to model in practice.

In this study we choose to adjust parameter values automatically to changing circumstances so that the model accuracy is improved upon (of course, within the limitations of the model structure itself). With this principle a model can be developed that only describes the main dynamics of the greenhouse, and uses lumped parameters that cover un-modeled processes. This greatly improves the applicability of optimal control in practice.

The outline of this chapter is as follows. First some examples of optimal greenhouse controllers from literature are presented. Second, the methodology of the adaptive optimal control scheme is discussed, including some considerations on the goal function. In the third part, results of the controller in the Watergy greenhouse are given, followed by simulations with an improved version of the Watergy greenhouse. Finally a discussion on the applicability of the control method in practice and conclusions are presented.

Control inputs

As an optimal controller quickly becomes more complicated with an increasing number of controls, not all controls are considered independent. For example the fan speed is coupled to the pump speed; if the pump is on, so is the fan. This is a natural choice, since the heat exchanger only works well when both the fan and the pump are on. The inlet and outlet of the heat storage tank are selected so that the stratification is maintained to maximize the amount of stored coolant. The sprinkler installation in the inner roof compartment is assumed to be active constantly during the day, as it always adds to the amount of produced water. Of all the possible controls, only the pump speed for the cooling water remains as manipulated variable.

5.2 Background

Currently, most greenhouse controllers work with rules that are specified by the growers. For all common crops, blue prints are available that help the grower selecting the right rules (Van Straten et al., 2002). This system works well, although large differences in yield and energy efficiency amongst growers are reported. This can be improved by applying optimal model-based control – a control strategy that will calculate the optimal settings (temperature, CO_2-level and humidity) for the greenhouse climate automatically using advanced dynamic optimization algorithms. For optimal control three building blocks are required: (i) a model of the system, (ii) a goal function and (iii) a method or algorithm to solve the optimal control problem.

Optimal control problems in horticulture have typically two (and sometimes three) timescales. Plant growth and fruit production are slow processes that have large time constants (days/weeks). Fluctuations in the exogenous signals (e.g. solar radiation, wind speed) are in the order of minutes, which is a completely different timescale. The use of a heat buffer introduces a third timescale (Willigenburg et al., 2000) (typically changing in terms of hours). The fast dynamics of the greenhouse and the weather are highly relevant if the controller should exploit the effects of the external disturbances. This is not the standard approach in current horticultural practice, but it may be an important opportunity (Tap and Willigenburg, 1996). A way to deal with the combination of slow and fast dynamics is to split the optimal control problem into a long term and a short term optimization. The long term optimization contains the long term goals, which are subsequently taken into account in the short term optimization problem. In this way, it is possible to exploit the fast dynamics optimally and at the same time keep the system within the long term goals.

Long term economic optimization is not possible if reliable crop development models are not available. Van Straten et al. (2000b) argue that the long term goals must be set by the grower, whereas the short term effects are handled by a receding horizon optimal controller. If the crop development models are reliable, the long term problem can be solved off-line, which lead to a seasonal pattern for the co-states of the amount of assimilates (produced by photosynthesis), the fruit and leaf weights (Van Straten et al., 2002). These co-states are used in a receding horizon optimal controller with short prediction horizon. In this framework, the short term receding horizon controller could have a prediction horizon of and hour to a day, with an update interval of one minute. This means that each minute inputs, states and disturbances are measured and an optimal control trajectory is calculated for the next hours. From this trajectory the first control action is send to the greenhouse. This process is repeated every minute.

The goal function should combine expected benefits, costs and risks. Examples of goals for an optimal controller are (Van Straten et al., 2000b):

1. Focus on maximal output, such as crop yield and quality.

Cost are not considered. This approach follows the line of the blue prints that are available for the current cultivations.

2. Focus on maximum product yield per unit of resource input.
   Cost are not directly taken into account, but since heating is a major consumer of resources (and thus money), they are indirectly taken into account. As early as 1984 (Gall et al., 1984) attempts have been made to control a greenhouse in an optimal way. Later Seginer (2000), and Van Henten (2003b) studied optimal temperature regimes.

3. Focus on minimal resource input per unit product.
   Plants can average out temperature variations during a specific period of time (Körner, 2003), usually this effect is referred to as the temperature integral of the plant. This means that lower temperatures can be compensated by higher temperatures later on. This approach gives the possibility to save energy by waiting for the sun to appear, without turning on the heater.

4. Focus on expected economic return.
   When economic return is used in the goal function, the three points above re-appear. Rapid fluctuations can have a large effect on the control actions that must be taken, so the dynamics of the greenhouse will have to be taken into account. Also constraints and the effects of humidity control have a large effect. Finally, the actual weather conditions must be fed back to the controller.

Examples from literature: relatively simple approaches

Chalabi et al. (1996) minimize energy use (q) inside the greenhouse under the constraints of a minimum temperature, a maximum temperature and a required average value of the temperature over the control horizon (24h). So, the problem is to find the heating temperature setpoint trajectory $T_s(t)$, such that the total energy consumption is minimized:

$$\min_{T_s} \int_{t_i}^{t_f} q \quad dt \tag{5.1}$$

subject to constraints imposed concerning the average temperature ($\bar{T}$) and the upper and lower limit to the temperature in the greenhouse (T_u and T_l).
:

$$\frac{1}{t_f - t_i} \int_{t_i}^{t_f} T_s\left(t\right) dt \;=\; \bar{T} \tag{5.2}$$

$$\text{and } T_l \leq T_s\left(t\right) \leq T_u \tag{5.3}$$

This control strategy was implemented in an existing greenhouse and tested for a period of three months. Every hour, a new temperature setpoint was calculated for the low level climate computer, which was assumed to be ideal. Weather forecasts for the coming 24h period were obtained online. Unfortunately, it was not possible to measure the energy consumption experimentally, so the total energy savings could not be determined.

Piñón et al. (2005) optimally control the temperature in a greenhouse with a combination of two control schemes; feedback linearization and model predictive control. They found that the combination of these schemes results in much lighter computational requirements than the full nonlinear model predictive control scheme.

The crop temperature was estimated with an extended Kalman filter. The goal function is a combination of the deviation from a certain trajectory and the required control actions:

$$J\left(k\right) = \sum_{i=1}^{NP} \parallel y\left(k+i|k\right) - y_r\left(k+i|k\right) \parallel_Q^2 + \sum_{i=1}^{NC} \parallel v\left(k+i|k\right) \parallel_R^2 \tag{5.4}$$

The predicted output at k is given by $y\left(k+i|k\right)$, the reference trajectory by $y_r\left(k+i|k\right)$. The sequence of computed control inputs at time k is given by $v(k)$, the prediction horizon by NP and the control horizon by NC.

To save energy, the error and the control signal are weighted differently during day and night. During the day temperature is not allowed to deviate more than 3 $^\circ$C from the reference (25 $^\circ$C). During the night, temperature is allowed to drop to 10 $^\circ$C. During the simulations, the main advantage of the combination of feedback linearization and model predictive control is that it turned out to be much more efficient than MPC alone, offering a general approach to the solution of nonlinear control problems. The main drawback is tat the goal function of the type of equation 5.4 is difficult to interpret in economic terms.

Gutman et al. (1993) propose a method of solving an optimal control problem by linear programming. They use the minimization of energy ($h(t)$ in the goal function (c is the cost per heating unit):

$$J = \int_{t_0}^{t_f} -ch\left(t\right)dt \tag{5.5}$$

Constraints for the plants were given and the tolerance of the plants to deal with temperature variations was set to 20Kh (meaning 20 hours a 1 K deviation from the setpoint). No constraints or setpoints for air humidity were taken into account. The simplex algorithm in the optimization package GAMS is used to calculate the optimal control sequence. Gutmans work can be considered as a first step towards the development of a model predictive controller that contains a model of the system, a disturbance predictor, sensors to observer the measurable outputs and a state estimator (if necessary).

Examples from literature; taking the plants into account

Ioslovich et al. (1995) describe an application of sub-optimal control of CO_2 enrichment in ventilated greenhouses. In their goal function, they maximize the amount of the CO_2 that is fixed in the plants with respect to the total amount of CO_2 supplied to the plants. Constraints on the temperature in the greenhouse were not taken directly into account. Instead, high temperatures were avoided by the controller because they have a diminishing effect on the photosynthesis rate (and thus on the amount of CO_2 that is fixed in the plants). Extremely high CO_2 rates were avoided by the control due to the costs of CO_2 and the diminishing fraction of CO_2 that is fixed in the plants.

By using quasi steady state setpoint sequences, robustness was gained at the cost of some performance. The difference between the quasisteady state and the optimal solution was especially present at fast changing weather conditions. However, if the short-term weather forecast is not accurate and/or the control system is not fast enough, the suboptimal solution may be even better than the true optimum.

Van Straten et al. (2002) choose a goal function with an economic basis. It contains the costs (CF) and penalties (Pen) that arise in a growing season:

$$J = \int_{t_0}^{t_f} (CF + Pen)\, dt \tag{5.6}$$

This function can be extended with the investments in plant material (Inv) (Van Straten et al., 2000b):

$$J = \int_{t_0}^{t_f} (CF + Pen + Inv)\, dt \tag{5.7}$$

where:

$$CF = -p_F \dot{W}_{HF} + p_c \phi_{inj} + p_H H_u$$

$$Pen = P_c + P_T + P_V$$

$$Inv = \lambda_n \dot{x}_n + \lambda_{sL} \dot{x}_{sL} + \lambda_{sF} \dot{x}_{sF}$$

In this equation fruit yield ($\dot{W}_{HF}$), energy consumption (H_u), CO_2 cost (ϕ_{inj}) penalties for excess of temperature (P_T), humidity (P_V) and CO2 bounds (P_c) are taken into account.

Tap and Willigenburg (1996) give a goal function that looks similar to the one given above:

$$J = \int_{t_0}^{t_f} \left(-\lambda_n \dot{W}_n + \lambda_s \dot{W}_s - \alpha_2 \Phi_i - \alpha_3 H_u - P_R\right) dt \tag{5.8}$$

Here, a distinction is made between non structural dry weight (W_n) and structural dry weight (W_s). The CO_2 input is noted by Φ_i, the heat input into the greenhouse by H_u. The penalty functions for the humidity level is denoted by P_R and λ and α are the cost of the subsequent elements.

Van Henten (2003c) describes an optimal control strategy that optimizes the economic value of lettuce growth in a greenhouse. The goal function is given by:

$$J = \left(c_{pri,1} + c_{pri,2}\, X_d\left(t_f\right)\right) - \int_{t_b}^{t_f} \left(c_q\, U_q\left(t\right) + C_{CO_2}\, U_c\left(t\right)\right) dt \tag{5.9}$$

where the lettuce price is given by $(c_{pri,1}+c_{pri,2}\, X_d\,(t_f))$, the heating costs by $(c_q\, U_q)$ and the cost of CO_2 by $(c_q\, U_q)$.

Bounds are a way to ensure that the control model stays in its validity range. For example, in the case of the lettuce, the plant model did not contain enough information about the negative effects of high temperature and/or humidity levels. Instead of including these effects in a (more complicated) model, a penalty function is used that puts bounds on the temperature, CO2 and humidity-levels. These penalties are such that exceeding the bounds is penalized. Various forms have been proposed to achieve this. A form that is differentiable, which may be desirable for numerical solution of the problem, is the soft penalty form:

$$p\left(t\right) = c_\sigma \left[\frac{2X\left(t\right) - X_{\min} - X_{\max}}{X_{\min} - X_{\max}}\right]^{2k} \tag{5.10}$$

where c_σ is a weighting factor, X the state variable and X_{min} and X_{max} the lower and upper bounds on state variable (and $k = 1, 2, \ldots$).

Ooteghem (2007) presents a study in which the methods above are applied to an advanced, energy saving, greenhouse (the Solar Greenhouse). Grid search methods make the calculations fast enough to calculate year round control trajectories for ventilation and heating.

5.3 Method

The adaptive receding horizon optimal controller that is designed for the Watergy greenhouse consists of an optimal controller and a parameter estimation algorithm (EKF). First, an optimal control input profile is calculated over the control horizon using the last updated values of the parameters and the states. The controller uses the gradient method (described in the following section). Second, the control signal is sent to the actuators in the real greenhouse and measured values are taken from it (y). The third step is to estimate and adjust the model parameters, based on measured values. This process is, in our case, 6 times faster than the rhoc algorithm (the rhoc has a time-interval of once per hour, the parameter estimation occurs every 10 minutes). Figure 5.1 gives an impression on the functioning of the adaptive optimal control algorithm.

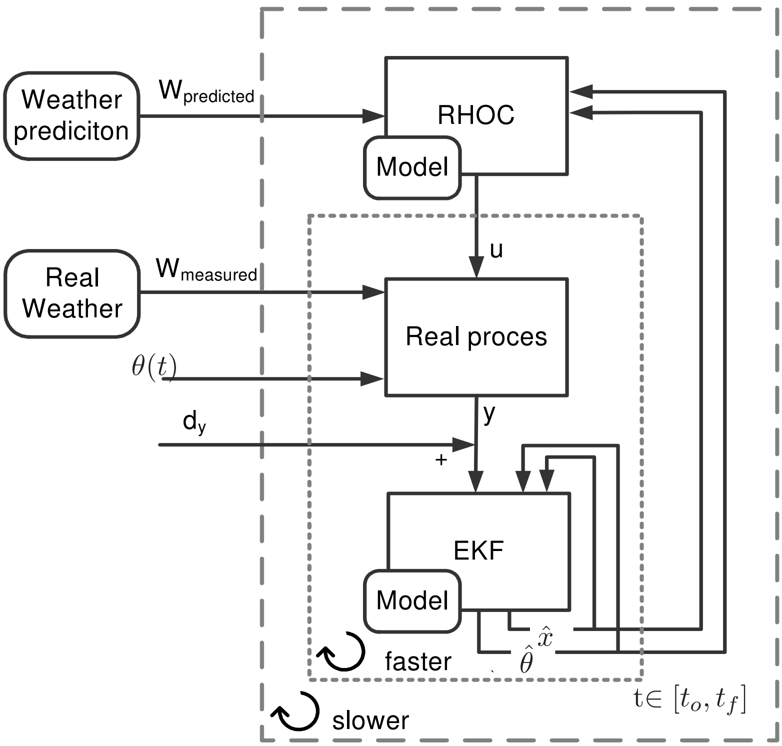


Figure 5.1: Adaptive receding horizon optimal control

5.3.1 Optimal controller

Given the system:

$$\dot{x} = f\left(x, u, t\right) \tag{5.11}$$

The goal of the optimal controller is to minimize the performance index (J):

$$J = \phi\left[x\left(t_f\right)\right] + \int_{to}^{tf} L\left(x, u, t\right) dt \tag{5.12}$$

Many books describe methods to solve this type of problems and their implementation in software (e.g. (Kirk, 2004; Bryson, 1999)). The *gradient method* is used to solve this problem. For the general case, the solution is briefly described here (Bryson, 1999).

The system equation 5.11 acts as constraints that can be adjoined to the performance index (5.12) with a time-varying Lagrange multiplier (λ(t)) to yield:

$$J = \phi\ \left[x\left(t_f\right)\right] + \int_{to}^{tf} \left\{\ L\left[x\left(t\right), u\left(t\right), t\right] + \lambda^T\left(t\right)\left[f\left[x\left(t\right), u\left(t\right), t\right] - \dot{x}\right]\ \right\}\ dt \tag{5.13}$$

The Hamiltonian is defined as:

$$H =\ L\left[x\left(t\right), u\left(t\right), t\right] + \lambda^T\left(t\right)\ \ f\left[x\left(t\right), u\left(t\right), t\right] \tag{5.14}$$

Using variation calculus necessary conditions can be derived for J to reach an extreme as follows:

$$\dot{x} = f\left(x, u, t\right) \tag{5.15}$$

$$\dot{\lambda} = -H_x^T = -L_x^T - f_x^T\lambda \tag{5.16}$$

u(t) is determined from:

$$H_u = -L_u + \lambda^T f_u \quad = 0 \tag{5.17}$$

with boundary conditions:

$$x\left(t_0\right) \ \ must \ be \ \ specified \tag{5.18}$$

$$\lambda\left(t_f\right) = \phi_x^T \tag{5.19}$$

This is a two-point boundary value optimization problem.

Goal function

The goal function that is used in a rhoc gives the user the opportunity to specify the demands for the system and make sure the controller satisfies these demands in the best possible way. As the goal function is of prominent importance in the concept, several options were considered for the Watergy greenhouse:

- Maximize water production
  As the greenhouse should produce both plants and water, a goal function that contains a combination of both seems a natural choice. However, due to the lack of proper plant models only water production is modeled accurately. A work-around is to define a goal function that maximizes water production under the constraint that the climate inside the greenhouse stays within acceptable limits.

- Minimize energy use
  The main energy use of the greenhouse is the coolant pump and the (relatively small) fan in the tower. There is no additional cooling or heating capacity installed in the greenhouse, so the energy consumption is in any case quite limited. This leads to the conclusion that optimizing on energy use is not needed.

- Minimize fresh water use
  By controlling the climate in the greenhouse, it is possible to limit the evapo-transpiration of the plants (which could save water in traditional greenhouses). However, in practice the control freedom is limited, as a climate must be maintained that does not propagate diseases (e.g. in a very humid climate, plants will not transpire much, which saves water. But at the same time the humid climate will stimulate fungi to grow.).

- Follow a given temperature trajectory
  A simple way of greenhouse control is to specify a temperature (and/or

humidity) trajectory for the climate inside. However, this limits the freedom for the controller drastically, probably such that the main aim of the project - water production - is lost. Therefor this seems to be a bad choice as a goal function.

- Maximize cooling of the coolant at night
  The greenhouse system does not have an external source for cooling, which implies that the energy taken from the greenhouse during the day must be used/dumped at night. A strategy to maximize the available cooling capacity during the day is to cool the cold/heat storage tanks as far as possible at night.

- Use the heat storage tank as efficiently as possible
  The limited amount of cooling liquid should be used in the best way to keep the temperature in the greenhouse within certain bounds. This will have an effect on the control actions at night (cool the coolant as much as possible) as well as during the day (do not spend all coolant during the first hours of the day, but save capacity for the hottest hours).

A major restriction in the selection process to select a suitable goal function is the lack of a plant development model for the crops grown in the Watergy greenhouse (green bean and okra). As argued earlier, a plant model must be detailed and accurate to be used in an optimal controller. At present, these models are only available for the most common crops (in the Netherlands) like tomato and cucumber. As it was out of the scope of this research to develop a plant model for green bean and okra, only goal functions that do not require such a model are taken into account.

As the goal of the Watergy greenhouse is to produce both plants and water and no crop development model is available, a goal function was chosen that *maximizes water production ($a_1\phi_{condens}$)*, while maintaining a suitable climate for the plants by keeping the temperature within soft bounds. This is assured by a penalty function ($a_2 P_{temp}$):

$$J = \int_{t_0}^{t_f} (a_1\, \phi_{condens} - a_2\, P_{temp})\, dt \tag{5.20}$$

$$P_{temp} = \sum_{t_0}^{t_f} (T - T_{max})^2 \quad \text{if } T(t) > T_{max}$$

$$P_{temp} = \sum_{t_0}^{t_f} (T - T_{min})^2 \quad \text{if } T(t) < T_{min}$$

Control horizon and constraints

The control and prediction horizon are chosen to be 48 hours. This forces the controller to take into account that during the night the storage must be cooled in order to have enough cooling capacity for the next day.

Input constraints to the maximum pump capacity are taken into account in the optimization. According to Pontryagin's maximum principle, inputs can simply be clipped at the lower and upper bounds, provided that there are no terminal constraints. If the optimization calculates a setting that is outside the physical bounds of the controller, the input setting is clipped.

Weather

One of the main benefits of receding horizon optimal control is that weather predictions are explicitly taken into account in the calculated control trajectories. In our case this calls for reliable, local predictions of 48 hour ahead predictions. Unfortunately, these predictions were not available. Instead the "modified lazy man weather prediction" is used. This method assumes the weather of the coming two days to be the same as the weather of the previous day (Ooteghem, 2007; Tap and Willigenburg, 1996). For solar radiation, exactly the same pattern is assumed. For outside temperature, the prediction assumes the temperature of the previous day, corrected by an offset. This offset is the difference between the currently measured weather and yesterdays weather (so, the temperature profile of the previous day is shifted up or down). Figure 5.2 shows the results of the weather prediction for three representative days in spring 2006. The prediction of solar radiation is quite good, as is shown in sub-figures 5.2(a) and 5.2(c). However, when the weather is more unstable and clouds are frequent, the prediction quality becomes substantially less (figure 5.2(e)). Prediction of the outside temperature is less good than solar radiation. The pattern is acceptable, but often an offset remains (sub-figures 5.2(b), 5.2(d) and 5.2(f)). It must be noted however, that the weather prediction is refreshed every control interval (hour), so the short-term prediction is usually better than the figure suggest. As this prediction is the best we can use, it will be used in the receding horizon optimal controller.

5.3.2 Greenhouse emulation

Due to time limitations it was unfortunately not possible to apply the controller to the real greenhouse. Instead, the greenhouse model (described in chapter 3) is used to emulate the behavior of the greenhouse. To make this simulation study approach the reality as much as possible, values of the plant parameters (α_p and β_p) were fluctuated in the emulation model. Also, normally distributed measurement noise was added to the emulated measured values to test whether the EKF was able to reconstruct the state (moisture content in the plant compartment).

5.3.3 Parameter estimation

An extended Kalman filter (EKF) for recursive parameter reconstruction is used to estimate new values for the parameters in the plant model; α_p and β_p. The use and calibration of the EKF is described in more detail in chapter 4, here only a short overview is presented.

The plant evapo transpiration model is given by:

$$E_p = \alpha_p \, G_o + \beta_p \, D_p \tag{5.21}$$

The values for α_p and β_p are difficult to estimate independently from each other, as they influence each other. For instance, if α_p becomes larger, β_p could become smaller, resulting in the same plant evapo-transpiration. In chapter 4 the filter was already tuned to estimate parameters from year-round measurement data. In this chapter, the filter is used in a control setting, which has a different time-scale, so the filter needed to be tuned again. While making the filter respond faster, the issue of the coupled parameters became more pronounced, so it was needed to decouple the estimation of both parameters.

By manipulating the spectral density matrix Q, α_p is only estimated at times when the solar radiation is larger than 50 W m^{-2} and β_p is only estimated when α_p is fixed. To achieve this, Q is set to 0 when the parameter should not be changed. Also the error covariance matrix (P) is set to zero for the subsequent element. When the light intensity passes the threshold of 50W m^2, both P and Q are restored to their previous values.

Measurement noise covariance matrix (R)

The measurement noise covariance matrix R in the extended Kalman filter is deduced from the accuracy of the sensors. It is reasonable to assume that sensor errors are uncorrelated, so R is a m $\times$ m diagonal matrix with the noise covariance on the diagonal and the off-diagonal elements equal to zero. Our humidity sensors have an accuracy $\pm$ 0.5 g kg^{-1}. This results in a R-matrix with (0.5^2=) 0.25 on the diagonal.

Spectral density matrix (Q)

As described in chapter 4, the spectral density matrix (Q) contains the noise in the model. This noise is more difficult to quantify than the noise in the measurements, since it is a collection of factors like errors in model structure, errors in the parameter values, spatial distribution, etc. The values for Q must be tuned as they cannot be directly derived from data. In our case, the parameters should adapt relatively slowly (hours/days), so Q should be chosen small. A good compromise appeared to be the choice diag(Q)=[$2 \cdot 10^{-6}$ (g/kg)^2 $1 \cdot 12^{-9}$ $1.5 \cdot 3^{-9}$] (for [$(x_p)^2$ $(\alpha_p)^2$ $(\beta_p)^2$].

5.3.4 Implementation

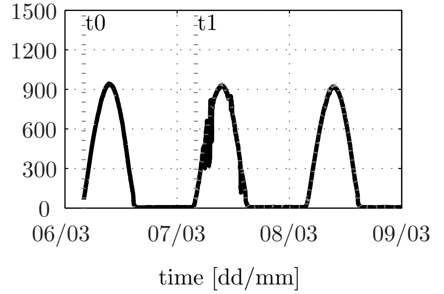
The software used to calculate the optimal trajectory originates from the book by Bryson (1999) and was modified to accommodate the greenhouse model. To solve an optimal control problem with the gradient method, the following algorithm was used (Bryson, 1999):

1. choose integration step, if no variable gain (or step size) is used
2. enter data, including a guess of u(t) at N+1 future points
3. **forward integration**. Compute and store x(t) at all time steps for current time to t_f = current time $+t_h$ (prediction horizon)
4. evaluate $\phi[x(t_f)]$ and $\lambda^T(tf) = \phi_x(tf)$
5. **backward integration.** Compute and store impulse response function H_u(t) for all time steps

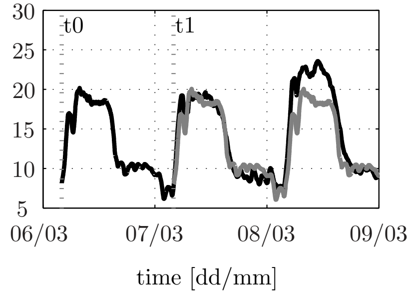
6. compute the change in control signal: $\delta\, u(t) = -kH_u^T(t)$. Gain ($k$) is variable for better speed of convergence and accuracy
7. stop if average $|\delta \mathrm{u(t)}| <$ *tolerance*
8. calculate new $u(t)$ =old $u(t)$ + $\delta u(t)$
9. goto (3)

To improve the convergence speed, the gain (k) is varied. In our case, a varying value for k was determined by calculating input patterns (du and u) for three values of k ($0.5k_0$, k_0, $2k_0$); J_1, J_2, J_3. If J_2 was not the maximum of the three, another value for J was calculated using a value for k that was either $0.25k$ or $4k$. This procedure was continued until J_2 was the optimal value, with a maximum of three iterations. In our case, an initial value for k of -0.55 was a good compromise between calculation speed and accuracy.

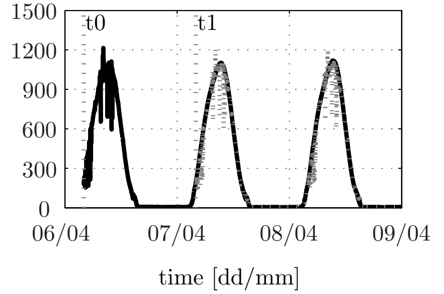
The implementation of the extended Kalman filter is described in chapter 4 and is not repeated here.



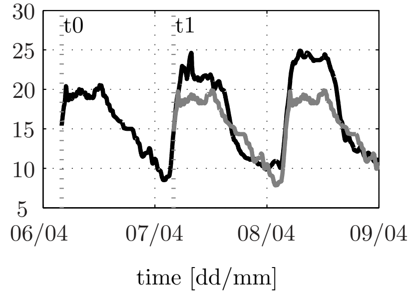
(a) Solar radiation (Wm^{-2}), 6^{th} of March 2006



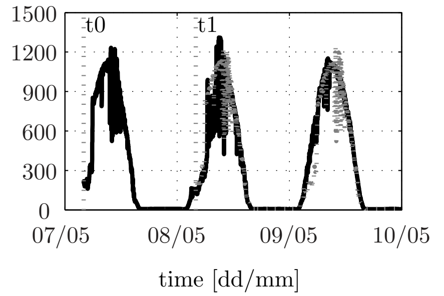
(b) Outside temperature ($^\circ C$), 6^{th} of March 2006



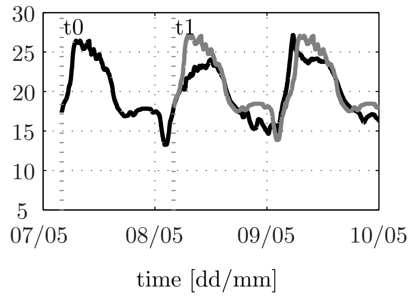
(c) Radiation (Wm^{-2}), 6^{th} of April 2006



(d) Outside temperature ($^\circ C$),6^{th} of April 2006



(e) Radiation (Wm^{-2}), 6^{th} of May 2006



(f) Outside temperature ($^\circ C$), 6^{th} of May 2006

Figure 5.2: Instantaneous lazy man weather prediction over the coming two days; at t1, the weather of the preceding 24 hours is projected to the future. At the next control interval, a new prediction is made in the same fashion, shifting the curves as described in the text.

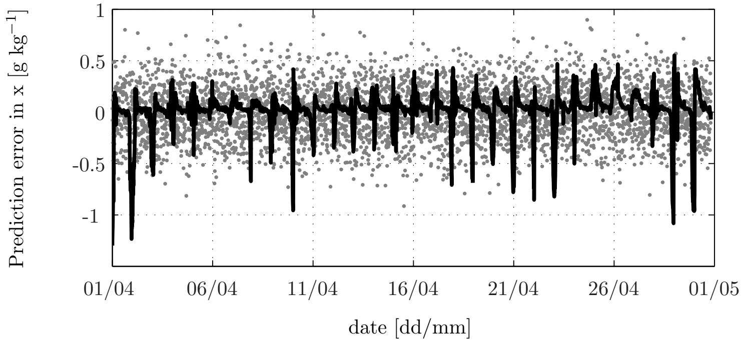
5.4 Simulation results for the existing greenhouse

In this section results are shown for the simulations of the receding horizon optimal controller with the model of the Watergy greenhouse. It is shown that the cooling capacity of the greenhouse is fairly limited, leading to high temperatures inside the greenhouse. Later in this section the effect of increasing the water and airflow is studied as a way of increasing the cooling capacity without having to make difficult physical changes to the greenhouse.

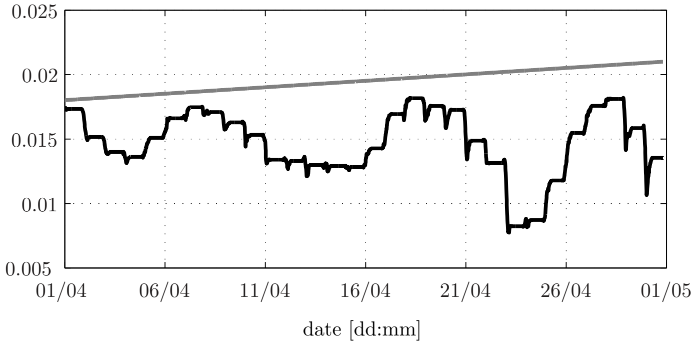
5.4.1 Parameter adaptation with the extended Kalman filter

The extended Kalman filter needs calibration before it can be used to generate reliable parameter estimates. Figure 5.3 shows the output of the Kalman filter for the period of one month in spring 2006. The greenhouse emulation model was used to emulate the greenhouse behavior, thus to calculate the moisture content in the plant compartment (x_p, [g kg^{-1}]). White (measurement) noise with a mean of zero and variance of $\pm$ 0.5 g kg^{-1} was added to these emulated values to generate virtual measurements, which were used as input for the EKF. For control inputs, a fixed water flow of 2.8 kg s^{-1} was used. The parameters in the plant evapo-transpiration emulation model (α_p^{real} and β_p^{real}) were slowly increased over time (the gray line in figures 5.3(b) and 5.3(c)). Ideally, the estimated values (black lines) should follow this increase, so that the black lines in figures 5.3(b) and 5.3(c) are close to the gray lines.

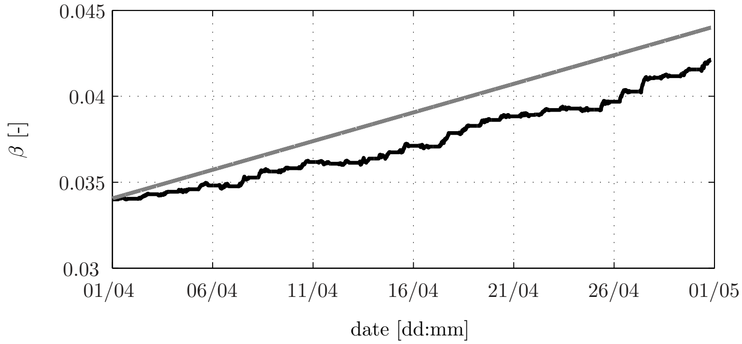
The estimated values are not always close to the 'real' parameter values. Obviously, a day/night effect shows in the estimates, despite the fact that α is only changed during sun-up hours and β_p during sun-down hours. A more advanced implementation of the EKF, in combination with automatic tuning could possibly solve these issues in further research. Still, the prediction error on moisture content is quite low, as seen in figure 5.9(a), so that the estimated value of the moisture content in the plant compartment (x_p) follows the emulated value well, despite the relatively large measurement noise that was added to the emulated values.



(a) Error between emulated state and 'measured' value (gray ...), and error between emulated state and estimated state (black –)



(b) α (gray = 'real'; black = estimated value)



(c) β (gray = 'real'; black = estimated value)

Figure 5.3: Results of an EKF simulation run, without rhoc.

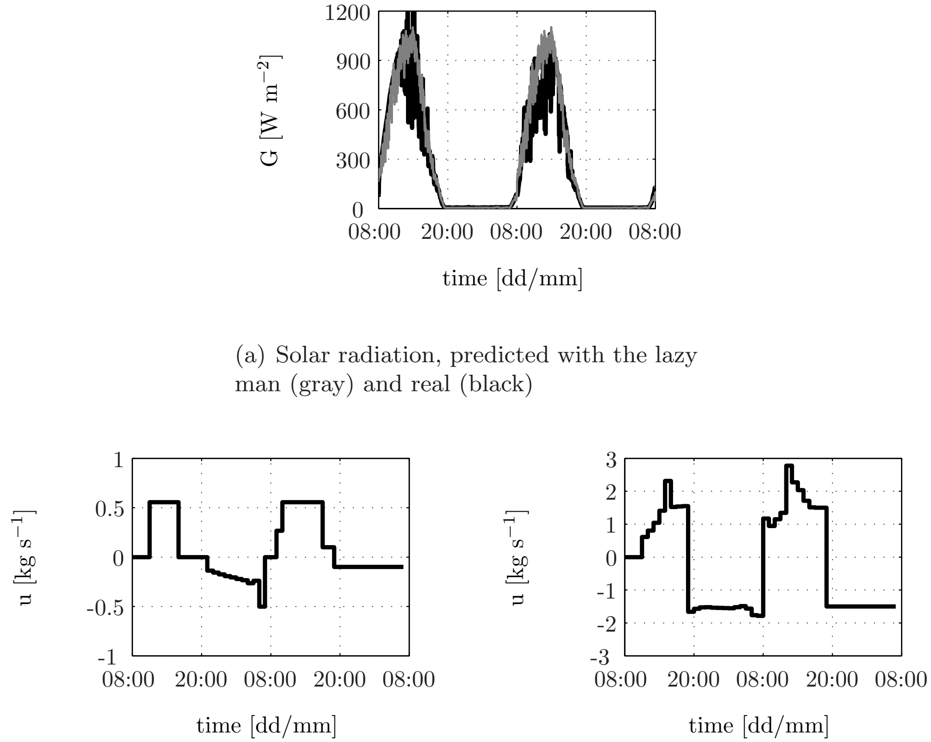
5.4.2 Open loop optimal control

Open loop optimal control trajectories were calculated to verify the software. Figure 5.4 shows the (real and predicted) weather and the control inputs for a two day ahead prediction horizon (1^{st} to 2^{nd} of April 2006). The resulting greenhouse and heat storage temperatures are shown in figure 5.5. Note that the negative value of the pump rate indicates that the water flow has reversed to maintain counterflow in the heat exchanger.

In both figures two situations are shown; the left sub-figures show the case with the water flow maximized to 0.6 [kg s^{-1}] and the airflow to 1.9 [kg s^{-1}], which were the real capacities installed in the greenhouse. The right sub-figures show results with increase water and airflow; maximum water flow is 2.8 [kg s^{-1}], the airflow is set to 5.1 [kg s^{-1}] at times when the pump is on. These values are larger than the installed capacities. This was done to avoid the situation where there is not enough cooling capacity and the controller results in a on-off control (as in the next paragraph). At the start of the simulations, the water temperature in the heat/cold storage was quite low; about 12 $^\circ$C. This temperature was measured at the day of the simulations; the tanks were filled with cold water early in the morning.

Both simulations show that the coolant temperature increases rapidly during the day to a maximum of around 35 $^\circ$C. The increase of the water and airflow has a quite limited effect on the plant compartment temperature. At night, the gained heat is used to heat the greenhouse thus cooling the coolant to temperatures in the range of 19 to 23 $^\circ$C. Obviously, these temperatures are warmer than the day before, resulting in less cooling capacity. This more limited cooling capacity shows in the greenhouse temperatures during the day; these are some degree higher, even though the solar radiation is slightly less. During both days the plant compartment temperatures are above the limit for the penalty function, which was set at 30°C. The more limited cooling capacity on the second day shows more clearly in the amount of condensated water in the heat exchanger. During the first day, with low water temperatures, around 150 kg of water condensated inside the heat exchanger, both with the high and low water and air flows. During the second day, only around 130 kg water condensated in the low coolant flow case. With higher coolant flows, the buffer is exhausted quicker and the airflow too high, so that only around 90 kg of condensation is produced.

The effect of the control horizon shows in the graph for u(t) (figure 5.4(c)); during the first night the pump is active to cool the heat buffer for the next day. During the second night the control setting stays on its initial profile (which was -1 kg s^{-1}). The reason for this is that there is nothing to gain for the controller if it cools the storage, because it does not have to take into account that the heat buffer should be cold for the third day. For application of the controller in the greenhouse, this behavior is no problem, because as the control horizon shifts forward in time the controller will take into account future cooling needs.

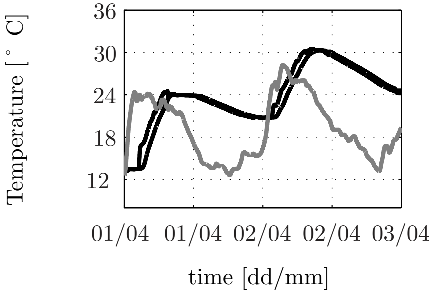


(a) Solar radiation, predicted with the lazy man (gray) and real (black)

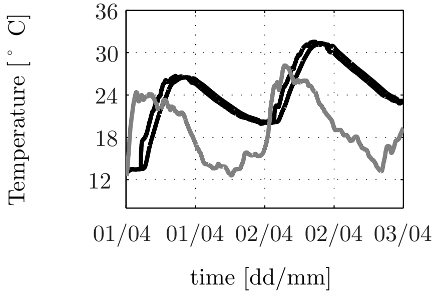
(b) Optimal control pattern (u)

(c) Optimal control pattern (u), improved flows

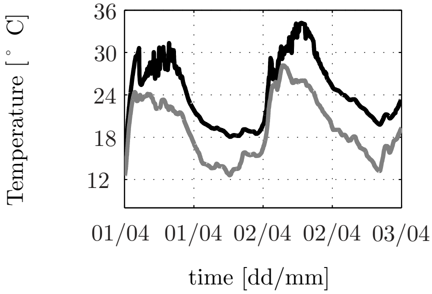
Figure 5.4: Open loop optimal control for the 1^{st} and 2^{nd} of April 2006



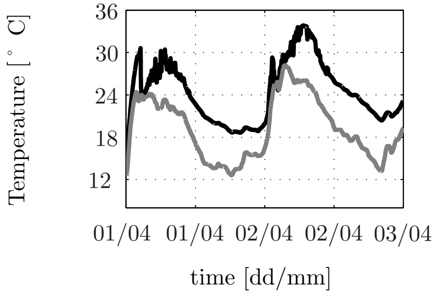
(a) High and low temperature in the heat storage for u(t)= $u_{optimal}$, and outside temperature (gray)



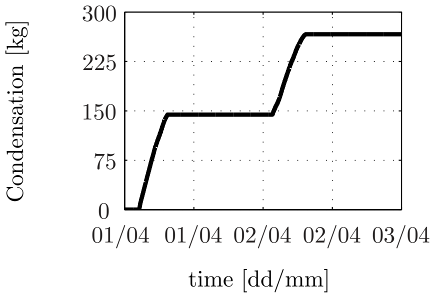
(b) High and low temperature in the heat storage for u(t)= $u_{optimal}$, and outside temperature (gray), improved flows



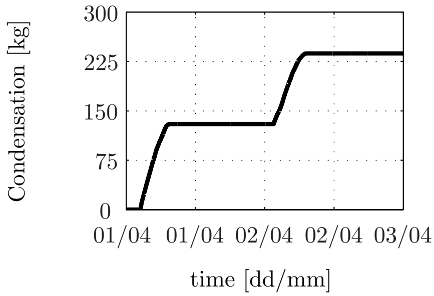
(c) Temperature in the plant compartment for u(t)= $u_{optimal}$ and outside temperature (gray)



(d) Temperature in the plant compartment for u(t)= $u_{optimal}$ and outside temperature (gray), improved flows



(e) Condensation in the heat exchanger



(f) Condensation in the heat exchanger, improved flows

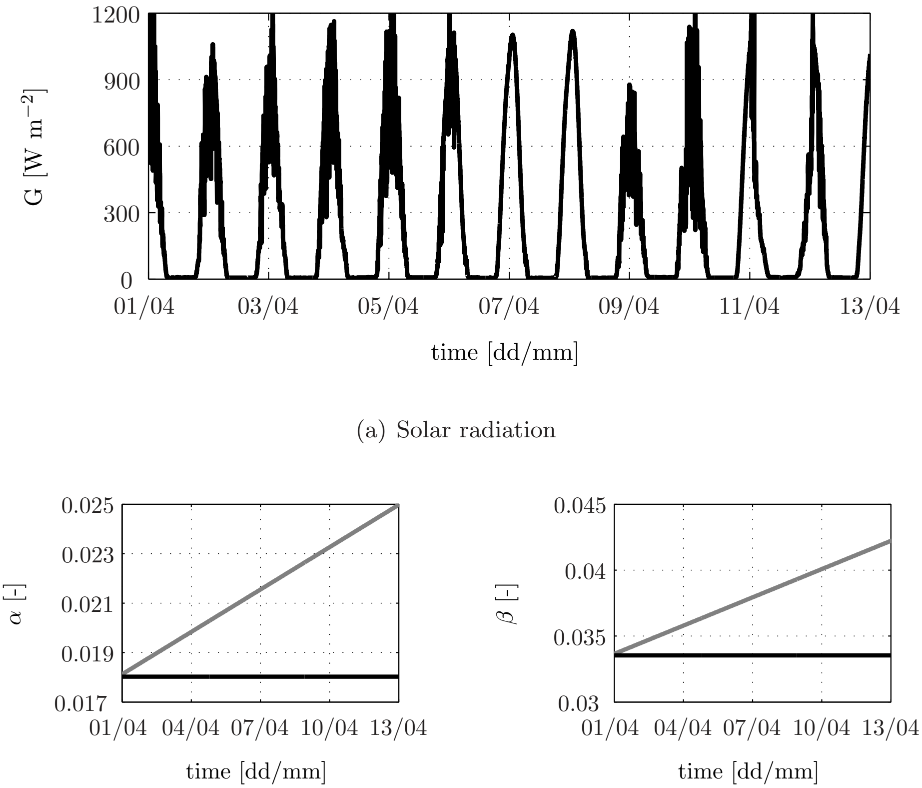
Figure 5.5: Open loop optimal control for the 1^{st} and 2^{nd} of April 2006

5.4.3 Receding horizon optimal control

After the open loop calculations, the receding horizon controller is implemented and tested. Figures 5.6 to 5.8 show the control profile and the resulting temperatures for a simulation period of two weeks, with a control horizon of 48 hours and a control interval of one hour. Parameters α_p and β_p slowly increase in the emulation model, whereas they remain constant in the control model (figure 5.6(b) and 5.6(c)). This creates a difference between the emulated, 'real' process and the model that is used by the optimal control algorithm. In the next section, the same settings are used in combination with an adaptive receding horizon optimal controller to show the effect of online parameter adaptation.

The optimal control trajectory (figure 5.7(a)) is highly cyclic; during the day the pump speed increases, until the upper bound is reached (2.8 [kg s^{-1}]). At night, the water is cooled to have enough cooling capacity during the next day. This results in coolant temperatures of 20 to 24 $^\circ$C in the morning (figure 5.8(a)). The temperature in the plant compartment is well over 30 $^\circ$C at the hottest time of the day, even at days when the ambient temperature is relatively low (like the 6^{th} of April, figure 5.8(b)).

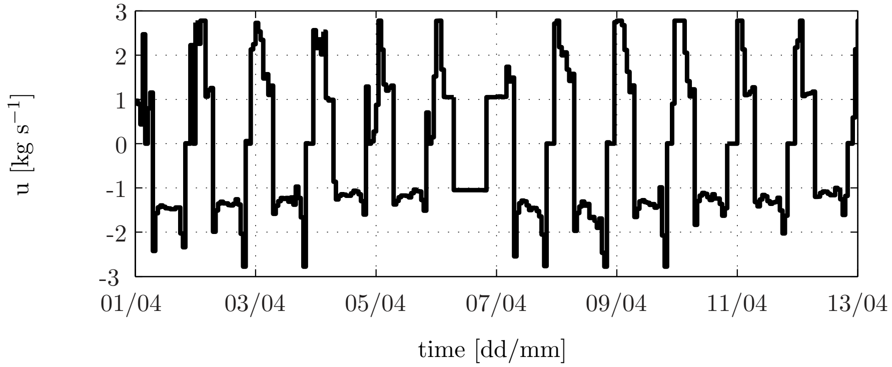
It must be noted that the maximum water and airflow are well over the capacity of the installation in the real greenhouse. Despite this increase the temperature inside the greenhouse has quite high maxima. To further decrease the temperature, other measures like increasing the heat exchanger are probably needed, some suggestions are described in section 5.5.



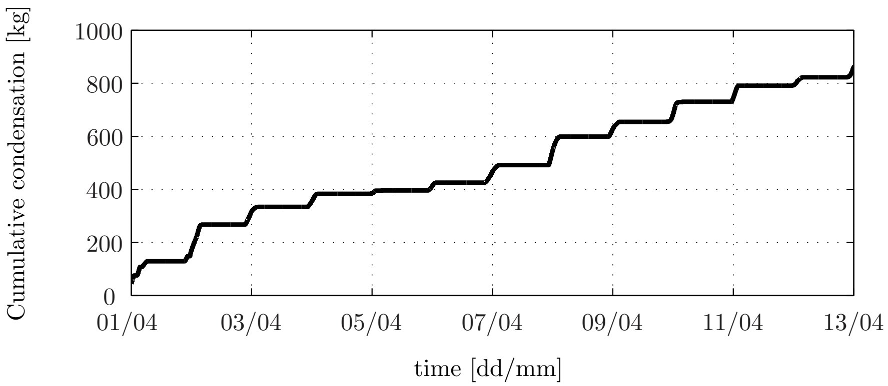
(b) α_p ('real' value = black, value in control model=gray)

(c) β_p ('real' value = black, value in control model=gray)

Figure 5.6: Conditions for the receding horizon optimal control simulation; (a) solar radiation (b and c) varying parameters α_p and β_p in the real (emulated) greenhouse, and constant(grey line) assumed in the controller.

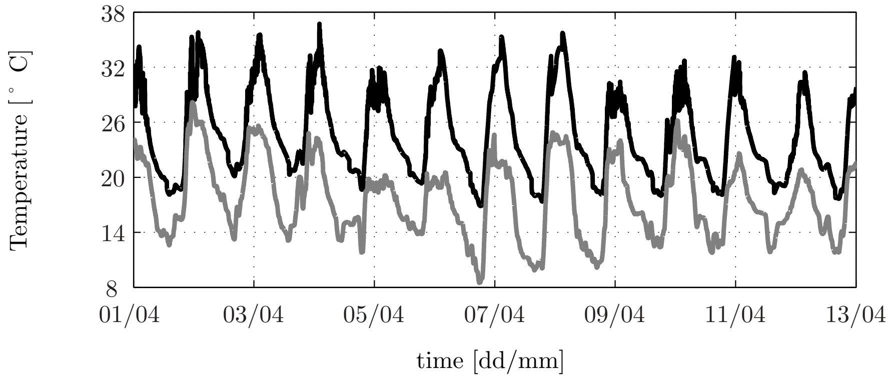


(a) Control (u)

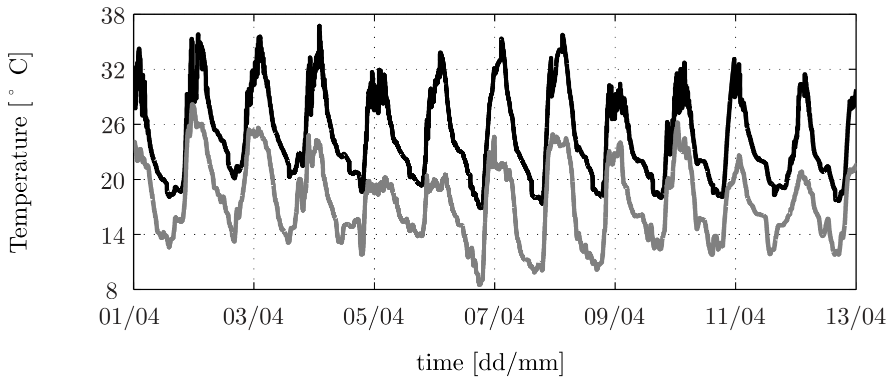


(b) Cumulative condensation

Figure 5.7: Results of a receding horizon optimal control simulation without adaptation. (a) calculated control settings; (b) resulting cumulative condensation.



(a) Temperature in the heat storage (min and maximum value; black) and outside temperature (gray)



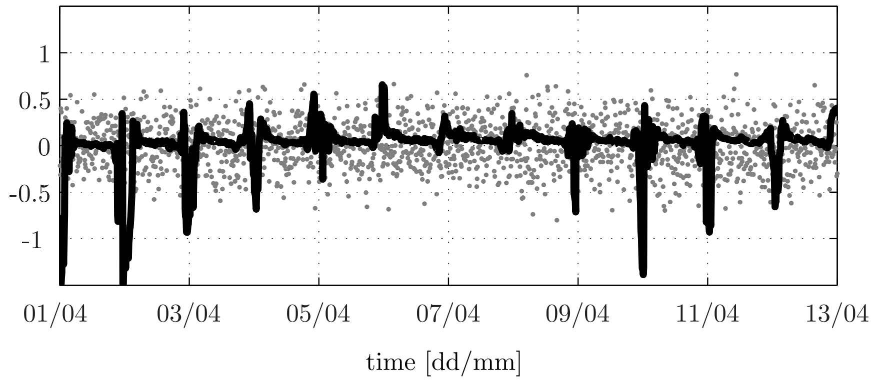
(b) Temperature in the plant compartment (black) and outside (gray)

Figure 5.8: Results of a receding horizon optimal control simulation with varying parametersα_p and β_p; temperatures in the system.

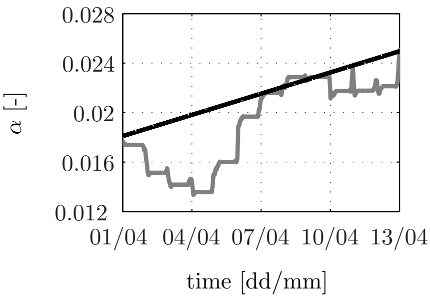
5.4.4 Adaptive receding horizon optimal control

Simulation results of the adaptive receding horizon optimal controller are shown in figures 5.9 and 5.10; the solar radiation is shown in figure 5.6(a). As in the previous section, parameters α_p and β_p slowly increase (simulating plant growth). The parameters are estimated by an extended Kalman filter and adjusted in the control model; the trajectory of the 'real' parameters and the estimates is shown in figures 5.9(b) and 5.9(c). The weather is again predicted with the lazy-man method, the control horizon is 48 hours and the simulation period 2 weeks.

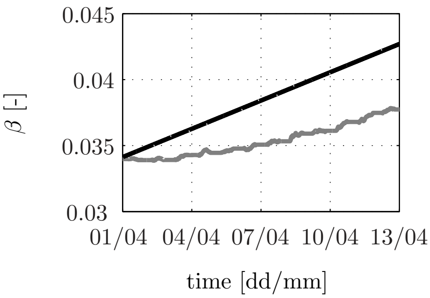
As during the simulations without parameter adaptation, the temperature in the plant area still becomes quite high. A comparison between the adaptive and non-adaptive rhoc-algorithm is given in the next section.



(a) Error between emulated state and 'measured' value (gray ...), and error between emulated state and estimated state (black –)

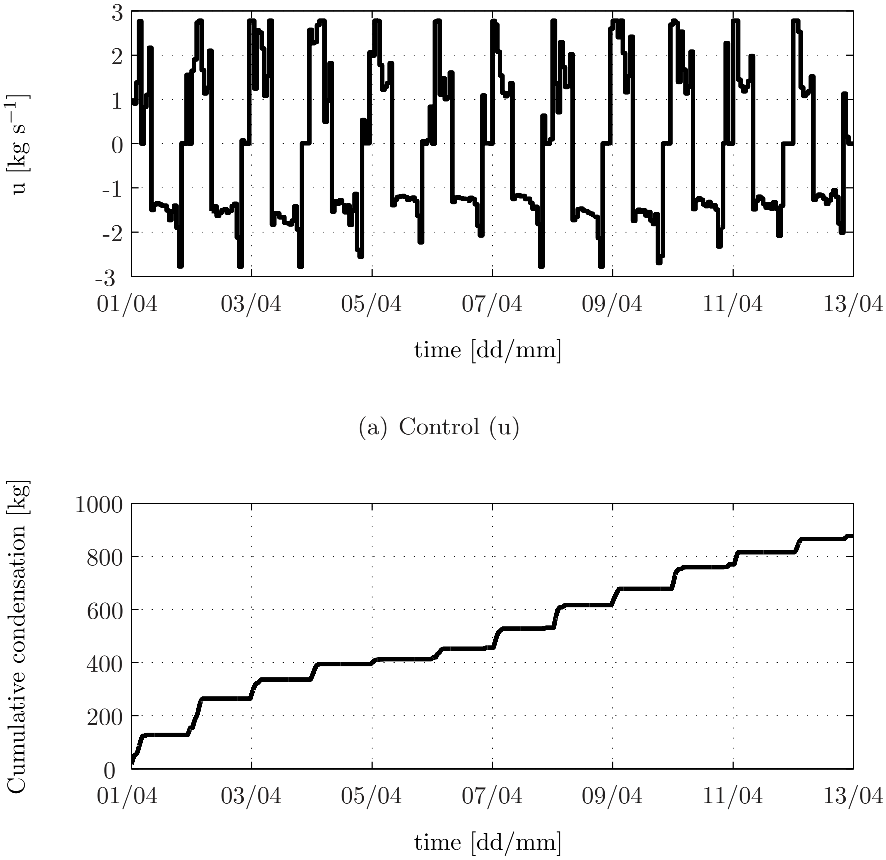


(b) α (– emulated value; -. estimated value)



(c) β (– emulated value; -. estimated value)

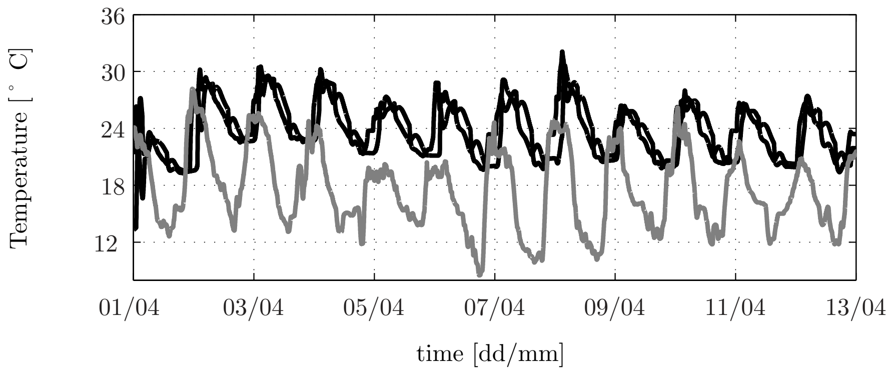
Figure 5.9: Results of an adaptive receding horizon optimal control simulation; solar radiation and estimated parameters.



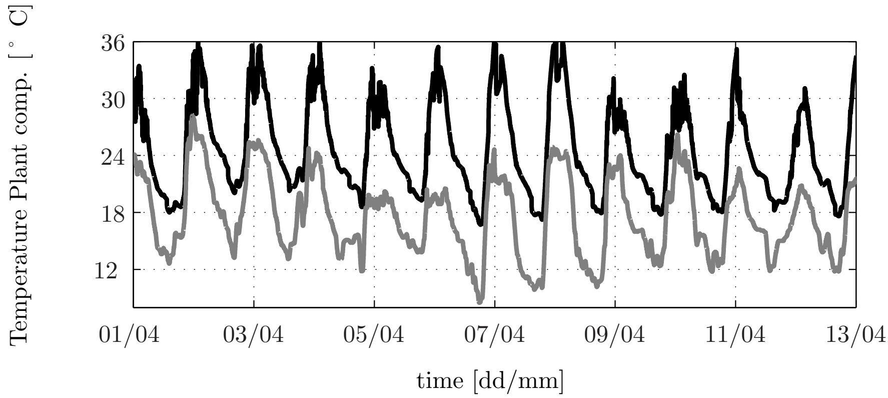
(a) Control (u)

(b) Cumulative condensation

Figure 5.10: Results of an adaptive receding horizon optimal control simulation; calculated control settings and resulting cumulative condensation.



(a) Temperature in the heat storage (min and maximum value)

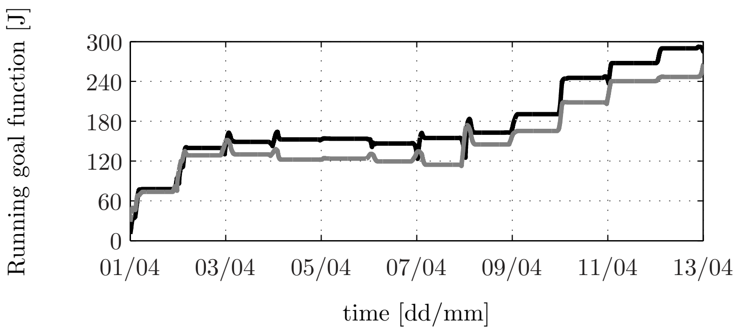


(b) Temperature in the plant compartment

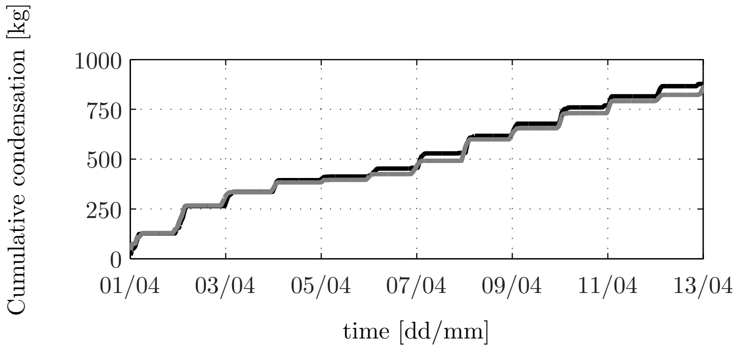
Figure 5.11: Results of an adaptive receding horizon optimal control simulation; temperatures in the system.

5.4.5 Compare rhoc with a-rhoc

When parameters change over time, an adaptive controller that can adjust its model parameters theoretically has an advantage over a non-adaptive controller. In the simulations with the optimal controller for the Watergy greenhouse, the adaptive controller does perform better than the non-adaptive version (see figure 5.12). The difference between the two controllers is not large though; after 13 days, the difference in cumulative condensation is around 50 kg. The difference in the goal function is larger, because with the non-adaptive controller the greenhouse gets slightly warmer, resulting is a larger penalty for the rhoc.



(a) Running goal function value for rhoc (gray) and arhoc (black)



(b) Cumulative condensation for rhoc (gray) and arhoc (black)

Figure 5.12: Goal functions and cumulative condensation for a rhoc (gray) and a arhoc (black) simulation with the same settings.

5.5 Simulation results for an improved design

From the previous section it becomes clear that the currently built greenhouse has a limited functionality, meaning that the temperature inside the greenhouse reaches levels that are not beneficial for the plants. Due to the insufficient cooling capacity, the results of the optimal controller are quite straightforward; when cooling is needed, the full available capacity is almost always needed, resulting in on-off control patterns.

To show the behavior and the applicability of the receding horizon optimal controller, simulations have been done pretending that the cooling capacity of the greenhouse was large. Some simulations with this improved, virtual greenhouse are presented in this section. First, the real greenhouse was compared with the modified greenhouse with on/off inputs. In the second part, optimal control trajectories are calculated for the modified greenhouse.

To enhance the cooling capacity of the greenhouse, some of its characteristics are changed (note that the approach here is not the same as lifting the control input constraints in the previous sections):

- The cooling of the coolant at night is improved by application of a virtual radiator. At night, the warm water from the cold/heat storage is lead through the greenhouse heat exchanger, into the outside radiator that cools the water to the air temperature. Obviously, cooling only works when night temperatures get low enough. At clear nights cooling can also occur by radiation against the sky temperature. As this was not measured, the effect is ignored here, but it will probably make the cooling more efficient than assumed. Another well known way of cooling is the use of a cooling tower, which could cool the coolant to approximately 3 $^\circ$C above the wet-bulb temperature (which is well below the air temperature in semi-arid climates). The main drawback of a cooling tower, its water use, could be alleviated by using sea-water. However, as this limits the applicability of the greenhouse to coastal regions, the cooling tower is for the moment not further studied.
- The outer surface of the heat exchanger itself is doubled in size (250 m^2 in the old situation to 500 m^2 in the new).
- The heat/cold buffer is increased from 45 to 60 m^3.
- The maximum water flow through the heat exchanger is highly increased

to 10 kg s^{-1}. This is based on the assumption that the maximum cooling capacity required to cool the greenhouse is in the order of 500 Wm^{-2} $\times$ 200 m^2 = 170 kW. With a temperature difference between greenhouse air and coolant of 8 $^\circ$C (and the given heat exchanger characteristics), the water flow is about 2.8 kg s^{-1} = 10 m^{3}h^{-1}.

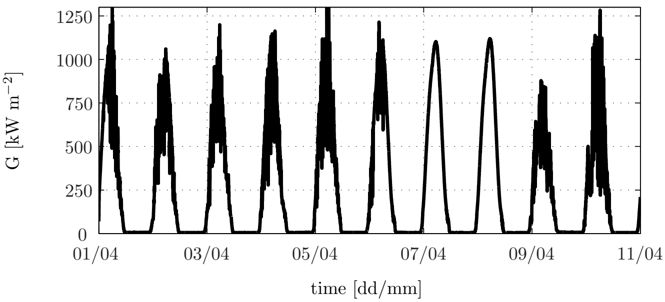
- The airflow through the greenhouse is improved. When more air flows through the heat exchanger in the tower, its capacity increases. As both latent as well as sensible energy is exchanged, the heat capacity of the air depends on the climate inside the greenhouse, making a reliable estimate of the airflow difficult. Therefore the airflow is increased with around the same percentage as the water flow, to 16$\cdot$10^3 m^{3}h^{-1}.
- The roof transmission for infra red radiation is reduced, which can be done in practice with radiation specific plastic foils. Assumed is a transmission coefficient for radiation that heats the plant compartment of 0.3 and 0.08 for the inner roof compartment.

Table 5.1: Modifications to the Watergy greenhouse to improve the cooling capacity

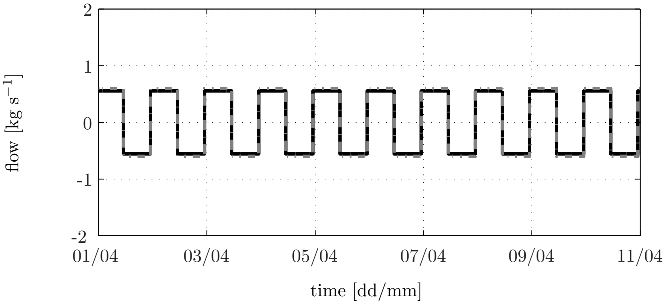
Parameter	**Units**	**Default value**	**New value**
$\Phi_{v,air}$	m^{3}h^{-1}	6 $\cdot$10^3	16$\cdot$10^3
$\Phi_{v,water}$	m^{3}h^{-1}	2 $\cdot$10^3	10$\cdot$10^3
A_{hex}	m^2	250	500
V_{hs}	m^3	20 $\cdot$10^3	60 $\cdot$10^3
η_{pa}	-	0.56	0.3
η_{pa}	-	0.14	0.08

5.5.1 Comparison between the real and the modified greenhouse

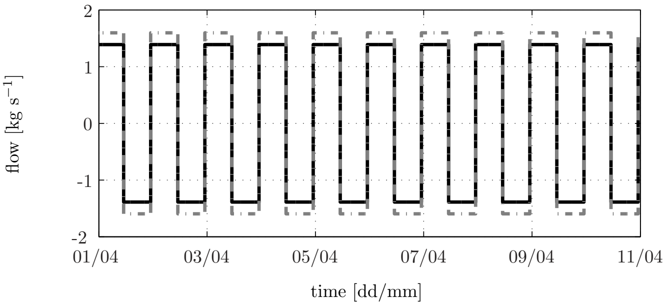
To show the effect of the proposed modifications, the real greenhouse is compared to the modified greenhouse over a 10 day period with weather data of April 2006 (figures 5.13 to 5.15). On/off control inputs were used with the maximum water flows. Because of the larger heat/cold buffer, more coolant is available. This means that the water flow can be larger without emptying the stored coolant before the end of the day. This keeps the maximum temperatures in the cold buffer lower than in the original case. The effect of the increased coolant availability in combination with the larger heat exchanger and improved airflow results in temperatures in the plant compartment that are much lower than originally. Also the different properties of the plastic film, to reflect heat radiation, help to keep the required cool duty low. In the improved greenhouse, temperatures are slightly higher than outside temperatures, but they do not reach the penalty-border of 30 $^\circ$C. The relative humidity in the modified greenhouse is slightly higher, but does not reach alarming values.



(a) Solar radiation

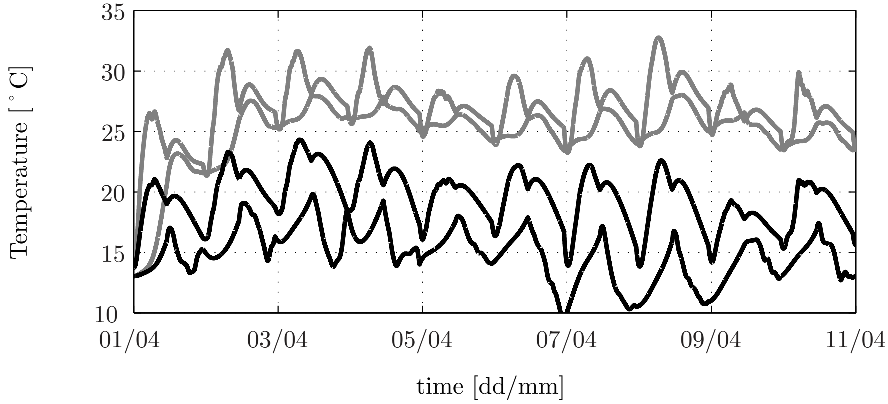


(b) Inputs for original greenhouse (legend: gray=airflow, black=water flow, both (kg s^{-1}))

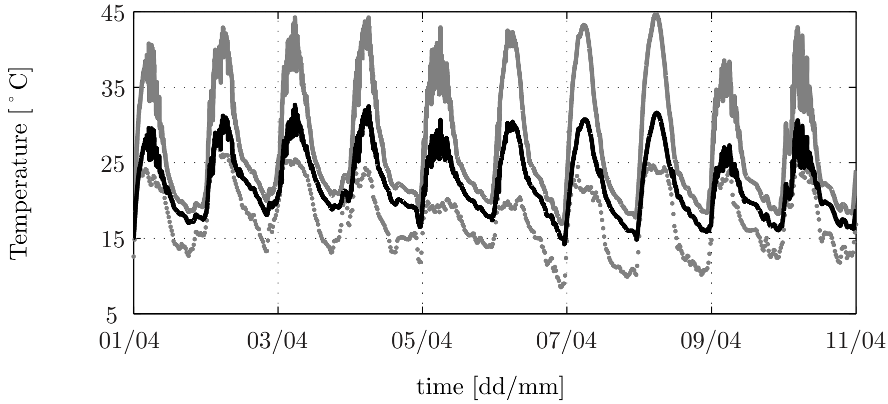


(c) Inputs for improved greenhouse (legend: gray=airflow, black=water flow, both (kg s^{-1}))

Figure 5.13: Effects of improving the cooling capacity of the Watergy greenhouse in simulation; inputs for improved greenhouse; simple on/off control (legend: gray=airflow, black=water flow, both (kg s^{-1}))

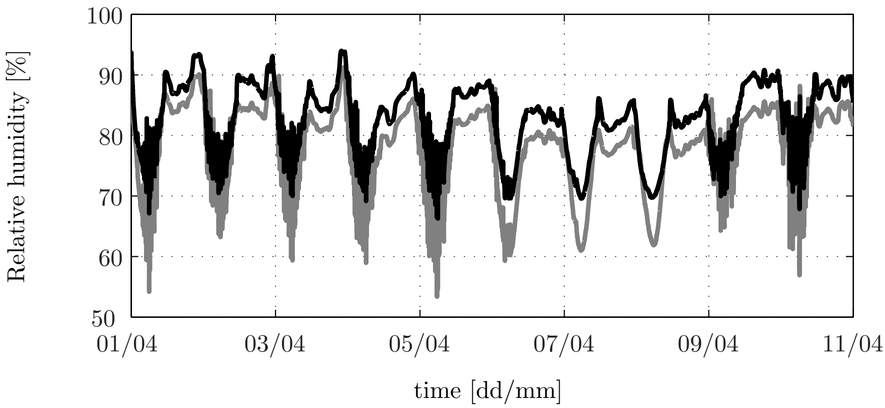


(a) Temperature in the heat storage (legend: gray=original greenhouse, black=improved greenhouse)

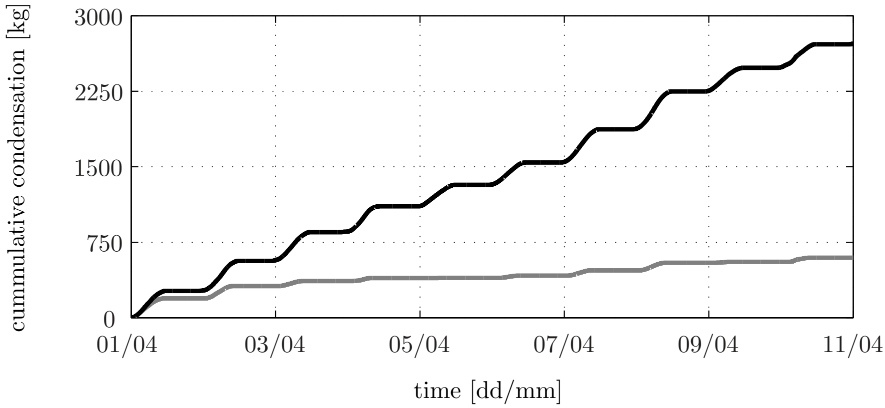


(b) Temperature in the plant compartment (legend: gray=original greenhouse, black=improved greenhouse, gray dotted=outside)

Figure 5.14: Effects of improving the cooling capacity of the Watergy greenhouse in simulation; simple on/off control



(a) Relative humidity in the plant compartment (legend: gray=original greenhouse, black=improved greenhouse)



(b) Cumulative condensation in the heat exchanger (legend: gray=original greenhouse, black=improved greenhouse)

Figure 5.15: Effects of improving the cooling capacity of the Watergy greenhouse in simulation; simple on/off control

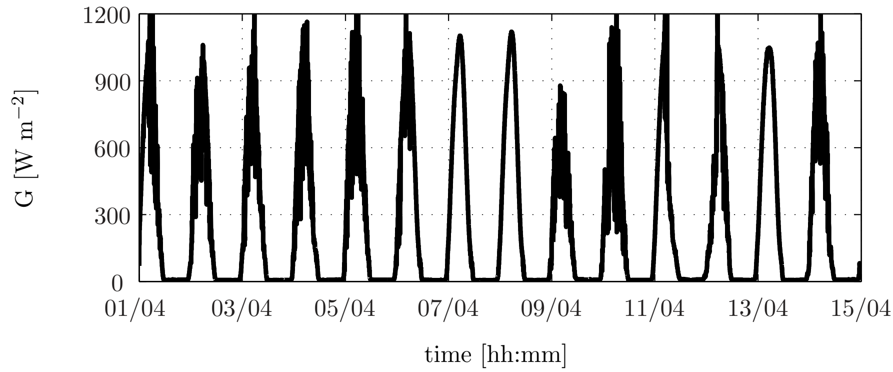
5.5.2 Receding horizon optimal control for the modified greenhouse

Figures 5.16 and 5.18 show results for a rhoc simulation with the modified greenhouse. As in the simulations with the real greenhouse, a lazy man weather prediction is used, the prediction and control horizons are 48 hours, the control interval 1 hour and the total duration is 14 days. Comparison with the simulations in the previous section will allow to examine the benefits that can be gained from advanced control over simple on/off control strategies.

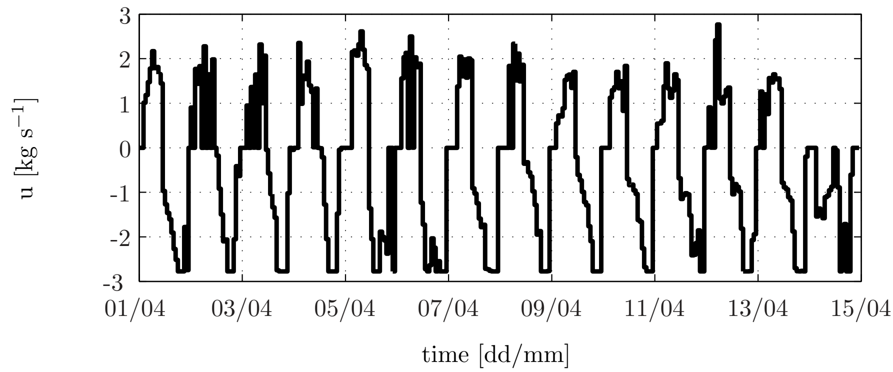
Compared to the realized Watergy greenhouse (both with and without improved water and airflows), the improved greenhouse has much more cooling capacity. As a result the temperature in the plant compartment is around 8 $^\circ$C lower than in the simulations with the real greenhouse. Also the produced condensation inside the heat exchanger is higher. The controlled pump speed hardly ever reached its bounds during daytime, indicating that there is not much to be gained by improving the pump speed. At night, the lower bound of the pump speed is touched upon more frequently. This is probably because the controller tries to cool the heat storage as far as possible at night to have cooling capacity during the day. Again, this indicates the importance of the coolant cooling at night.

Compared to simple on/off control, the amount of produced water is much higher when the greenhouse is controlled with the optimal controller; 2700 vs. almost 3100 kg water over 14 days. This increase can partly be explained by the higher maximum pump rate, and partly by the 'smartness' of the optimal controller, that uses the coolant at times when it is most effective.

The increase of cooling in the greenhouse influences the relative humidity quite negatively; it is quite high, and often exceeds 90%. When moisture condensates on the crop diseases are to be expected. To reduce the humidity in the greenhouse, several options are available, ranging from drying the air by (very limited) ventilation with outside, to drying the air with an additional cooling device that operates on lower temperatures than the central heat exchanger. This is an important issue to study in further research.

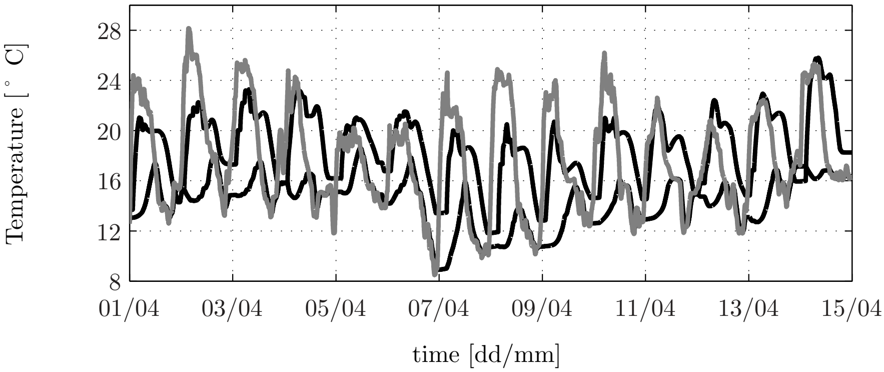


(a) Solar radiation

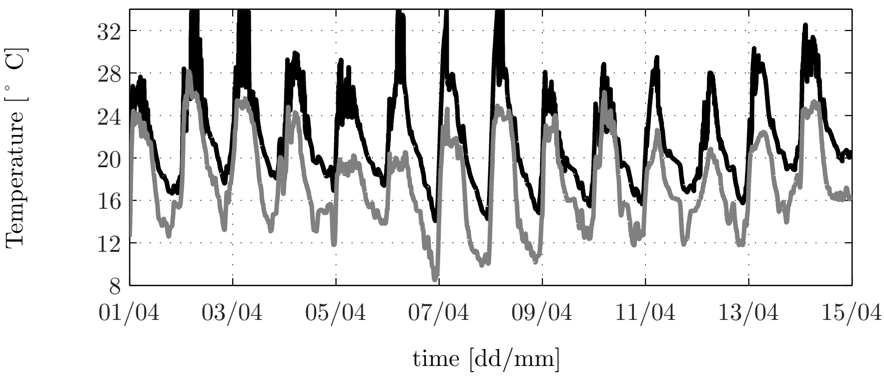


(b) Optimal control pattern (u)

Figure 5.16: Rhoc simulation for improved greenhouse

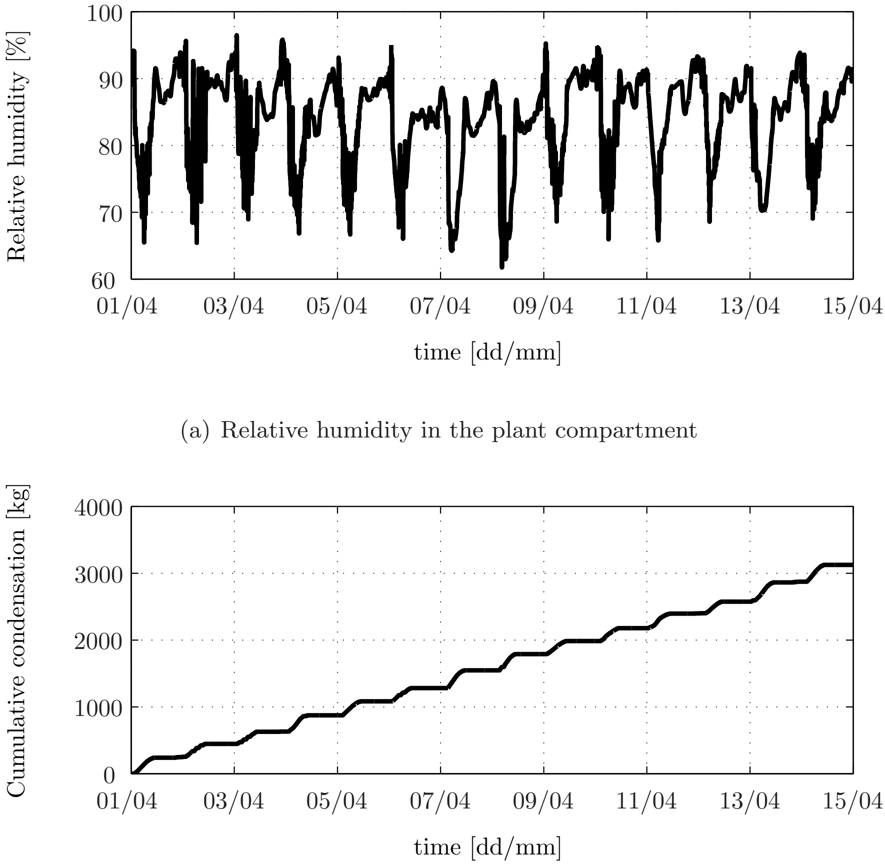


(a) Temperature in the heat storage (min and maximum value), and outside temperature(gray)



(b) Temperature in the plant compartment, and outside temperature (gray)

Figure 5.17: Rhoc simulation for improved greenhouse; Temperatures in the heat storage (a) and plant compartment (b)



(a) Relative humidity in the plant compartment

(b) Cumulative condensation

Figure 5.18: Rhoc simulation for improved greenhouse; relative humidity in the plant compartment (a) and total condensation (b)

5.6 Discussion and conclusions

In this chapter, simulation results for receding horizon optimal control of the Watergy greenhouse are presented. Also, the performance of an adaptive optimal controller is compared to a non-adaptive controller. As the goal function plays a very important role in optimal control, many possible functions were considered. Eventually, the choice was made to use a function that optimizes the water production of the greenhouse as this is one of the main goals for the system. For some part, the choice for this goal function was inevitable, as no model was available that describes the plant development of the crop that were grown (okra and green bean). A favorable climate for the plants was taken into account in the goal function by putting penalties to temperature levels exceeding pre-set bounds.

The weather prediction that is needed in optimal control was generated with the adapted lazy man method, as no local weather prediction was available. We argued that as the weather in Spain is fairly stable, the lazy man would give acceptable predictions. Despite this, still the predicted weather deviates substantially from the real weather, which has could have some negative effect on the optimality of the control settings that are calculated by the rhoc algorithm. Application of a more advanced prediction method would improve the control, as is shown by Doeswijk (2007).

The results of the open-loop simulations show that the hardware as it is installed in the greenhouse cannot deliver the amount of cooling that is required to keep the temperatures in the plant compartment under 30 ˚C, even in April. The control actions calculated by the controller result in on-off control, meaning that the controller is (almost) always at the physical bounds of the hardware (e.g. pump speed). To make the simulations more interesting and to truly test the adaptive receding horizon control algorithm, some improvements to the greenhouse system were proposed and implemented. First the bounds on pump speed and airflow were alleviated, a change that could be implemented in practice without much trouble. Second, some structural changes to the design were proposed and used in simulations.

When the maximum water and air flow were increased, the temperature in the greenhouse did not decrease compared to the original case. Also, the amount of condensing water in the heat exchanger did not increase with the higher flows. With the configuration of increased water and airflow, both the receding horizon controller and the adaptive-rhoc were simulated. In both cases the calculated control trajectory was cyclic; during the day the pump rate increased to the upper bound and at night the pump rate reached the lower bound (indicating that the water flow has reversed to maintain counter flow in the heat exchanger). The adaptive controller does perform slightly better than the non-adaptive controller, although the difference in produced, condensated water is quite small (around 50 kg in 13 days). Partly, this small difference is due to the limited effect of the parameter variation on the model outcome; when the evapotranspiration increases (as α_p and β_p are increased), the temperature in the plant compartment goes down (evaporative cooling). The total moisture content of the air does increase, which explains the higher condensation in the heat exchanger, but the effect is not very large. Probably the effect of estimating other parameters, that have a more significant effect in the model outcome, would show a more distinct difference between the adaptive and non-adaptive controller.

The second improvement to the greenhouse's cooling system beheld more than just increasing the maxima for the controls. The heat/cold storage was improved, the heat exchanger doubled in size and the air and water flows increased. These changes result in more cooling capacity, which gives the controller more freedom in its control actions. The results of these simulations show that the controller is most of the times not hampered by the maximum pump capacity (it does not reach its bounds often). It is also here - under this less restrictive design - that the advantages of advanced controllers such as the developed rhoc become most apparent. With advanced control, considerable gains can be achieved, resulting, in this case, in much higher water production as compared to experience based on/off control.

Future work

The choices to improve the cooling capacity of the greenhouse control system were made in an ad-hoc way, more based on educated guesses than on thorough analysis. As the purpose of the increase in capacity was to test the control algorithm, we think this approach is justifiable. However, before adjusting the real greenhouse and fitting new hardware into the system, further simulation and design studies should be done. Also more research is needed into ways to cool the heat/cold storage at night so that enough cooling capacity is available for daytime. Ideally, the buffer is cooled to at least the outside air temperature but preferably even lower. Possible ways to achieve this are cooling towers (which use evaporative cooling and thus water) and/or radiating heat to the (cold) sky.

In the original plans testing the adaptive receding horizon optimal controller in the Watergy greenhouse was anticipated upon. Unfortunately, due to various reasons, this could not be done in the time available. The optimal control trajectory for the real greenhouse (with the limitations on water and airflow rates) is an on/off control. Only when the bound on the flow rates are alleviated, an optimal controller has advantages over an on/off time clock. In future work, the greenhouse cooling system could be improved and can be controlled by an optimal controller. Then, simulation results can be verified and the controller improved upon further.

The adaptive part of the controller, the EKF, is quite sensitive to tuning. A badly tuned filter does not yield any usable results. For practical applications, automatic tuning is an important issue. Without auto-tuning implementation in commercial horticultural automation systems is (almost) impossible due to the ever changing system that greenhouses are. Another line of research is to look at the theoretical implications on the choices for the EKF that were made in this chapter, where the parameters were only estimated during either day (α_p) or night (β_p), and the correlation between the two parameters.

Acknowledgments

This research was partly done at the dynamic systems group of IIASA, Austria. The author is very thankful for the help he received from the members of the group and especially wants to thank Dr. Sergey Aseev for his great help with the mathematics.

6

Conclusions

This thesis describes the design and development of an adaptive, receding horizon optimal controller the Watergy greenhouse. The greenhouse was designed by partners in the Watergy project, with the aim to combine water and food production and extend the growing season in hot, dry climates. The greenhouse was built in Almeria (Spain) in 2004 and has been operational for the last four years. Many experiments were undertaken to gain insight in the possibilities of the concept with respect to plant growth and water re-cycling. Published results show that around 65% of the irrigation water is re-gained in the heat exchanger (Buchholz et al., 2006). At the same time production levels were comparable to traditional greenhouses (with heat tolerant crops). This proves that, although improvements are possible, the basic idea of the Watergy greenhouse works well.

As defined in the introduction, the main aim of this thesis is
"to study a complete model-based control-design and to move forward towards an experimental setup for adaptive, receding horizon optimal control in the Watergy greenhouse".

The work described in this thesis is a contribution to the introduction of advanced adaptive control methodologies in the context of greenhouse horticulture. Simulations in chapter 5 show that these methodologies can be rewarding, and the fact that it has been applied to a completely novel design underlines the versatility of the approach. Although no new theory has been presented regarding the methodology of estimating time varying parameters and the application of this knowledge in a model-based controller, its application is very important and significant for the greenhouse industry. The introduction of these methodologies addresses one of the main drawbacks of optimal control, being the need for good, well calibrated models. Instead of using models that describe every tiny detail of a system or process, lumped parameters could be used to avoid time consuming detailed modeling for which in practice there is usually not enough time. These lumped parameters can be estimated and adjusted online by an extended Kalman filter. The method introduced here could be coined 'self-tuning', and this is very significant for the industry. This is not to say that no further research is needed in these areas, with special emphasis to the problems encountered in greenhouses. Examples of such research topics are: the fundamentals of calibration in parts, in particular the data reconciliation on the level of the model as a whole; tuning rules for the extended Kalman filter to make the method more robust and less vulnerable to the skills of the researcher; development of methods to really integrate design and control (very relevant for the advancement of solar stills and modern integrated greenhouse concepts); rethinking the relationship between off-line optimization, and on-line implementation issues.

The control system that is shown in this thesis is not only applicable to the Watergy greenhouse. The latest trend in Dutch horticulture is the introduction of closed greenhouses (Ooteghem, 2007), that are cooled in summer and heated in winter. Although water saving is not an issue in The Netherlands, the function of the Watergy greenhouse and the closed greenhouse are basically equal. Both try to keep the windows closed as long as possible to keep the CO_2 inside the greenhouse. Both use the heat that is taken out of the greenhouse at times when cooling is needed, and use the heat usefully at other times.

Sub-questions related to main research question that were raised in the introduction are:

- Into what extend does the currently available commercial hardware for greenhouse climate and irrigation control facilitate adaptive receding horizon control and, if it does not facilitate our demands, how can we address this problem in the best possible way?

- Given the high computational demands of dynamic optimization, how can the dynamic behavior of the climate in the Watergy greenhouse be modeled with a relatively small number of states so that receding-horizon optimal control becomes feasible for a practitioner?

- Into what extend are the (lumped) parameters in the greenhouse model changing over the seasons and how could this issue be dealt with, within the constraints of application in an optimal controller?

- Given a choice for the goal function in the receding-horizon optimal controller (which will be studied separately), what does the optimal control pattern for the Watergy greenhouse look like?

- How does the optimal control pattern change if the model parameters are changed online?

- What do we really gain if online parameter adaptation in receding horizon optimal control is included?

In the next sections, these questions are answered.

Hardware for the control system

Commercially available hardware for greenhouse climate control are not able to facilitate research to advanced controllers, so a suitable measurement and control system had to be newly designed. Commercially available systems do not have the required flexibility and versatility. The measurement and control system presented in chapter 1 is flexible because of the generally available components that are connected in a modular way. For the development of the measurement and control system the methodology of methodic design was used. This method is commonly used in engineering of for example machinery. However for control systems it has, to the best of our knowledge, not been applied. The advantages of methodic design over a more ad-hoc approach are: (1) the objective of the system is clearly defined, (2) all functions are systematically reviewed and (3) the construction phase is shortened.

The measurement and control system measured data that are relevant for later research, like temperatures and humidities at various places in the greenhouse and in the cooling/heating system, air and water flows, solar radiation, etc. All this data was stored in a central database that also contains the settings for the controllers (e.g. pumps and valves). The data logger, power supply, patch panel (for sensor connections) and network equipment in one process control unit (PCU) proved to be quite robust. The use of the patch panel with standard (computer network) cable makes it easy to connect and disconnect the sensors, which is often needed for checking and cleaning of the sensors. Another difference with commercial greenhouse control systems is the distribution of the low level technical equipment like motor control, relays, etc. over the greenhouse. This reduced the number of cables and the systems remained more flexible than when all the hardware installation would have been centrally installed.

The measurement and control system, the graphical user interface and the data storage in a database are programmed in LabVIEW. The programs that were developed for the group and low level controllers run in embedded processors, the software at supervisory level (GUI and database) runs on a personal computer. It is possible to operate the system both in direct as in cascade control. In the direct control mode, set points for the low level controllers are generated at the supervisory level, e.g. when model predictive controllers are used. In the cascade control mode, setpoints for the group level are generated at the supervisory level and setpoints for low level controllers are generated at the group level. The system is accessible through the internet, making it possible to maintain the software and access the data at a distance.

Compared to commercially available greenhouse control systems, the system at hand is very much suited for the research done with the Watergy greenhouse. The system is easy to expand, stores all the necessary data and is easy to operate.

6.1 Greenhouse model for optimal control

For the model based control of the greenhouse, the main goal of this thesis, a model of the system is needed. As the model will be used in a receding horizon optimal controller, some restraints were put on it. First, the model needed to be able to accurately predict the greenhouse climate for at least a few days ahead. Furthermore the number of states was kept low, to ensure that the computational load remained reasonable (as an optimal greenhouse controller should be able to calculate new control settings every 1 to 10 minutes). These constraints lead to the decision to develop a model that only describes the key-dynamics of the greenhouse and that uses lumped parameters for less significant processes. For example, pollution of the roof with dust changes its transmissivity, but is a difficult process to model. Instead the transmissivity parameter can be estimated (and adjusted on-line).

To estimate these lumped parameters a controlled random search algorithm was used. This method is very robust and the risk of local minima is quite small as the method searches through the whole parameter space. Convergence however is slower than more advanced methods and thus the computational loads are quite high. The algorithm works well in cases with limited number of parameters to be identified and when the model has a low calculation time. Therefor the method of *estimation in parts* was applied; only the part of the whole model that contains the to-be-identified parameters is used. Accurate measured data for the states of the neighboring compartments is used, resulting in in parameter estimates that converge well and relatively quickly.

6.2 Parameter estimation

Simulations with the greenhouse model showed that the model fit is especially good in the *same period* as was used for parameter estimation. In other periods, the model fit is less good. This leads to the conclusion that some (lumped) parameters change over time, which pleads for the use of adaptive mechanisms with the model.

The extended Kalman filter is a well-known filter for (online) state and parameter estimation. The main parameters in the model that are subject to change over time are estimated: parameters of the plant evapo-transpiration model (α_p and β_p) and parameters in the heat balance of the plant compartment (η_p and θ_p). These parameters were selected because of their major influence on the model output. The estimation of parameters only works well if the number of parameters to be estimated is not too large compared to the available measurement data. Splitting a large compartment model in smaller pieces with the use of (accurate) measurement data for the inputs at the boundary is a way to deal with parameter estimation in practical situations. Still, it must be said that further study to the theoretical implications of parameter estimation in parts and its effects on the final estimates is needed.

Tests showed that calibration of the EKF parameters is crucial to achieve good estimation results. After the filter was carefully calibrated, the parameter values were estimated over the period of a whole year. The model fit (for periods longer than 2 weeks) was much better with the adaptive parameters than with fixed values. Also the estimated values for the parameters turned out to be good indicators for changes in the systems. For example, in the values of the plant model is was possible to identify events like pruning of the crop (which showed as a sudden, sharp decrease in the parameters).

Despite the remaining theoretical questions on estimation in parts and the filter calibration, the use of an EKF is a valuable addition to current greenhouse climate models to bridge the gap between current practice in commercial greenhouse control and more advanced control systems.

Adaptive receding horizon optimal control

The results of the open-loop simulations show that the hardware as it is installed in the greenhouse cannot deliver the amount of cooling that is required to keep the temperatures in the plant compartment under 30 $^\circ$ C, even in April. The control actions calculated by the controller result in on-off control, meaning that the controller is (almost) always at the physical bounds of the hardware (e.g. pump speed). To make the simulations more interesting and to truly test the adaptive receding horizon control algorithm, some improvements to the greenhouse system were proposed and implemented. First the bounds on pump speed and airflow were alleviated, a change that could be implemented in practice without much trouble. Second, some structural changes to the design were proposed and used in simulations.

When the maximum water and air flow were increased, the temperature in the greenhouse did not strongly decrease compared to the original case. The amount of condensing water in the heat exchanger did not increase with the higher water flow. With the configuration of increased water and airflow, both the receding horizon controller and the adaptive-rhoc were simulated. In both cases the calculated control trajectory was cyclic; during the day the pump rate increased to the upper bound and at night the pump rate reached the lower bound (indicating that the water flow has reversed to maintain counter flow in the heat exchanger). The adaptive controller does perform slightly better than the non-adaptive controller, although the difference in produced, condensated water is quite small (around 50 kg in 13 days). Partly, this small difference is due to the limited effect of the parameter variation on the model outcome; when the evapotranspiration increases (as α_p and β_p are increased), the temperature in the plant compartment goes down (evaporative cooling). The total moisture content of the air does increase, which explains the higher condensation in the heat exchanger, but the effect is not very large. The adaptation was performed on a selection of important parameters only; incorporating the other sensitive parameters is likely to have an additional effect on the difference between non-adaptive and adaptive control.

The second improvement to the greenhouse's cooling system beheld more than just increasing the maxima for the controls. The heat/cold storage was improved, the heat exchanger doubled in size and the air and water flows increased. These changes result in more cooling capacity, which gives the controller more freedom in its control actions. The results of these simulations show that the controller is most of the times not hampered by the maximum pump capacity. Moreover, under such circumstances advanced control shows its true benefits as it brings significant improvements over straight-forward on/off control.

Future challenges

The adaptive part of the controller, the EKF, is quite sensitive for tuning. A badly tuned filter does not yield any usable results. For practical applications, automatic tuning is an important issue. Without auto-tuning implementation in commercial horticultural automation systems is (almost) impossible due to the ever changing system that greenhouses are. Further research to methods of automatic tuning of the Kalman filter and their applicability in horticultural practice will be fruitful.

The application field of on-line parameter adaptation in horticulture reaches further than just control purposes. One trend in current horticulture is the introduction of so-called 'soft-sensors'. Mostly these are observers that reconstruct states that can not be measured, like ventilation flux (Bontsema et al., 2006) or plant evaporation (Gieling et al., 2005). The models that these observers use are relatively simple and require at least some basic parameter estimation before they give reasonable results. By introducing automatic parameter estimation, as shown in this thesis, the hand-calibration of the observers is not necessary anymore and their predictions would become more reliable.

In the original planning, testing the adaptive receding horizon optimal controller in the Watergy greenhouse was anticipated upon. Unfortunately, due to various reasons, this could not be done in the time available. In future work, the controller should be implemented in the control system of the Watergy greenhouse. When that is done, the simulation results can be verified and the controller improved.

Furthermore, the goal function could be improved, for example by taking the plants more into account. If a detailed plant growth model is included in the control model, it becomes possible to find the optimal balance between a good climate for the plants and water production. Another possibility is to try to balance the water production with the water need of the crop.

According to the simulations and practical observations, the cooling capacity of the greenhouse is quite limited. This results in quite high temperatures, that are not favorable to the plants. In chapter 5, the cooling capacity was enlarged (in simulation) by making some assumptions in an ad-hoc way, more based on educated guesses than on thorough analysis. To adjusting the real greenhouse and fit new hardware into the system, further simulation and design studies should be done. Also more research is needed into ways to cool the heat/cold storage at night so that enough cooling capacity is available for daytime. Ideally, the buffer is cooled to at least the outside air temperature but preferably even lower. Possible ways to achieve this are cooling towers (which use evaporative cooling and thus (sea-)water) and/or radiating heat to the (cold) sky.

Notation

Symbols and their units

	description	Units
α	radiation conversion coefficient	kg J^{-1}
α_p	radiation coefficient crop	kg J^{-1}
α_h	heat transfer coefficient	W $m^{-2}K^1$
β	vapor pressure deficit coefficient	kg $m^{-2}Pa^{-1}s^{-1}$
β_p	vapor pr. deficit coefficient crop	kg·$m^{-2}Pa^{-1}s^{-1}$
η	solar radiation efficiency factor	-
ϕ_a	air flow rate	kg s^{-1}
ϕ_w	water flow rate	kg s^{-1}
Φ^{con}	condensation flux	kg s^{-1}
Φ^{conv}	Energy flux due to convection	W
ρ	density	kg m^{-3}
θ_1	$= cp_{s_p}\, m_{s_p}$	JK^{-1}
θ_2	$= \eta_{s_p}\, A_{s_p}$	m^2
θ_3	$= U_{s_p}\, A_{s_p}$	WK^{-1}
θ_5	$= Cp_{s_i}\, m_{s_i}$	JK^{-1}
θ_6	$= \eta_{s_i}\, A_{s_i}$	m^2
θ_7	$= U_{s_i}\, A_{s_i}$	WK^{-1}
A	area	m^2
cp	specific heat dry air	kJ $kg^{-1}K^{-1}$
D	vapor pressure deficit	Pa
E	evapo-transpiration	kg s^{-1} m^{-2}
G_o	solar radiation	W m^{-2}
k	mass transfer coefficient	m s^{-1}
l_e	latent heat of evaporation	J $kg^{-1}K^{-1}$
Le	Lewis number	-
m	mass	kg
r	specific heat of evaporation of water	J kg^{-1}
R	heat resistance	m^2K W^{-1}
t	time	s
T	temperature	$^\circ$C
T_o	temperature of outside air	$^\circ$C
U	heat transfer coefficient	W $m^{-2}K^{-1}$
u^{con}	virtual control parameter for condensation	-
u_i	control parameter for sprinklers (on/off)	-
x	moisture content	kg $_{(water)}kg^{-1}_{(dryair)}$

Symbols for the optimal control review in chapter 5

	description
q	energy use
$\bar{T}$	average temperature
s	setpoint
NP	prediction horizon
NC	control horizon
T_l	upper bound to temperature
T_u	lower bound to temperature
y_r	reference trajectory
y	measured value
k	time step
J	goal function
h	energy use
c	heating cost
CF	cost in goal function
Pen	penalty in goal function
$\dot{W}_{HF}$	fruit yield
H_u	energy consumption
ϕ_{inj}	CO2 cost
P_T	penalties for excess of temperature
P_V	penalties for excess of CO2 bound
W_n	non-structural dry weight of plants
W_s	structural dry weight of plants
$c_{pri,1} + c_{pri,2}\, X_d\,(t_f)$	lettuce price
$c_q\, U_q$	heating costs by
$c_q\, U_q$	cost of CO_2
$\lambda(t)$	time-varying Lagrange multiplier
H	hamiltonian
P_{temp}	penalty function for temperature

Subscripts

	description
a	air
con	condensation
$conv$	convection
h	heat exchanger compartment
i	inner roof compartment
in	air flow direction is into compartment
m	compartment number in heat storage
n	compartment number in heat exchanger
o	outside
out	air flow direction is out of compartment
p	plant compartment
r	roof
rad	solar radiation
s	solids
s_i	solids in the inner roof compartment
s_p	solids in the plant compartment
sat	saturated
tot	total
w	water

Default values or value ranges used in simulations

	description	Default value	Units
A_p	area	200	m^2
A_{po}	roof area plant compartment	204	m^2
A_i	area inner roof compartment	150	m^2
A_{io}	roof area inner roof compartment	207	m^2
$A_{h,tot}$	heat exchanger surface area	250	m^2
cp_a	specific heat dry air	1005	kJ $kg^{-1}K^{-1}$
cp_w	specific heat water	4186	J $kg^{-1}K^{-1}$
k	mass transfer coefficient		m s^{-1}
l_e	latent heat of evaporation	$2.5e^6$	J $kg^{-1}K^{-1}$
Le	Lewis number $=a/D_c$		-
where: a	thermal diffusivity of air	0.021	W m^{-2} k^{-1}
D_c	diffusion coefficient of water vapor in air	0.22e-4	-
$m_{h_{a,tot}}$	total mass air in heat exchanger	24	kg
$m_{h_{w,tot}}$	total mass water in heat exchanger	53	kg
m_{hs}	mass water in the cold/heat storage	20e3	kg
m_p	mass air in plant compartment	704	kg
m_i	mass air in inner roof compartment	307	kg
R_{tot}	total roof heat resistance		m^2K W^{-1}
R_p	roof heat resistance on plant compartment side		m^2K W^{-1}
U_{po}	heat transfer coefficient; plant compartment–outside	7.9	W $m^{-2}K^{-1}$
U_{ps_p}	heat transfer coefficient; plant compartment–solids in plant compartment		W $m^{-2}K^{-1}$
U_{pi}	heat transfer coefficient; plant compartment–inner roof compartment	10	W $m^{-2}K^{-1}$

	description	Default value	Units
A_p	area	200	m^2
A_{po}	roof area plant compartment	204	m^2
A_i	area inner roof compartment	150	m^2
A_{io}	roof area inner roof compartment	207	m^2
$A_{h,tot}$	heat exchanger surface area	250	m^2
cp_a	specific heat dry air	1005	J $kg^{-1}K^{-1}$
cp_w	specific heat water	4186	J $kg^{-1}K^{-1}$
l_e	latent heat of evaporation	$2.5e^6$	J $kg^{-1}K^{-1}$
Le	Lewis number $=a/D_c$		-
where: a	thermal diffusivity of air	0.021	W m^{-2} k^{-1}
D_c	diffusion coefficient of water vapor in air	0.22e-4	-
$m_{h_{a,tot}}$	total mass air in heat exchanger	24	kg
$m_{h_{w,tot}}$	total mass water in heat exchanger	53	kg
m_{hs}	mass water in the cold/heat storage	20e3	kg
m_p	mass air in plant compartment	704	kg
m_i	mass air in inner roof compartment	307	kg
R_{tot}	total roof heat resistance	0.17	m^2K W^{-1}
R_p	roof heat resistance (inside – roof)	0.13	m^2K W^{-1}
U_{pi}	heat transfer coefficient; plant compartment–inner roof compartment	10	W $m^{-2}K^{-1}$

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Summary

Many parts of the world face increasing problems due to water shortage, a situation that is likely to be worsened by population growth and global climate change. Since agriculture is a major water consumer, much can be gained if water use efficiency is improved upon. One of the initiatives to improve water use efficiency in horticulture is the Watergy project, of which this thesis is part.

The Watergy project

The main goals of the Watergy project are twofold: First, we wish to study the possibilities of local energy savings and waste water treatment in an urban environment. Second, the possibilities of year-round plant production combined with fresh water production (from salt or grey water) are studied with the construction of a new type of greenhouse. The partners in the Watergy project are the department of architecture at the Technical University of Berlin (TUB), the experimental plant research station of Cajamar, Las Palmerillas, in Almeria, Spain, and two groups at Wageningen University and Research Center, namely the Systems and Control group, and the WUR greenhouse horticulture group at Plant Research International.

Watergy greenhouse in Spain

The Watergy greenhouse built in Almeria (Southern Spain) is a closed greenhouse of 14×14 meters with indoor air-cooling during the day. This enables extension of the growing season when compared to traditional greenhouses in warm countries where a summer-break is common practice. The excess heat in the greenhouse is used to produce clean water from either salt or grey water. The most remarkable feature is the double walled tower with a height of 10 m. During the day the sun heats the (humid) air inside the plant compartment. The heated air rises through the inner roof compartment into the outer duct of the tower where it is further heated by the sun. As the tower is closed at the top, the air does not leave the greenhouse but is cooled with a heat exchanger in the central duct of the tower. The coolant is stored in a heat buffer. The cooled air flows back into the warm greenhouse, closing the cycle. During the night, the heat exchanger heats the air and the air movement reverses; hot air rises through the heat exchanger to the top of the tower and flows down through the outer duct. The cooled cooling-water returns to the storage for later use. Since the air cycle in the greenhouse is closed, the water evaporated by the plants stays inside. During the day, warm, moist air flows into the tower, where the moisture condenses against the cold surface of the heat exchanger. To facilitate water desalination, a so-called inner roof is used over which (salt) water is sprayed. The water that evaporates from the inner roof follows the air flow and condensates in the heat exchanger.

The crop (first green bean, later followed by Okra) was grown in soil with a balanced texture of about 20-30 cm deep. A sand bed with a thickness of about 10 cm was placed on top of the soil. Drip irrigation was used, controlled by an autonomous fertigation system. The drain water was recovered and recycled.

The condensate coming from the heat exchanger and from the roof is recovered, the quantity is measured automatically and it is used again for irrigation. Temperature and humidity are measured at all vital places inside and outside the greenhouse and technical installation. Other measured quantities are outside global radiation, wind speed and -direction and the CO_2 concentration. All pumps and valves are controlled by data loggers that are connected to a personal computer on which a database runs. This enables implementation of controllers in several software packages, including Matlab and LabVIEW.

Watergy greenhouse control system

In this thesis our primary focus is on the closed greenhouse in Spain and, more specifically, on the development of an advanced control system for the climate in this greenhouse. The requirements for the control system hardware are quite different from the current horticultural standards. Hence, it was decided to design the control system from scratch, using a so-called methodic design method. This allows the design of the control system in a methodic way where, at each stage, sub-goals and hardware requirements are summarized as to make an optimal choice for an innovative new control system for the greenhouse. More specifically, the design method divides the design process in three different phases; (i) problem definition, (ii) alternatives that solve the problem in (i) and (iii) the construction phase. The objective of our measurement and control system is “to measure all relevant states and to be able to control all actuators with advanced software controllers in the experimental greenhouse". The requirements are defined in more detail in chapter 2, and these range from measurement specifications to requirements on the flexibility of the control system.

Separate functions in the control system were identified (e.g. 'measure data', or 'calculate setpoints') and for all functions alternative solutions were studied in chapter 2 of this thesis. After weighting alternative solutions, the final system was designed and built. The control system contains data loggers installed near the greenhouse to log the required data and send control signals to the actuators. Furthermore, a personal computer was installed that contains a database for data storage and software to calculate new setpoints. The PC is connected to the data loggers over a standard wireless computer network. The installed sensors include temperature sensors for air, soil and water temperature, and also sensors for the measurement of humidity, air velocity, water flow, CO_2-level, global radiation, wind speed and wind direction. All sensors are low in maintenance and have a good accuracy. To control the actuators, a flexible system of distributed relay technique is deployed.

Due to the use of the methodic design method, the measurement and control system that is developed for the greenhouse in Spain is generally applicable for development of an advanced greenhouse climate control system in horticulture. This is illustrated by the fact that another control system was developed for the second prototype in Berlin (also part of the Watergy project), which is designed along the same lines and the same methodology.

Climate model

The third chapter describes the development of a physics based state-space model of the climate inside the Watergy greenhouse in Spain. To keep the number of states in the model limited, it was decided to aggregate underlying process details into (lumped) compartments. The values of the parameters in each compartment are location specific so that these values must be calibrated carefully. Calibration is performed with a controlled random search (CRS) algorithm that is used on partial models, a method we refer to as 'estimation in parts' in this thesis. This means that only a part of the whole model was used in combination with measured data for state values of neighboring compartments. This method results in parameter estimates that converge well and computation times are much faster in comparison to a full-model calibration. The parameter fluctuations over the year were studied by repeated parameter estimation for each month. Since some parameters fluctuate significantly, the use of adaptive mechanisms to change model parameters is motivated which leads us to chapter 4 of the thesis.

Model adaptation and adaptive receding horizon optimal control

In chapter 4 an extended Kalman filter (EKF) is introduced to allow on-line estimation of parameter values over the year. The application of an EKF for parameter estimation is tested with measured data recorded over a period of one year using a model that describes the air temperature and moisture content in the Watergy greenhouse. To increase the accuracy of the estimates, partial models are used in combination with observations at the borders of these partial models. The filter adequately adjusts parameter values, which improves the model fit substantially compared to simulations with non-varying parameters. Furthermore the filter tracks sudden changes in the system adequately and events such as pruning of the plants or opening of the greenhouse windows can be observed through sudden variations in the on-line estimated parameter values. For horticultural practice, these results are significant since application of advanced model-based controllers in horticultural practice is often hampered by the laborious work to derive good models for specific situations. As adaptive models (including an EKF recursive algorithm) calibrate their parameters online, application of these models is much easier and this result paves the way for self-learning controllers in practice.

Finally, in chapter 5 the adaptive model (including an EKF for parameter adjustments) is utilized in a simulation exercise of a receding horizon optimal controller (based on Bryson's well-known dynamic optimization algorithms) for truly model based optimal control of the Watergy greenhouse. First we make a motivated choice of 'optimality' through the choice of a goal function that leads the dynamic optimization algorithm in its search for an optimal control strategy. The adaptive model-based receding horizon controller is then exploited to study the benefits of adaptive receding horizon optimal control by introducing a drift on two plant evapotranspiration parameters and comparing this situation with the case where only nominal (constant) values of these parameters were used. As expected, the results are in favor of the adaptive setup.

Other benefits of the model-based approach become apparent when making a model based ‘what-if’ analysis in which some of the limitations of the current setup are remedied in simulation study. We found that if the cooling capacity is increased by improving the night-cooling of the cold storage, around 3 times as much condensation can be captured in the heat exchanger. Also the temperatures in the plant compartment would be drastically lower (5 to 8 $^\circ$C) than in the standard case, which would favor plant growth. Moreover, under such circumstances advanced control shows its true benefits as it brings significant improvements over straight-forward on/off control.

Samenvatting

Grote delen van de wereld hebben te kampen met toenemende water tekorten. Deze situatie zal in de toekomst waarschijnlijk verder verslechteren door bevolkingsgroei en klimaatverandering. Omdat de landbouw een grootverbruiker van water is, is in deze sector veel te winnen door de efficientië van watergebruik te verhogen. Eén van de initiatieven hiertoe is het Watergy project, waarvan dit proefschrift deel uitmaakt.

Het Watergy project

Het doel van het Watergy project is tweeledig; allereerst worden de mogelijkheden van lokale energie besparing en afvalwaterzuivering in een stedelijke omgeving onderzocht. Ten tweede worden de mogelijkheden voor jaarrond plantproductie in combinatie met de productie van zoet (uit zout) water bestudeerd in een nieuw type kasontwerp. De partners binnen het Watergy project zijn: leerstoel architectuur van de Technische universiteit in Berlijn (TUB), onderzoeksinstituut Cajamar, Las Palmerillas, in Almeria, Spanje, en twee groepen van Wageningen Universteit en Research Center; te weten WUR glastuinbouw en de leerstoel Meet-, Regel- en Systeemtechniek (waaraan dit onderzoek is uitgevoerd).

De Watergy kas in Spanje

De Watergy kas – die is gebouwd in Almeria (zuid Spanje) – is een gesloten kas van 14×14 meter waarin de lucht gedurende de dag gekoeld kan worden. Door deze koeling is het mogelijk het productie seizoen te verlengen in vergelijking tot de traditionele kassen in warme landen, waar een productie stop in de zomer gebruikelijk is. Het energieoverschot wordt gebruikt om zoet water te produceren uit zout of 'grijs' water. Het meest opvallende onderdeel van de kas is de dubbel-wandige toren met een hoogte van 10 m. De werking van het systeem is als volgt: gedurende de dag warmt de zon de (vochtige) lucht in het plant compartiment op. De verwarmde lucht stijgt op door het 'inner roof' compartiment (de ruimte tussen het verlaagde plafond en het kasdek), naar de buitenste kanaal in de toren, waar de lucht verder wordt verwarmd door de zon. Aangezien de toren bovenaan is gesloten, verlaat de lucht de kas niet, maar wordt gekoeld door de warmtewisselaar in het centrale kanaal in de toren. De koelvloeistof hiervoor wordt opgeslagen in een warmte buffer. De gekoelde lucht stroomt onderuit de toren terug de warme kas in, waarmee de cirkel gesloten is. Gedurende de nacht verwarmt de warmtewisselaar de lucht waardoor de luchtstroom omdraait: warme lucht stijgt door de warmtewisselaar naar de top van de toren en stroomt door het buitenste kanaal terug. Het koelwater wordt hierdoor gekoeld en opgeslagen in de opslag tanks voor later gebruik. Aangezien geen luchtuitwisseling met de buitenlucht plaatsvindt, blijft het vocht dat door de planten is verdampt in de kas. Gedurende de dag condenseert het vocht uit de in de warmtewisselaar in de toren. Om ontzilting van zout of brak water mogelijk te maken, wordt over het verlaagde (folie) plafond zout water gesproeid. Dit water verdampt, volgt de luchtstroom en condenseert in de warmtewisselaar.

Het gewas (eerst snijbonen, later Okra) werd geteeld in de volle grond met gebalanceerde structuur met hierop een zandbed van 10 cm. De druppel irrigatie werd aangestuurd door een autonoom irrigatie systeem. Het drainwater is opgevangen en opnieuw gebruikt.

De condensatie die is opgevangen uit de warmtewisselaar en van het kasdek werd gemeten en opnieuw gebruikt voor irrigatie. De temperaturen en luchtvochtigheden zijn gemeten op alle belangrijke plaatsen in de kas, buiten en in de technische installatie. Overige gemeten grootheden zijn globale zoninstraling, wind snelheid en richting en de CO_2 concentratie in de kas. Alle pompen en kleppen werden bestuurd door dataloggers die verbonden zijn met een personal computer waarom een database loopt. Hierdoor is het mogelijk om regelaars te implementeren in verschillende software pakketten, waaronder Matlab en LabVIEW.

Besturingssysteem van de Watergy kas

De primaire focus van dit proefschrift is de gesloten kas in Spanje en, meer specifiek, de ontwikkeling van een geavanceerd regelsysteem voor het klimaat in deze kas. De eisen die aan het regelsysteem gesteld worden verschillen behoorlijk van de huidige standaards in de (Nederlandse) tuinbouw. Daarom is besloten het regelsysteem van nul af te ontwikkelen met behulp van de methodisch ontwerp methode. Hierdoor kon het ontwerp voor het regelsysteem op een methodische manier, waarbij tijdens iedere fase in het proces (sub)doelen en eisen worden gespecificeerd om te komen tot een zo goed mogelijke keuze. Methodisch ontwerpen bestaat uit drie fasen; (i) probleem definitie, (ii) zoeken van alternatieven om het probleem in (i) op te lossen, en (iii) de constructie fase. De doel van ons meet-, en regelsysteem is "het meten van alle relevante toestanden en het mogelijk maken alle actuatoren te besturen met geavanceerde software regelaars in de experimentele kas". De eisen die aan het systeem gesteld zijn, staan beschreven in hoofdstuk 2, en lopen uiteen van specificaties met betrekking tot de metingen tot eisen over de flexibiliteit van het regelsysteem.

Losse functies binnen het regelsysteem zijn geïdentificieerd (bijvoorbeeld 'meet data', en 'bereken gewenste waarde'). en voor alle functies zijn alternatieve oplossingen bestudeerd en beschreven in hoofdstuk 2. Na weging van deze alternatieve oplossingen is het totale systeem ontworpen en gerealiseerd. Het regelsysteem bevat datalogers, geïnstalleerd bij de kas, die relevante data registeren en de actuatoren aansturen. Een personal computer bevat een database voor opslag van de meet en regeldata, en sofware om nieuwe gewenste waarden voor de kas uit te rekenen. De PC is verbonden met de dataloggers over een standaard draadloos computer netwerk. De geïnstalleerde sensoren meten de temperatuur van lucht, water en bodem, de luchtvochtigheid, luchtsnelheid, waterdebieten, CO_2-niveau, globale zoninstraling, windsnelheid en windrichting. Een flexibel systeem van gedistribueerde relais-techniek bestuurde de actuatoren.

Door de het gebruik van de methodisch ontwerp methode is het meet- en regelsysteem dat nu is ontworpen voor de Watergy kas algemeen toepasbaar voor het ontwikkelen van een geavanceerd kas klimaat regelsysteem in de tuinbouw. Dit wordt geïllustreerd door het tweede prototype binnen het Watergy project dat in Berlijn is gebouwd en waarvoor het regelsysteem is ontworpen volgens dezelfde methode als hier beschreven.

Kas klimaat model

Hoofdstuk drie beschrijft de ontwikkeling van een fysisch toestandsmodel model van het klimaat in de Watergy kas te Spanje. Om het aantal toestanden binnen het model laag te houden zijn ingewikkelde, onderliggende processen samengevoegd in compartimenten. De waarden van de parameters in deze compartimenten zijn locatie specifiek en moeten dus nauwkeurig gekalibreerd worden. De kalibratie is gedaan met het zg. 'controlled random search' algoritme toegepast op deel-modellen, een methode die we 'estimation in parts' (schatting in delen) zullen noemen in dit proefschrift. Dit betekent dat slechts een deel van het hele kasmodel wordt gebruikt in combinatie met gemeten data voor de waarden van de toestanden van buurcompartimenten. Deze methode resulteert in parameter schattingen die goed convergeren en rekentijden die veel korten zijn vergeleken met parameter kalibratie met het hele model. Parameter fluctuaties over het hele jaar zijn bestudeerd door elke maand opnieuw een parameterschatting uit te voeren. Sommige parameters fluctueren significant, wat het gebruik van adaptieve mechanismen om de model parameters aan te passen motiveert hetgeen ons bij hoofdstuk vier brengt.

Model aanpassing en adaptieve optimale regelaar met wijkende horizon

In hoofdstuk vier wordt een extended Kalman filter (EKF) geïntroduceerd ten einde de waarden van parameters online te schatten gedurende het jaar. Het gebruik van het EKF voor parameter schatting is getest met meetdata van één jaar en een model dat de lucht temperatuur en vochtigheid in de Watergy kas beschrijft. Deelmodellen in combinatie met meetdata zijn gebruikt om de nauwkeurigheid van de schattingen te verhogen. Het Kalman filter past de parameter waarden aan, waardoor de modelfit substantieel beter is in vergelijking met simulaties met vaste parameter waarden. Ook detecteert het filter plotselinge veranderingen in het systeem zoals snoeien van de planten of openen van de ramen doordat de on-line geschatte parameter waarden plotseling van waarde veranderen. Voor de tuinbouwpraktijk zijn dit belangrijke resultaten aangezien het afleiden van goede modellen voor specifieke situaties veel tijd vergt en dit een grote bottleneck is voor toepassing van geavanceerde model-gebaseerde regelingen in de praktijk. Aangezien adaptieve modellen (in combinatie met een EKF recursief algoritme) hun parameter waarden online bijstellen is het gebruik van deze modellen veel makkelijker. Dit heft dus een van de grootste beperkingen op voor de toepassing van zelf-lerende regelingen in praktijk toepassingen.

In hoofdstuk vijf wordt het adaptieve model gebruikt in een simulatie met een wijkende horizon optimale regelaar (eng. receding horizon optimal controller; RHOC), gebaseerd op de dynamische optimalisatie algoritmes van

Bryson.

Eerst wordt een gemotiveerde keuze gemaakt voor een doelfunctie die wordt gebruikt door het dynamisch optimalisatie algoritme bij het zoeken naar de optimale regelacties. De adaptieve model gebaseerde regeling met wijkende horizon wordt gebruikt om de voordelen van adaptieve regeling te bestuderen door twee parameters in het plantverdampingsmodel te laten variëren. Deze situatie wordt vergeleken met een situatie waarbij de parameters niet worden gevarieëerd. Zoals verwacht zijn de resultaten van de adaptieve regeling beter dan van de niet adaptieve.

Meer voordelen van de model-gebaseerde aanpak worden duidelijk bij het doen van 'wat-als' simulatie analyse waarin enkele limitaties van de huidige kas worden opgeheven. We vonden dat als de capaciteit van het koelsysteem wordt vergroot door de nacht-koeling van de koude opslag te vergroten, de hoeveelheid geproduceerde condensatie met een factor 3 stijgt. Ook wordt in deze situatie de temperatuur in het plant compartiment drastisch lager (5 to 8 $^\circ$C) dan in de standaard case waardoor de plantgroei bevorderd wordt. Bovendien worden onder deze omstandigheden de voordelen van geavanceerde regelstrategieën duidelijk, aangezien er significante verbeteringen zijn ten opzichten van simpele aan/uit regelaars.

Dankwoord

Een proefschrift schrijf je voornamelijk alleen. Maar ieder systeem dat onderhevig is aan weerstand, heeft aandrijving van buitenaf nodig om op gang te blijven. Net als een wielrenner die een berg beklimt en een duwtje krijgt van iemand uit het publiek, ben ik in de afgelopen vijf jaar door vele gesteund of 'uit de wind gezet'. Al deze mensen (en ongetwijfeld zijn het er meer dan genoemd in het namenlijstje op volgende pagina) wil ik van harte bedanken; samen hebben jullie eraan bijgedragen dat het proefschrift uiteindelijk toch is afgekomen.

Enkele mensen verdienen een speciaal woord van dank; Om te beginnen is de hulp van mijn begeleider Hans Stigter en promotor Gerrit van Straten natuurlijk onontbeerlijk geweest. De discussies over de inhoud en richting van het proefschrift waren soms wat confronterend, maar toch hoofdzakelijk leuk en leerzaam. Het contrast tussen jullie beiden bleek al vrij snel en is tot het einde gebleven; Hans die enthousiast en opbeurend bleef. Gerrit die de kwaliteit goed in de gaten hield door tot het laatst kritische vragen te stellen. Zelfs op het kerstdiner presteerde je het nog om te zeggen dat we 'nog eens naar de resultaten van hoofdstuk 3 moesten kijken', terwijl ik het toch echt voor publicatie geschikt vond. Al met al waren jullie samen een prima team, waarvoor hartelijke dank.

Los van het inhoudelijke aspect van mijn promotie periode heb ik de sfeer in de leerstoelgroep altijd als erg leuk en bijzonder ervaren. De dagelijkse, stevige, discussies waren altijd gepassioneerd en bijna altijd amusant. Ook de weekendjes weg of ons volleybalspel op de WE-day waren ieder jaar opnieuw een groot succes (sociaal gezien dan; sportief hebben we helaas nooit iets klaargemaakt. De (voor MRS begrippen) grote groep AIO's die bijna gelijktijdig begon zorgde voor een gezellige sfeer waarin het goed klagen was over begeleiders en ander promoveer-ongemak.

In het eerste deel van mijn AIO periode hebben we met veel mensen hard gewerkt om de kas in Spanje te automatiseren. Voor mij de eerste keer dat ik in zo'n groot project meeliep, maar gelukkig bracht de ervaring van Hans Janssen vaak uitkomst. Samen hebben we veel tijd doorgebracht in Spanje waar altijd te veel werk en te weinig vrije tijd was. Toch hebben we veel van de omgeving van Almeria gezien en uitgebreid genoten van de Spaanse keuken. Hans, de vele discussies en je nuchtere kijk op het vele werk dat steeds op ons wachtte, heeft ervoor gezorgd dat het toch vooral leuk was om naar Spanje toe te gaan en dat het niet te veel op een werkkamp leek. Overigens past het hier om alle overige mensen die hebben meegewerkt aan het tot standkomen van het meet- en regelsystem van harte te bedanken; zonder jullie was het niet gelukt twee werkende prototypes te automatiseren.

Voor het Watergy project was ieder half jaar overleg met alle partners, waarin de stand van zaken besproken kon worden en aan de contacten kon worden gewerkt. Ondanks dat er zo nu en dan wat hete hangijzers besproken moesten worden, was het avondprogramma zonder uitzondering geweldig leuk. Dat ik ooit met jullie op kroegentocht door nachtelijk Almeria zou dwalen was een zeer aangename verrassing.

Nadat de officiele looptijd van het Watergy project verstreken was, kreeg ik de mogelijkheid nog meer ervaring met internationaal onderzoek op te doen door deel te nemen aan de summer school van IIASA, in Oostenrijk. Hier kon ik me in alle rust richten op het uitwerken van de optimale besturing voor de kas, geholpen door Sergey Aseev en de dynamic systems groep. Dit was een erg leuke tijd waarin ik veel geleerd heb over optimale besturing en culturele verschillen.

Sinds oktober vorig jaar werk ik buiten de universiteit en het afronden van een proefschrift naast een gewone baan bleek niet de best denkbare combinatie. Dat dit toch is gelukt, is voor een groot deel te danken aan de flexibele opstelling bij Ecofys waar ik de ruimte kreeg tijdelijk minder te werken; hartelijk bedankt voor het begrip.

Als AIO heb je de neiging om te denken dat je het druk hebt en dat je werk erg belangrijk is. Ook ik ontkwam soms niet aan dit soort gedachten. Dan was het heel fijn dat Charlotte hiervoor begrip kon opbrengen, zonder al te ver in mijn zelfmedelijden mee te gaan. Je steun, begrip tijdens tegenslagen en vreugde tijdens de successen maakten de pieken hoger en de dalen minder diep. Ook mijn vrienden, zussen hen hun aanhang droegen hieraan bij; relativeren en het in het juiste perspectief zetten van mijn werk lukte jullie goed. De gezamelijke wandelvakanties en kroegavonden waren een welkome afleiding van het werk.

En, zoals de Engelsen het zo mooi zeggen, 'last but not least' gaat mijn dank uit naar mijn ouders. Toen ik de kans kreeg AIO te worden waren jullie erg enthousiast over het onderwerp en de mogelijkheden van het werken in een Europees project. Dat enthousiasme is nooit afgenomen; altijd waren jullie geïnteresseerd en motiverend. Maar ook wisten jullie op tijd de dagelijkse beslommeringen te relativeren; 'als je alles van tevoren weet, kom je met een dubbeltje de wereld om' is een veel gehoorde uitspraak bij ons thuis. Het kostte meer dan een dubbeltje, maar het is af.

Claus Hans Hans Kees
Kees Dirk Reiner
Reinier Kfir Gert-Jaap
Guillermo Theo Timo
Wilko Hadiyanto Paco
Arjan Derk-Jan Esteban
Geerten Jan Jin John
Maarten Martijn Martin
Stefan Tijmen Ton
Ruben Harm Sam Tom
Karel Michael Michel
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Gerrit Cheng Olaf Olaf
Charlotte Ilse Anneke
Hanneke Ingrid Ard
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Paula Ellen Renee
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Curriculum Vitae

Bas Speetjens was born the 14th of Januari 1979 in The Hague, The Netherlands. In 1997 he completed high school at the IMC in Rijswijk (zh).

From 1997 until 2003 he studied Agriculatural Engineering at Wageningen University. During his studies he did an internship for 6 months at HortResearch, Palmerston North, New Zealand, after which he completed his studies with a major thesis in applied physics and a minor in control engineering.

After finishing this study, there was the opportunity to join the Systems and Control group in a PhD position within the Watergy project. As part of his PhD studies in 2006 he joined the young scientist summer program at IIASA, Laxenburg, Austria. The results of the PhD study are described in this thesis.

Since October 2007 the author works at Ecofys, Utrecht, NL.

PE & RC PhD Education Certificate

With the educational activities listed below the PhD candidate has complied with the educational requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE & RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

Review of Literature (5 credits)
- Model types and applicability of the various modeling methodologies that can be used for the Watergy greenhouse (deliverable for the EU project)

Laboratory training and working visits (14 credits)
- Watergy project, prototype 1; CajaMar, Spain (2003)
- Watergy project, prototype 2; TU Berlin (2004)
- Young Scientist Summer Program; IIASA, Vienna (2006)

Post-Graduate Courses (10 credits)
- Ethical dilemma for life scientists (2005)
- Model predictive control; DISC (2005)
- Design methods for control systems; DISC (2005)

Competence Strengthening / Skills Courses (3.3 credits)
- Techniques for writing and presenting a scientific paper; PE & RC (2004)
- Time planning and project management (2004)
- Workshop scientific publishing: an introductory workshop for PhD students and young authors (2004)
- Tools of systems analysis; IIASA (2006)

Discussion Groups / Local Seminars and Other Scientific Meetings (5.8 credits)
- Tuesday presentations SCO (2003-2006)
- Statistics, maths and modelling; PE & RC (2005)
- Fieldrobot (2006)
- Philosophy in science; IIASA (2006)
- Late summer workshop; IIASA (2006)

PE & RC Annual Meetings, Seminars and Introduction Days (3.9 credits)
- PE & RC day; 4 × 1 day (2003-2006)
- DISC; 3 × 3 days (2003-2006)

International Symposia, Workshops and Conferences (6 credits)
- Greensys (2004)
- Hortimodel (2006)

Supervision of MSc students (4)
- Modelling of the Watergy heat exchanger
- PIP control for the CO_2 level in the Watergy greenhouse
- Water balance in the Watergy greenhouse
- Greenhouse climate model for the Watergy greenhouse