Optimal management of energy resources in greenhouse crop production systems

P.J.M. van Beveren

Propositions

1. Dynamic control of energy equipment is crucial in greenhouse production systems.
   (this thesis)
2. Problem formulation is the most important step to solve an optimal control problem.
   (this thesis)
3. Playing a musical instrument contributes to improving both cognitive and social skills.
4. Highly optimized systems are vulnerable to crisis situations.
5. The Dutch privacy regulations have gone too far.
6. Social service enhances communal cohesiveness.

Propositions belonging to the thesis entitled

Optimal management of energy resources in greenhouse crop production systems

P.J.M. van Beveren

Wageningen, 31 January 2023

Optimal management of energy resources in greenhouse crop production systems

P.J.M. van Beveren

Thesis committee

Promotors
Prof. dr. ir. E.J. van Henten
Professor of Farm Technology
Wageningen University

Prof. dr. ir. G. van Straten em.
Professor of Systems and Control
Wageningen University

Co-promotor
Dr. J. Bontsema
Senior Scientist
Bontsema Consultancy

Other members
Prof. dr. ir. K.J. Keesman, Wageningen University & Research
Prof. dr. ir. J.M.A. Scherpen, Rijksuniversiteit Groningen
Prof. dr. ir. L.F.M. Marcelis, Wageningen University & Research
Dr. ir. A.N.M. de Koning, Ridder Growing Solutions B.V.

This research was conducted under the auspices of the Graduate School of Production Ecology and Resource Conservation (PE&RC)

Optimal management of energy resources in greenhouse crop production systems

P.J.M. van Beveren

Thesis
submitted in fulfilment of the requirements for the degree of doctor
at Wageningen University
by the authority of the Rector Magnificus
Prof. Dr. A.P.J. Mol,
in the presence of the
Thesis Committee appointed by the Academic Board
to be defended in public
on January 31, 2023
at 4 p.m. in the Omnia Auditorium.

Pieter Jacobus Matthias (Peter) van Beveren
Optimal management of energy resources in greenhouse crop production systems
182 pages

PhD thesis, Wageningen University, Wageningen, NL (2023)
With references, with summaries in English and Dutch

ISBN 978-94-6447-536-4
DOI https://doi.org/10.18174/583595

Contents

Chapters 2, 3, 4, and 5 have been published as a journal article, as indicated on the first page of each chapter. Except for a different font, the addition of chapter-based numbering, and the addition of extra information in the footnotes (explicitly stated), the text of the manuscripts was integrally adopted and maintained throughout this thesis. Citations should be made to the original published article(s).

1

General Introduction

P.J.M. van Beveren

1.1 Background

A greenhouse is a permanent glass or plastic covered building for the production of fruits, vegetables, flowers, or ornamentals that has means for controlling the crop environment (Stanghellini et al., 2019). Cultivation in greenhouses is found in many places all over the world. Protected horticulture around the world has grown to an estimated area of 500 000 ha of commercial vegetable production in greenhouses of which 40 000 ha is glass-covered (Stanghellini et al., 2019). The technology level of protected cultivation differs hugely world-wide.

The total area of glasshouses in The Netherlands increased from approximately 3300 ha in 1950 to 9600 ha in 1990 (Bakker et al., 1995). In the years 2000 to 2005, the area was relatively stable around 10 500 ha. From 2005, the Dutch glasshouse area decreased to just over 9000 ha in 2017 (LEI Wageningen UR, 2015). The number of companies started decreasing earlier, resulting in a trend of less and bigger companies. The average company size was 1 ha in 2000 and 2.6 ha in 2017 (LEI Wageningen UR, 2015). Nevertheless, the production per square meter greenhouse area increased by about 40 % between 1990 and 2013 due to, among other reasons, better light use efficiency and increased use of artificial lighting (Van der Velden and Smit, 2014). New cultivars and improved cultivation strategies also enhanced production (Hemming et al., 2017).

Although the average energy consumption per square meter reduced from 45 m^3 gas equivalents in 1990 to 27.5 m^3 gas equivalents in 2013 (Van der Velden and Smit, 2014), greenhouse horticulture in the Netherlands remains a major energy consumer. The horticultural sector accounted for about 10 percent of the total Dutch natural gas consumption and about 5 % of the total Dutch electricity consumption in 2011 (Van der Velden and Smit, 2013). Because of the increasing area of artificially lighted greenhouses and increasing lighting levels, the proportion of electricity in the total energy consumption of greenhouses increased from 10 % in 2010 till 26 % in 2017 (Van der Velden and Smit, 2018).

Besides the costs of gas and electricity, growers have different motivations to reduce the energy consumption of their greenhouse. Reasons are, among others, social acceptance of greenhouse crop production and agreements of the horticultural sector with the government. Goals were formulated in the 'Action plan for climate-neutral greenhouse horticulture' (Van der Valk and Van der Poll, 2007). The main goal of this plan to reduce CO_2 emissions by 45 % in 2020 (compared to 1990) by decreasing energy demand and increasing the amount of energy from sustainable sources. Furthermore, the Dutch horticultural sector agreed to increase energy-efficiency by 2 % per year till 2020 (Van der Velden and Smit, 2014). Later on, the sector agreed in the 'Multi-year agreements on Energy' ('Meerjarenafspraak Energie') to produce without CO_2 emissions in 2050 (Van der Velden and Smit, 2019).

High-tech greenhouses in temperate climates, like the Netherlands and Belgium (Van Den Bulck et al., 2013), need heating in order to maintain optimal growing conditions. Ventilation is needed in warmer periods to lower greenhouse temperature and to prevent too high humidity levels. High humidity levels could increase the risk of fungi and diseases e.g. *Botrytis cinerea*, that decreases yield and post-harvest quality (Körner and Holst, 2005; Cámara-Zapata et al., 2019). The disadvantage of cooling by natural ventilation is that at the same time CO_2 is removed from the greenhouse air, while CO_2 is needed for photosynthesis and thus production.

In some greenhouses, active cooling can be applied next to natural ventilation. Those greenhouses are often referred to as semi-closed greenhouses (De Zwart, 2008; Campen and Kempkes, 2011; Gieling et al., 2011; Qian et al., 2012). The ventilation windows are opened when the cooling system has insufficient capacity (Qian et al., 2011). When active cooling is applied, higher CO_2 concentrations can be achieved in the greenhouse, and consequently, a higher potential plant production at lower CO_2 injection rates (Dieleman and Hemming, 2011; Gieling et al., 2011; Teitel et al., 2012). The semi-closed greenhouse can save a lot of energy by minimizing the ventilation and storing the surplus heat. In this way, natural gas consumption for heating is reduced. Additional benefits of semi-closed greenhouses are better control of the greenhouse climate, reduced water vapour loss through ventilation, and reduced use of pesticides because of the reduced entry of insects and fungal spores into the greenhouse (Sapounas et al., 2020).

Besides the concept of the semi-closed greenhouse, an increasing number of greenhouses are equipped with a complex technical infrastructure to modify the indoor environment. A broad range of options are available; air conditioning units for heating and cooling, pipe rail heating systems, a CO_2 supply system, insulating (energy) screens, shadow screens, ventilation windows, and supplementary lighting (Vanthoor et al., 2011). CO_2 and electricity are commonly generated by a combined heat and power installation (CHP). Sometimes CO_2 is obtained from external sources. Equipment for production, storage, and conversion of thermal energy include (a combination of) CHP's, boilers, heat pumps, short-term buffers, aquifer heat storage, cooling towers, and geothermal sources.

The climate in high-tech greenhouses is usually controlled via a process control computer. First, the climate recipe in terms of the desired temperature, humidity level, CO_2 level, and lighting throughout the day is defined. Second, this climate recipe is translated by the grower into settings and operating strategies for running the climate conditioning equipment as well as the equipment for generation and storage of energy. Operating these systems relies on long-term experience of the grower and heuristic rules (Berenguel et al., 2003; Van Straten, 1999). Greenhouse process control computers have many settings and configuration options available (Kamp and Timmerman, 1996). For complex configurations of energy equipment, a separate management system is installed next to the process control computer. This additional system operates often based on a set of pre-defined rules. This set of rules is tailor-made. The grower supervises the operation and can overrule the controller manually when necessary. Due to the inherent complexity of the systems and lack of insight in all operations and associated costs at the same time, the operation is usually not optimal with respect to energy consumption, production, and costs.

1.2 Problem description

The quest for energy saving in modern greenhouse horticulture has led to investments in a wide variety of (energy) equipment. In the daily operation of the greenhouse, growers have to decide about the desired growing conditions in the greenhouse and the deployment of the available equipment. Environmental variables that have to be controlled in order to control the greenhouse climate (and thus crop production) include light, temperature, humidity, and CO_2 concentration. An overview of different approaches to control the greenhouse environmental variables is provided by Rodríguez et al. (2015b). Bakker et al. (1995), Von Zabeltitz (2010), and ASHRAE (2011) provide an overview of the available technologies for controlling the indoor climate and design considerations when constructing a greenhouse. Actuators to control the greenhouse climate include heating systems, ventilation windows, screens, and artificial lighting. Given the broad range of available climate conditioning equipment and energy sources, their optimal deployment in view of energy conservation has become a complex matter. The operation of the equipment is complex due to, among other reasons, varying heat and cooling demands of the greenhouse, varying prices of gas and electricity, varying prices of the salable crop produce, uncertainty in outdoor weather conditions. Because of these reasons, the need for energy and cost-effective control schemes to support the grower in this process increases.

The infrastructure for energy equipment is not only complex at the level of a single greenhouse, there could also be a complex relationship between the greenhouse system and its environment. A growing number of greenhouses also share heat. CO_2 can be obtained from the boiler, the CHP, or other industrial resources. Electricity from the CHP is used for lighting and is sold to the grid. Furthermore, the prices of natural gas and electricity show strong fluctuations. Operating this complex technical infrastructure is a challenging task for growers. Therefore, more and more growers request support from research institutes, advisers, and suppliers of greenhouse equipment for (technical) support in solving the energy scheduling problem.

The motivation for this project was the practical question from growers and suppliers about how the management of increasingly complex systems in greenhouses could be improved in terms of minimal energy use, minimal energy costs, and easiness of use. The work in this thesis is the core of the STW project 'Optimal management of energy resources in greenhouse production systems' (OMER, SWT project number 11846).

1.3 Objective

Energy consumption is an important theme in (Dutch) greenhouse horticulture. The main objective of this thesis is to develop and demonstrate an optimization framework for minimizing the total energy consumption and energy costs of modern high-tech greenhouses while maintaining crop production. To stay close to current greenhouse practice, the optimization problem is split into two stages. The first stage focusses on the greenhouse climate and minimizes the total energy demand of the greenhouse while maintaining crop production. The second stage focusses on the utilization of equipment and minimizes the costs for implementing the minimal energy demand from stage 1.

Sub-objectives are to

1. develop an optimization framework that minimizes the total energy demand of greenhouses.
2. develop an optimization framework that minimizes the energy costs of greenhouses.
3. quantify the costs saving of the framework for a commercial test case.
4. quantify the energy saving of the framework for a commercial test case.

1.4 Approach

In order to fulfill the objective and sub-objectives of the research, a natural choice for the control structure is the optimal control concept. In general, optimal control deals with finding optimal control inputs for a given system, such that the goal function is optimized. In order to do this, a dynamic model of the system is needed. Optimal control techniques have been used in scientific studies in the field of greenhouse horticulture for more than thirty years (Seginer, 1989; Van Henten, 1994; Tap, 2000; Van Ooteghem, 2007b; Vanthoor et al., 2011; Bozchalui and Cañizares, 2014; Lopez-Cruz et al., 2018). It has been shown that the use of optimization techniques, and especially optimal control, contributes to lower energy consumption and/or higher income (Van Henten, 1994; Tap, 2000; Van Ooteghem, 2007b). The focus in the aforementioned studies was mainly on greenhouse climate management and control.

There are fewer studies about the deployment, operation, and control of all equipment that generates and stores warm water (used for heating) and cold water (used for cooling) for greenhouses. Molenaar et al. (2007) presented optimization of the energy costs for a closed greenhouse using a given heat, cold, and electricity demand for a typical year. Applications of various optimization techniques and analyses of energy systems with a wide variety of equipment in various configurations are present in other fields like office buildings, commercial buildings, and university campuses (Ooka and Ikeda, 2015; Cho et al., 2014). The studies mentioned in those articles mainly minimize total energy costs for heating and cooling based on a specified heat and cold demand. Greenhouses differ from the aforementioned buildings because of different heat and electricity demands, originating from different processes and requirements and a stronger thermal coupling to the outdoor climate. Furthermore, the greenhouse industry in the Netherlands is characterized by a wide deployment of CHP systems.

Despite their clear advantages, as far as known, none of the optimal control approaches published to date are currently being applied in modern process control computers in the greenhouse horticultural sector. Reasons include:

1. the lack of reliable crop production models for the wide range of crops and species grown in horticultural practice;
2. the limited trust of growers and doubts regarding the quality of crop models, and a lack of experimentally demonstrated advantages (Van Straten, 1999);
3. the widely felt desire to leave part of the decision making freedom in the

hands of the grower (Van Straten et al., 2000);

4. the lack of suitable on-line plant measurements. The best approach to any model-based control strategy requires feedback of the crop state (Van Henten (1994); Day (1998); Van Henten and Bontsema (2009)). Despite recent developments with e.g. vision techniques, on-line plant measurements are generally not available;

5. the absence of accurate predictions of market prices for gas, electricity, and produce.

In this thesis, a hierarchical two-stage approach is proposed (Fig. 1.1) to overcome most of these practical obstructions to apply optimal control in greenhouse practice. In stage 1, the grower defines desired trajectories for the greenhouse climate, for example, the lower and upper bounds of the desired temperature. In this way, objections 1, 2, and 3 are overcome. Then, the demand for heating, cooling, and CO_2 is calculated with optimal control techniques and a dynamic greenhouse climate model, including a generic transpiration and photosynthesis model. The goal of stage one is to minimize total energy input to the greenhouse. Therefore, the criterium in the optimal control formulation is the total energy input.

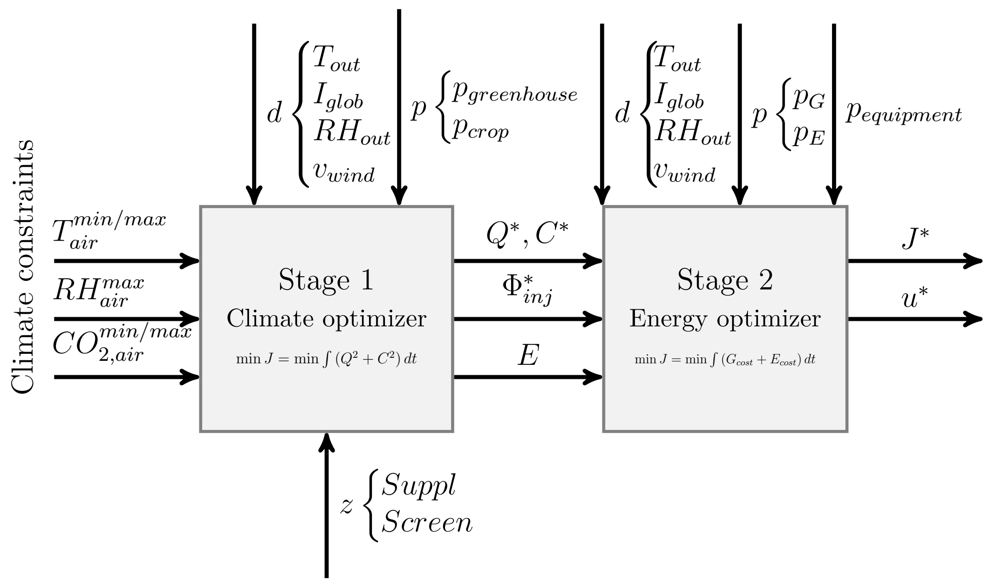


Figure 1.1: Overview of the 2-stage approach for minimizing energy input and costs for greenhouse crop production systems. In stage 1, the energy input to the greenhouse is minimized. In stage 2, the costs for production of heat, cold, and electricity are minimized. The climate optimization needs the climate constraints (set by the grower), outdoor climate measurements d, controls from the greenhouse z (here supplementary lighting $Suppl$ and screen position $Screen$), and greenhouse and crop parameters. The results of stage 1 are the optimal heat profile Q^*, optimal cold profile C^*, the CO_2 injection pattern Φ_{inj}^* and, electricity need of the greenhouse E. Those are fed into the energy cost optimizer. Here, the prices p of gas p_G and electricity p_E and parameters of the equipment are needed. The results of the optimization in stage 2 are the optimal controls u^* such as the power of the CHP and boiler, and heat fluxes to the buffers, which lead to the optimal value of the goal function J^*.

Many studies that minimize greenhouse energy costs include a crop development and production model e.g. Tap (2000); Van Ooteghem (2007b); Vanthoor (2011). The optimization method in stage 1 circumvents the need for crop development and production models (objection 1) yet still minimizes energy consumption. The principal idea is to exploit the dynamics of the ambient conditions as much as possible under given constraints with minimal energy input to the greenhouse. The method focuses on minimizing energy input to the greenhouse while obeying grower defined bounds for greenhouse air temperature, humidity, and CO_2 concentration. Thus, the responsibility for the crop yield and hence, income is left in the hands of the grower while the cost side is tackled by minimizing the resource input. The formulation of the optimal control problem allows for settings that are familiar to growers (e.g. minimum pipe temperature) to be easily taken into account in the optimization. The optimal control problem is formulated and designed to meet the perception of growers as close as possible.

In stage 2, the resulting energy demand from stage 1 serves as a reference, and optimal energy distribution of this demand over the various types of equipment is calculated with optimal control techniques and models of the technical infrastructure. The goal of stage 2 is to minimize total energy costs. Decoupling the optimization problem into two stages corresponds with the current situation in practice. A separate controller, next to the process control computer, commonly controls the energy equipment in greenhouses with a complex configuration of equipment.

Several issues that hamper the application of this optimization framework had to be resolved to be able to solve the resource allocation problem. In particular, the boiler and CHP installation operated in practice in a certain power range for efficiency and minimal wear. Therefore, zero-or-range constraints (Hansen and Huge, 1989) were implemented to operate the boiler and CHP between a specified range when they are active. Also, buffers for the storage of warm and cold water can not be loaded and unloaded at the same time because of physical limitations. Therefore, simultaneous loading and unloading of the buffer was prevented by defining the heat flux, from and to the buffers, as a single flux that can be positive or negative. Physical models of the equipment were kept as simple as possible so that most model parameters are known from the properties of the equipment itself or can be estimated with standard measurement data.

Calculating optimal control inputs used to be very time consuming because of the computational load of those problems. Due to developments in computational speed and software in the last decades, calculating optimal control inputs became more practical even for more complex dynamical system configurations. Different software packages are (commercially) available to solve optimal control problems in a much more user-friendly manner than in the past. In order to solve the problems described in this thesis different solvers from the Tomlab Optimization company were used (Holmström, 2001; Holmstrom et al., 2010). These solvers are especially suitable for solving applied optimization problems in MATLAB®.

1.5 Case-study

To demonstrate the benefits of the proposed two-stage approach over the standard operation, which, in general, is not an easy task, in this thesis, data from a real greenhouse served as a benchmark. In fact, the main research question was inspired by a real query of a commercial rose grower (Boonekamp in Bleiswijk). Their greenhouse served as a test case for the whole project. Because of the complex energy system present at the nursery, this greenhouse was assumed to be one of the most advanced systems present in the Netherlands at the start of the project in 2011. In Fig. 1.2 a schematic overview of the studied greenhouse with equipment for climate control and energy management is shown.

The greenhouse was a 40 709 m^2 Venlo-type greenhouse in Bleiswijk, the Netherlands (52 °N, 4.5 °E). Eave height was 6.4 m and ridge height was 7.2 m. The roof angle was 23°. The spans were equipped with 2020 ventilation windows 1.35 m × 1.67 m in size (1). A movable shadow screen (XLS 13 F Ultra) with 70 % light transmission was used (2), and a blackout screen was also present (3). In addition, the greenhouse was equipped with 4536 1000 W SON-T lamps (110 Wm^{-2}) for providing artificial lighting (4). A pipe rail heating system was installed, consisting of 1.1 m[pipe]m^{-2} (5). For each 80 m^2 area of greenhouse, one air-to-water heat exchanger (OPAC-106) was available and could be used to heat, cool, and dehumidify the greenhouse air (6). The greenhouse was connected to the OCAP (organic CO_2 for assimilation by plants) network in the Netherlands, which transports industrial CO_2 to growers (Ros et al., 2014). The maximum CO_2 injection capacity was 1200 kgh^{-1}. Two Avalanche+ rose cultivars were grown on a substrate (rockwool) in separate sections of the greenhouse.

The available pieces of equipment to supply the heating and cooling were an aquifer heat and cold storage (7), heat pump (8), short term low-temperature heat (LT) and cold (C) storage (9), a short therm high temperature (HT) buffer (10), boiler (11), CHP (combined heat and power installation, 12), and cooling towers (13). The heat was also delivered to the neighbouring greenhouse by filling a high-temperature buffer (14).

For 2012, greenhouse climate data and energy data (five-minute time interval) were obtained from the greenhouse process control computer (Hortimax) and the dedicated energy equipment controller (Lek Habo). The recorded data were obtained from different sensors and actuators that were already present at the nursery. In addition, a time series with real gas and electricity prices (15-minute time interval) was obtained via the electricity and gas supplier of the grower.

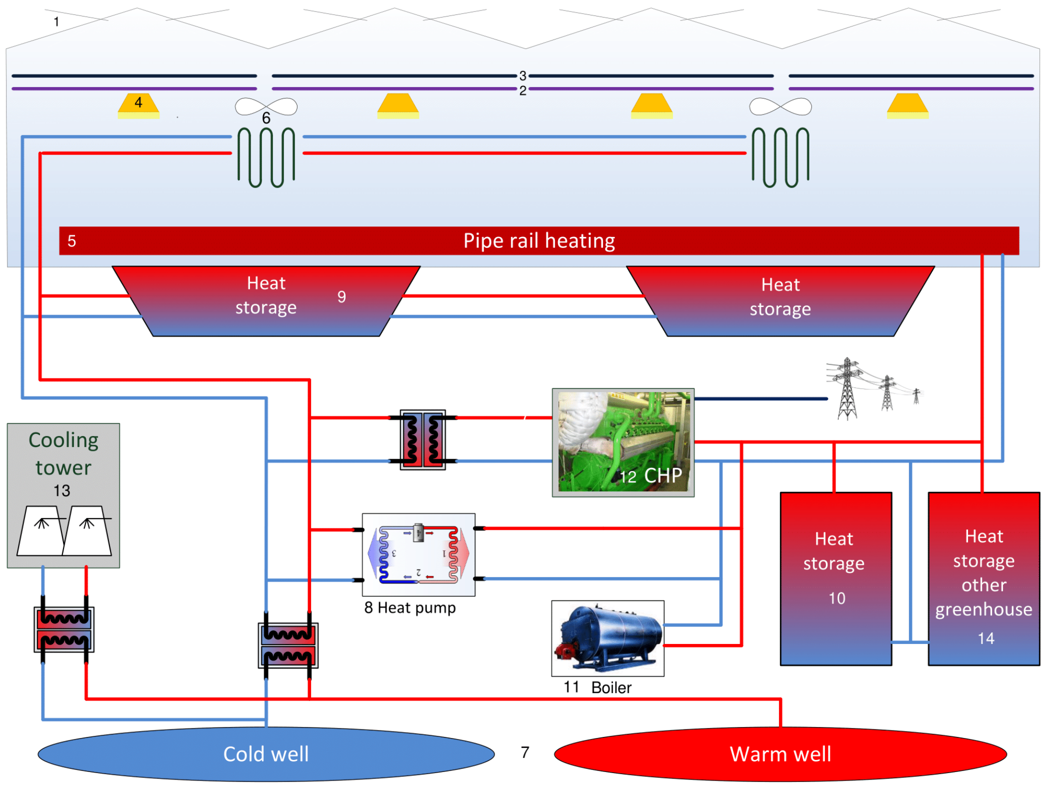


Figure 1.2: Schematic overview of the installations and equipment related to heating and cooling in the studied greenhouse. Numbers 1-6 are the actuators in the greenhouse that control the greenhouse climate. Numbers 7-14 are the installations that generate and store heat, cold, electricity, and CO_2 .

1.6 Demarcation

All optimizations in this thesis were performed afterwards on measured data of the greenhouse climate, outdoor weather, and equipment from the commercial case-study greenhouse. The prices of gas and electricity over time were given. So, no weather predictions or predicted prices were used for the optimizations. The whole case study focused on data from the year 2012. The configuration of the equipment in the case-study greenhouse was fixed.

The realized greenhouse climate by the grower is the result of all settings in the process control computer. This realized climate was assumed to be the desired climate and served as the basis for the climate constraints as set by the grower Fig. 1.1. The constraints around the realized climate were assumed to not affect crop quality and production. No crop development and/or production model was used. Nevertheless, crop assimilation and transpiration were incorporated in the greenhouse climate model.

1.7 Outline

In order to build up experience with the methodology and to reveal issues and peculiarities, in the various studies, climate components and greenhouse equipment were extended piece by piece. Chapters 2 and 3 deal with the first stage of the two-stage hierarchical optimization approach where the energy input is minimized. In Chapter 2, the model and optimization procedure for greenhouse temperature and humidity will be presented and evaluated. This model and the control problem formulation are extended with the carbon dioxide balance in Chapter 3. Chapters 4 and 5 deal with the second stage of generating the demanded energy given the available technical infrastructure at minimal costs. In the first part of Chapter 4, a system with a boiler and a heat buffer is optimized. Then, in the second part, this system is extended with a combined heat and power installation and an extra buffer for low-temperature heat storage. In Chapter 5, the system is further extended to the complete system as present in the studied nursery. Minimization of energy demand within climate constraints leads to a different demand pattern than realised by the grower in the greenhouse, so a comparison with both the actual (realised in the greenhouse) as well as the optimized demand profiles (resulting from Chapter 3) is possible. The optimization formulation and results for the total system are presented for both demand patterns.

2

Minimal heating and cooling in a modern rose greenhouse

P.J.M. van Beveren
J. Bontsema
G. van Straten
E.J. van Henten

Published as Van Beveren, P. J. M., Bontsema, J., Van Straten, G., & Van Henten, E. J. (2015). Minimal heating and cooling in a modern rose greenhouse. Applied Energy, 137, 97 109. doi.org/10.1016/j.apenergy.2014.09.083

Abstract

In a modern greenhouse there are a number of alternative systems that can be deployed to control the climate, and the choice what to use and when is not easy for the grower. A novel management system is proposed, consisting of an energy input minimizing module, and a module to realise the determined input with the available equipment. The current paper describes the energy minimization part.

A dynamic optimization tool based on optimal control theory was used to obtain time trajectories of the energy flux that minimizes total external energy input over the year, while maintaining greenhouse air temperature and humidity between grower defined bounds. By giving the grower the lead in defining the bounds, the method stays as closely as possible to the grower's daily practice and experience, and no crop production models and market prices are needed. The underlying dynamic model of temperature and humidity, based on known physical principles and parameters, compared very well with unique, year round high frequent data from a commercial rose greenhouse. A relatively simple crop transpiration model was validated separately, with very good results.

It was shown that over twelve selected days, distributed over the entire year, the energy saving potential as compared to the actual grower's practice is substantial. This potential was related to the definition of lower and upper bounds, less natural ventilation at colder days, and more natural ventilation and less heating at warmer days. The prominent role of the bounds was clearly demonstrated. Relaxing the temperature and humidity bounds decreases the energy input to the greenhouse. While this is obvious, the quantification of the effect as demonstrated here is of great interest to growers, and is essential for the development of the second part of the system.

2.1 Introduction

Greenhouse production is, at least in the Netherlands, a large consumer of energy. Pressure on Dutch growers to reduce energy consumption in greenhouse crop production has increased over the last years. On the one hand growers need, as part of reducing production costs, to increase energy efficiency as international competition increases. On the other hand growers are forced to save energy as legislation for reducing consumption of fossil fuel and exhaust of greenhouse gas emissions becomes more strict (Montero et al., 2009). One possible direction to realise the required energy saving is the semi-closed greenhouse, which is attractive for the greenhouse industry because of the increased CO_2 levels inside the greenhouse, reduced pesticide application, and potential water and energy savings (Teitel et al., 2012). These systems are characterized by a variety of equipment, i.e. combined heat and power generation, heat pump, aquifer seasonal energy storage, daytime energy storage and heat exchangers in the greenhouse for active heating and cooling. Different configurations of such systems are described and analyzed by Van 't Ooster et al. (2007), De Zwart (2008); Courtois et al. (2008); De Gelder et al. (2012); Vadiee and Martin (2012, 2013). These systems are complex regarding the control and utilization of the energy resources. To use all equipment in an energy optimal manner, while creating a desired greenhouse climate, is a complicated task, which has shown to be very difficult, even for experienced growers. Reasons for this are the number and interconnectivity of the equipment that is used, and the uncertainty in expected outdoor weather. The ultimate objective of this project is to support the grower in his decision making process concerning the optimal utilization of energy resources in semi-closed greenhouses.

The approach to greenhouse climate management taken in this research differs from previous work on various aspects. In this research, the total energy input to the greenhouse was minimized instead of maximizing the total economic profit, as was done by Gutman et al. (1993); Van Henten et al. (1997); Seginer and Ioslovich (1998); Van Straten et al. (2002); Van Ooteghem et al. (2005); Ioslovich et al. (2009). Gutman et al. (1993) used an economic criterion to minimize heating costs, while others, for example Ioslovich et al. (2009) and Van Straten et al. (2002) maximize profit.

However, these methods are not used in practice. This is because of the lack of reliable crop production models for the wide range of crops and species grown in horticultural practice and the need to leave part of the decision freedom to the responsibility of the growers (Van Straten et al., 2000). Yet another and maybe even more important reason not to use crop models is the fact that growers do not trust the current crop models, although these models are considered reliable in academia. Also proper on-line plant measurements to correct for model errors, and proper predictions of market prices are not available yet.

In current practice, growers set bounds for temperature and humidity usually according to a predefined pattern. They use weather predictions, status of the crop, specific knowledge of the crop, production prognosis, and experience to define the desired patterns for temperature, humidity, CO_2 concentration, and light levels. The equipment is controlled based on a set of rules and settings, which may not necessarily be the most energy-efficient. The goal of this paper is to present a novel method to minimize the total energy input to a greenhouse while maintaining grower defined bounds. The reasoning is that within the believes of the grower regarding the desired climate it is still useful to minimize the energy input.

Because of the complexity of the system, the idea is to split the problem of optimal utilization of energy resources into two parts. The first part, which is described in this paper, aims at the realization of a desirable greenhouse climate with a minimal energy input, given a grower defined lower and upper temperature and humidity bound. The second part, which is not described in this paper, then focuses on the optimal scheduling and utilization of the equipment needed to fulfill the required minimal energy input to the greenhouse.

Minimizing the total energy use without an economic criterion has, as far as we know, only be done by Chalabi et al. (1996), but they used a steady-state temperature model. Dynamic optimization of the total energy input to the greenhouse was previously presented in Van Beveren et al. (2013). In the current work, the greenhouse climate model is extended with a dynamic vapour balance, which is imperative to obtain realistic results. CO_2 control is taken for granted.

The paper is organized as follows. First, the dynamic greenhouse climate model is described in Section 2 together with the optimization procedure. Then, in Section 3, model simulation and validation results are presented, followed by the results of the optimization. Finally, the results are discussed and some concluding remarks and points for further research are made in Section 4 and 5, respectively.

2.2 Materials and methods

2.2.1 The greenhouse

The data that were used, were of a 40 709 m^2 Venlo-type greenhouse in Bleiswijk, the Netherlands (52 °N, 4.5 °E). Eaves height was 6.4 m and ridge height was 7.2 m. The roof angle was 23°. The spans were equipped with 2020 ventilation windows of 1.35 m × 1.67 m. The following equipment to influence the greenhouse climate was installed in the commercial greenhouse involved in this research: a shadow and black-out screen, artificial lighting, natural ventilation, pipe rail heating, and heat exchangers. The shadow screen (XLS 13 F Ultra) had a light transmission of 70 %. There were 4536 1000 W SON-T lamps (110 $\mathrm{W m^{-2}}$) for artificial lighting installed in the greenhouse. The pipe rail heating system consisted of 1.1 $\mathrm{m[pipe]m^{-2}}$. Per 80 m^2 greenhouse one air-to-water heat exchanger (OPAC-106) was available that can be used to heat, cool, and dehumidify greenhouse air. Industrial carbon dioxide was used for CO_2 enrichment. The greenhouse is shown in Fig. 2.1. Two different Avalanche+ rose cultivars were grown on substrate (rockwool) in the greenhouse.

Figure 2.1: The 4 ha greenhouse with rose crop, ventilation windows, screens, artificial lighting, pipe rail heating system, and OPAC-106 heat exchangers.

2.2.2 Model description

In order to minimize the total energy input to a modern greenhouse using optimal control, a model of the greenhouse air temperature and humidity is needed. While many dynamic models for greenhouse temperature and humidity have been presented in the literature, the focus on energy input, and the system configuration urged us to combine existing knowledge into a newly designed dynamical model that was suitable for this study. The model was designed such that the optimization method is easily applicable to different greenhouse configuration and different crops. To describe the indoor climate of the greenhouse, physics-based dynamical balances were set up yielding two differential equations, one for temperature and one for the absolute humidity (Eqs. (2.1) and (2.2)).

$$\begin{aligned}\frac{dT_{air}}{dt} &= \frac{1}{c_{cap}}(Q_{sun} - Q_{cov} - Q_{trans} + Q_{lamp} \\ &-Q_{vent} + Q_{he,heat} - Q_{he,cool} + Q_{pipe}) \quad (°\mathrm{Cs}^{-1})\end{aligned} \tag{2.1}$$

$$\frac{d\chi_{air}}{dt} = \frac{1}{h}\left(\phi_{trans} - \phi_{cov} - \phi_{he,cool} - \phi_{vent}\right) \quad (\mathrm{gm}^{-3}\mathrm{s}^{-1}) \tag{2.2}$$

These models were based on greenhouse climate models as described by Van Henten (1994), De Zwart (1996), Van Ooteghem (2007b), Van Henten and Bontsema (2009) and Vanthoor (2011). The energy balance is influenced by the following energy fluxes as shown in Fig. 2.2: incoming radiation Q_{sun}, heat losses through the cover Q_{cov}, transpiration by the crop Q_{trans}, artificial lighting Q_{lamp}, natural ventilation Q_{vent}, heating $Q_{he,heat}$ and cooling $Q_{he,cool}$ with the heat exchangers, and heating by the pipe rail system Q_{pipe} (Wm^{-2}). The vapour balance is influenced by crop transpiration ϕ_{trans}, condensation on the cover ϕ_{cov}, condensation in the heat exchangers due to cooling $\phi_{he,cool}$, and vapour exchange with outdoor air by natural ventilation ϕ_{vent} ($\mathrm{gm}^{-2}\mathrm{s}^{-1}$). The vapour fluxes are strongly coupled to the associated heat fluxes. In the next two sections the energy and vapour fluxes are worked out in detail.

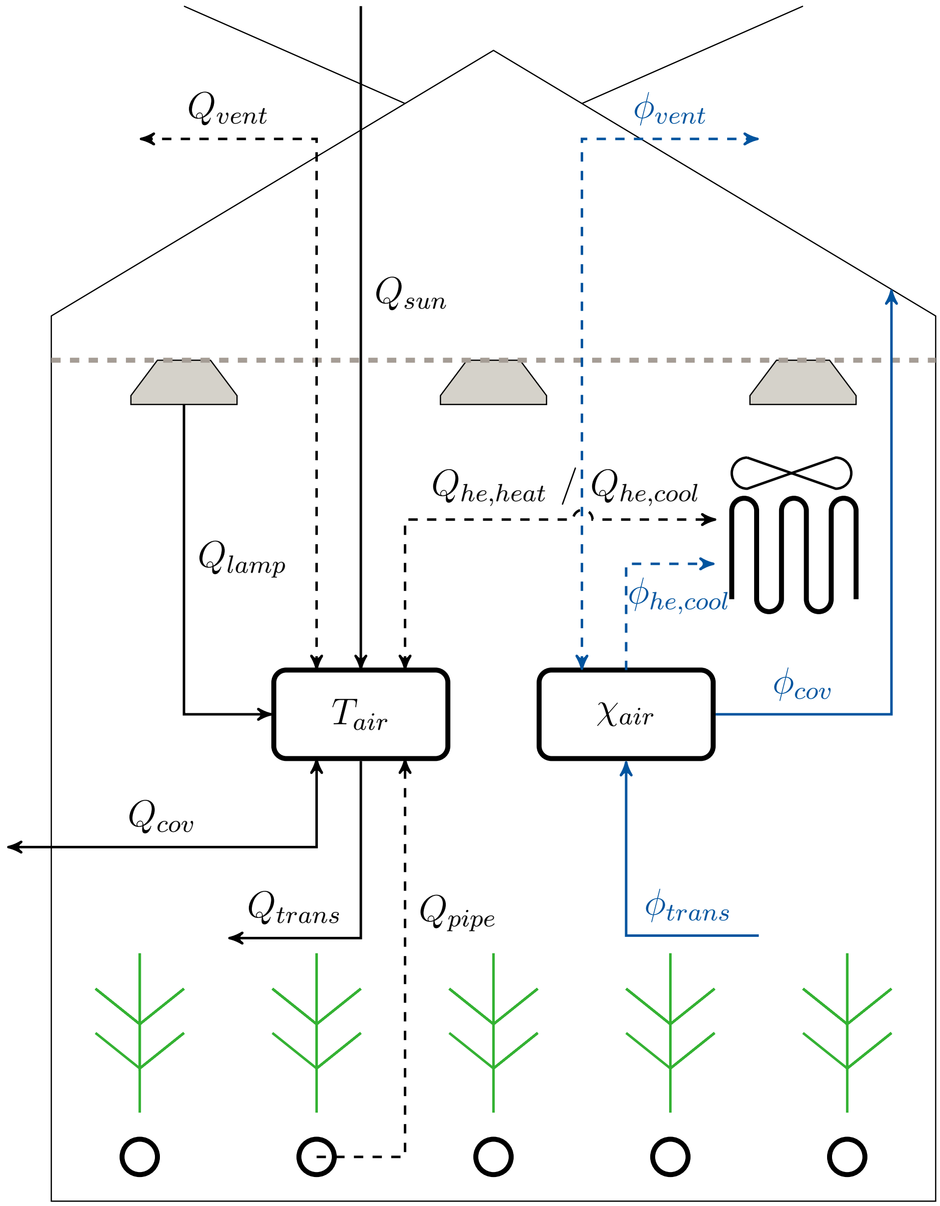


Figure 2.2: Overview of the climate variables T_{air} and χ_{air}, and corresponding energy fluxes Q and vapour fluxes ϕ. To validate the model, all fluxes were calculated using measured input data. Feed-back effects of changes in T_{air} and χ_{air} on the uncontrollable fluxes were taken into account. In the optimization mode the fluxes that can be controlled are represented by the dashed lines.

For model validation, the fluxes Q_{vent}, $Q_{he,heat}$, $Q_{he,cool}$, Q_{pipe}, ϕ_{vent}, and $\phi_{he,cool}$ were calculated based on measurements obtained from the greenhouse process control computer. For optimization, these fluxes were aggregated to produce one energy input Q_E to the system as will be shown in Section 2.2.4. Parameters and constants that are not mentioned in the text are listed in the Appendix in Table 2.3.

Energy fluxes

Energy added to the greenhouse air by incoming radiation Q_{sun} was computed using Eq. (2.3), where the measured outside radiation I_{rad} ($\mathrm{Wm^{-2}}$) is multiplied by the total light transmission of the cover τ_{tot} (−). Total cover transmittance is the constant cover transmission τ_{cov} (−), multiplied by a correction factor for closing of the shadow screen Cl_{scr} (%) and closing of the blackout screen Cl_{scr2} (Eq. (2.4)). In this equation, τ_{scr} is the transmissivity of the shadow screen and τ_{scr2} the transmissivity of the blackout screen. A screen closure of 100 % means that the screen is completely closed.

$$Q_{sun} = \tau_{tot}\ I_{rad} \quad (\mathrm{Wm^{-2}}) \tag{2.3}$$

$$\tau_{tot} = \tau_{cov} \left(1 - \frac{(1-\tau_{scr})\ Cl_{scr}}{100}\right)\left(1 - \frac{(1-\tau_{scr2})\ Cl_{scr2}}{100}\right) \quad (-) \tag{2.4}$$

Convective heat loss through the cover Q_{cov} was described by

$$Q_{cov} = \alpha_{cov} \frac{A_{cov}}{A_{floor}} (T_{air} - T_{out}) \quad (\mathrm{Wm^{-2}}) \tag{2.5}$$

where α_{cov} is the heat transfer coefficient of the cover material ($\mathrm{Wm^{-2}C^{-1}}$), A_{cov} is the greenhouse cladding area ($\mathrm{m^2}$), A_{floor} is the greenhouse floor area ($\mathrm{m^2}$) and T_{out} is the outdoor temperature (°C).

Reliable and relatively simple models are available to predict crop transpiration in a variety of different greenhouse crops (Stanghellini, 1987; Katsoulas, N., Kittas C., Baille et al., 2001; Medrano et al., 2005). Crop transpiration is needed in both the temperature and vapour balance. Here, the energy extraction from greenhouse air due to crop transpiration Q_{trans} was described by Eq. (2.6), based on a Pennman-Monteith equation for transpiration reported by Stanghellini and De Jong (1995).

$$Q_{trans} = g_e\, L\, (\chi_{crop} - \chi_{air}) \quad (\mathrm{Wm^{-2}}) \tag{2.6}$$

Here, χ_{crop} is the absolute water vapour concentration at crop level, χ_{air} the absolute water vapour concentration of greenhouse air ($\mathrm{gm^{-3}}$), L the amount of energy needed to evaporate water from a leaf ($\mathrm{Jg^{-1}}$), and g_e the transpiration conductance ($\mathrm{ms^{-1}}$). Transpiration conductance g_e was calculated as

$$g_e = \frac{2LAI}{(1+\epsilon)r_b + r_s} \quad (\mathrm{ms^{-1}}) \tag{2.7}$$

and depends on the leaf area index LAI, the ratio of latent to sensible heat content of saturated air ϵ, the boundary layer resistance parameter r_b, and the stomatal resistance r_s. The LAI of the rose crop is relatively constant during the year and was assumed to be $2.6\,\mathrm{m^2m^{-2}}$. The water vapour concentration at crop level χ_{crop} is calculated as

$$\chi_{crop} = \chi_{air,sat} + \epsilon\frac{r_b}{2LAI}\frac{R_n}{L} \quad (\mathrm{gm^{-3}}) \tag{2.8}$$

where χ^*_{air} is the saturated vapour concentration. For temperatures between 15 °C and 30 °C the saturated vapour concentration can be approximated, according to Bontsema et al. (2007), by

$$\chi_{air,sat} = 5.5638e^{0.0572T_{air}} \quad (\mathrm{gm^{-3}}). \tag{2.9}$$

Stomatal resistance r_s ($\mathrm{sm^{-1}}$) was calculated via

$$r_s = \left(82 + 570\, e^{-\gamma\frac{R_n}{LAI}}\right)\left(1 + 0.023\,(T_{air} - 20)^2\right) \tag{2.10}$$

where the crop specific parameter γ was reported to be 0.008 for roses, whereas for tomato γ was reported to be 0.4 (Stanghellini, 2010). In Eq. (2.10) $(T_{air} - 20)^2$ was used instead of $(T_{air} - 24.5)^2$ as in Stanghellini (2010); Bontsema et al. (2007) to adapt to the specific crop in this greenhouse. R_n is net radiation at crop level ($\mathrm{Wm^{-2}}$), based on Bontsema et al. (2007), calculated as

$$R_n = 0.86(1 - e^{-0.7LAI})(Q_{sun} + P_E\frac{f_{on}}{100}) \quad (\mathrm{Wm^{-2}}) \tag{2.11}$$

where P_E is the rated electric power of artificial lighting installed ($\mathrm{Wm^{-2}}$) and f_{on} is the fraction of lamps that is switched on (0, 33¹/₃, 66²/₃, or 100 % because they were divided into three separate groups that can be on or off). Lamps in the greenhouse produce, next to light, also heat that heats up greenhouse air. Heating due to artificial lighting was calculated via

$$Q_{lamp} = \eta\, P_E\, \frac{f_{on}}{100} \quad (\mathrm{Wm^{-2}}) \tag{2.12}$$

where η is the part of electric energy consumption of the lamps that is transformed into heat released to greenhouse air $(-)$.

The specific ventilation g_V was calculated with the ventilation model of De Jong (1990), which depends on window opening, in and outdoor temperature, and wind speed. Heat loss due to ventilation was then calculated as

$$Q_{vent} = g_V \rho_{air} C_{p,air} \left(T_{air} - T_{out}\right) \quad (\mathrm{Wm^{-2}}) \tag{2.13}$$

where g_V is specific ventilation ($\mathrm{m^3m^{-2}s^{-1}}$), ρ_{air} density of air ($\mathrm{kgm^{-3}}$) and $C_{p,air}$ specific heat capacity of air ($\mathrm{Jkg^{-1}C^{-1}}$).

The model for the heat exchangers was only used and needed to validate the greenhouse climate model. The model for the heat exchangers as used in (Van Beveren et al., 2013) was revised in order to get a more realistic model performance for different conditions. To do this, separate equations were used for the energy flux in heating mode $Q_{he,heat}$ (Eq. (2.14)) and cooling mode $Q_{he,cool}$ (Eq. (2.15)). Model results were then compared with the energy and condensation estimate from the model as described in De Zwart and Kempkes (2007). The heat transfer coefficient $\alpha_{he,heat}$ was set to be $1050\,\mathrm{Wm^{-2}C^{-1}}$ for heating and $\alpha_{he,cool}$ was set at $525\,\mathrm{Wm^{-2}C^{-1}}$ for cooling. After adjusting these parameters, the Spearman correlation coefficient between the two models was 0.90 for heating and -0.64 for cooling.

The energy fluxes $Q_{he,heat}$ and $Q_{he,cool}$ depend on the heat transfer α_{he} ($\mathrm{Wm^{-2}C^{-1}}$), the floor area per heat exchanger $A_{he,floor}$ ($\mathrm{m^2}$), and the temperature difference between air T_{air} and the sheet in the heat exchanger T_{sheet} (°C).

$$Q_{he,heat} = \alpha_{he,heat} \frac{T_{sheet} - T_{air}}{A_{he,floor}} \quad (\mathrm{Wm^{-2}}) \tag{2.14}$$

$$Q_{he,cool} = \alpha_{he,cool} \frac{T_{sheet} - T_{air}}{A_{he,floor}} \quad (\mathrm{Wm^{-2}}) \tag{2.15}$$

The temperature of the sheet was calculated based on the measured temperatures of water entering, $T_{he,in}$, and leaving, $T_{he,out}$, the heat exchanger (°C) and the empirically determined weighing factor β.

$$T_{sheet} = \beta T_{he,in} + (1-\beta)\, T_{he,out} \quad (°\mathrm{C}). \tag{2.16}$$

Heat added by pipe rail heating was calculated based on average pipe temperature obtained via averaging measured in and outgoing pipe temperature. The amount of heat added was described by

$$Q_{pipe} = \alpha_{pipe}\left(T_{pipe,avg} - T_{air}\right) \quad (\mathrm{Wm}^{-2}) \tag{2.17}$$

where α_{pipe} is the heat transfer coefficient from pipe to air ($\mathrm{Wm}^{-2}\mathrm{C}^{-1}$), and $T_{pipe,avg}$ the average pipe temperature (°C).

Vapour fluxes

The amount of energy released due to evaporation of the leaves was estimated via Eq. (2.6). The amount of vapour that is evaporated by the crop ϕ_{trans} was calculated as

$$\phi_{trans} = g_e\left(\chi_{crop} - \chi_{air}\right) \quad (\mathrm{gm}^{-2}\mathrm{s}^{-1}), \tag{2.18}$$

which is the same as $\phi_{trans} = Q_{trans}/L$, where L is the amount of energy that is needed to evaporate water.

Condensation to the cover ϕ_{cov} occurs when the temperature of the cover is below the dew point temperature of the air. Since Papadakis et al. (1992) showed that the slope of the cover did not influence the condensation estimate, the condensation conductance g_C (ms^{-1}) can be estimated based on mass transfer theory. Therefore, the equations as proposed by Stanghellini and De Jong (1995) could be simplified to Eq. (2.19) (Bontsema et al., 2007).

$$\phi_{cov} = g_C\left(0.2522e^{0.0485T_{air}}\left(T_{air} - T_{out}\right) - \left(\chi_{air,sat} - \chi_{air}\right)\right) \quad (\mathrm{gm}^{-2}\mathrm{s}^{-1}) \tag{2.19}$$

Condensation conductance g_C in Eq. (2.19) was calculated as

$$g_C = \max\left(0, p_{g_C}\left(T_{air} - T_{cov}\right)^{1/3}\right) \quad (\mathrm{ms}^{-1}) \tag{2.20}$$

where the parameter p_{g_C}, which is related to the properties of the condensation surface, was $1.8 \times 10^3\,\mathrm{m°C}^{-1/3}\mathrm{s}^{-1}$.

Condensation in the heat exchanger $\phi_{he,cool}$ was calculated with the following equation

$$\phi_{he,cool} = g_{C,he}(\chi^*_{sheet} - \chi_{air}) \quad \left(\mathrm{gm^{-2}s^{-1}}\right) \tag{2.21}$$

the saturated vapour concentration at the sheet was calculated via Eq. (2.9), where the air temperature T_{air} was replaced by the temperature of the sheet T_{sheet}. The condensation conductance $g_{C,he}$ was calculated, based on Stanghellini and De Jong (1995), as a function of the air temperature T_{air} and the temperature of the sheet in the heat exchanger T_{sheet}.

$$g_{C,he} = \max\left(0, p_{g_C,he}(T_{air} - T_{sheet})^{1/3}\right) \quad (\mathrm{ms^{-1}}). \tag{2.22}$$

In this equation the value of $p_{g_C,he}$ ($0.25 \times 10^3\ \mathrm{m°C^{-1/3}s^{-1}}$) was obtained by fitting Eq. (2.22) to the complex model of De Zwart and Kempkes (2007). A Spearmans correlation coefficient of 0.99 was found for the relation between those two estimates.

The vapour flux due to ventilation was calculated as

$$\phi_{vent} = g_V\left(\chi_{air} - \chi_{out}\right) \quad (\mathrm{gm^{-2}s^{-1}}) \tag{2.23}$$

where the specific ventilation term g_V is the same as in Eq. (2.13).

2.2.3 Data

The simulation model needs external input data to calculate and validate greenhouse air temperature and humidity. To validate the model, the energy and vapour fluxes related to the fluxes that can be controlled in the optimization procedure have to be calculated. To do this, for instance realised window opening for lee and wind side were used to calculate the energy flux due to ventilation. Inputs for the model were the mean values of the different control groups for lamps, screens etc.

Temperature and humidity were measured with eight HortiMaX® measurement boxes, two in each of the four greenhouse compartments. To compare simulation results with measurements, the box values were averaged to represent the spatial mean. Outside weather conditions (radiation, temperature, humidity, and wind) were measured with a HortiMaX® weather station. Data with a time interval of 5 min was collected from the HortiMaX® process control computer.

In this greenhouse also crop transpiration was measured. This was done by a HortiMaX® Prodrain® weighing gutter system. This gave the opportunity to validate the crop transpiration model with real measured data.

2.2.4 Optimization procedure

A general optimal control formulation was chosen to formulate the optimization problem. Given the model, initial conditions $T_{air}(0)$ and $\chi_{air}(0)$, constraints on the climate variables and control inputs, and external inputs, the optimal control trajectory that minimizes total energy input over time can be found by minimizing the cost function J over time:

$$\min_{Q_E, g_V} J(Q_E, g_V) = \int_{t_0}^{t_f} Q_E^2 \, dt \tag{2.24}$$

where t_0 is the initial time and t_f the final time. A quadratic cost function was chosen because it penalizes larger pertubations more than smaller ones. The optimal daily energy input $\sum Q_E^*$ was calculated as the integral of the absolute optimal energy input Q_E^* to account for both heating and cooling.

Two control inputs were defined. The first control input was defined as the aggregated controllable energy flux Q_E. This term includes both the heating flux of the pipe rail heating system and the heating or cooling flux from the heat exchangers (Eq. (2.25)).

$$Q_E = Q_{he,heat} - Q_{he,cool} + Q_{pipe} \quad \left(\mathrm{Wm}^{-2}\right) \tag{2.25}$$

All the terms have associated costs, but the cost-effective allocation of each of the terms to realise the minimized total energy input Q_E is of concern only in the second stage of the dual-stage approach of optimal utilization of energy resources in the greenhouse. However, since cooling and dehumidification via natural ventilation is cost-free, the specific ventilation g_V was defined as the second separate control input. This procedure assures that equipment energy, as in Eq. (2.25), is only requested if it is not possible to obey the air temperature and humidity bounds by natural ventilation alone. Heating with the pipe rail system or heat exchangers has no effect on the absolute vapour concentration of the air, but does affect the relative humidity of the air. Cooling with heat exchangers does affect the absolute vapour concentration of air due to condensation in the heat exchangers, which is represented in the vapour balance by $\phi_{he,cool}$.

Control inputs Q_E and g_V were constrained by the following control inequality constraints

$$Q_E^{min}(t) \leq Q_E(t) \leq Q_E^{max}(t) \tag{2.26}$$

$$g_V^{min}(t) \leq g_V(t) \leq g_V^{max}(t) \tag{2.27}$$

where Q_E^{min} was the maximal cooling capacity and Q_E^{max} was the maximal heating capacity. We assumed constant maximum capacities of 200 $\mathrm{W m^{-2}}$ for both cooling and heating. For the second control constraint Eq. (2.27), bounding the specific ventilation g_V, g_V^{min} was equal to the leakage ventilation and g_V^{max} was equal to the specific ventilation at 100 % window opening on both wind and leeward side. It depends on wind speed and indoor and outdoor temperature, and was calculated via the ventilation model of De Jong (1990).

The method requires the specification of the bounds. While in a future practical application this can be left without difficulty to the grower, it is necessary to make choices here in order to test the method and to show its potential. Hence, it was decided to take the realised trajectories of the grower, and to specify smooth bounds around these (moving average with a time span of 4 hours). The reasoning behind this is that the current trajectories were realised by the climate computer on the basis of settings that the grower believed to be beneficial to his crop.

The bounds are defined as

$$T_{air}^{min}(t) \leq T_{air}(t) \leq T_{air}^{max}(t) \tag{2.28}$$

$$RH_{air}(t) \leq RH_{air}^{max}(t) \tag{2.29}$$

where $T_{air}^{min}(t)$ was the lower temperature bound and $T_{air}^{max}(t)$ was the upper temperature bound defined by the grower. In Eq. (2.29), RH_{air} is a function of $T_{air}(t)$ and $\chi_{air}(t)$.

Settings for the deployment of lamps and screens are determined by the grower, and were therefore assumed to be given. In the practical application of new approach, the grower is given the lead in defining the bounds on the climate variables, thus giving the grower the possibility to influence crop growth, crop development, and crop production in a comparable way as in current practice.

The optimal control problem was solved with PROPT - Matlab Optimal Control Software, which is a platform for solving applied optimal control and parameter estimation problems (Rutquist and Edvall, 2010). PROPT uses a collocation method for solving optimal control problems, which means that the solution takes the form of a polynomial which satisfies the differential algebraic equations and path constraints at the collocation points (Edvall and Goran, 2009). The input data were interpolated in between the collocation points and an optimization horizon of one day was used. Data processing, model building, validation, and optimal control formulation with PROPT were done in Matlab (version 7, The MathWorks Inc., Natick, USA).

2.3 Results

First the results of the model validation are shown, followed by the results of minimizing the total energy input to the greenhouse.

2.3.1 Model validation

The presence of a weighing gutter to measure crop transpiration in the greenhouse gave the opportunity to compare calculated crop transpiration with measured crop transpiration. These results are presented first, followed by the simulation results for temperature and humidity of greenhouse air.

Crop transpiration

Crop transpiration was compared for 200 days in 2012. Recordings lower than 5 and higher than $500\,\mathrm{gm^{-2}h^{-1}}$ were excluded from the analysis because they were seen as measurement errors. This occurred 296 times out of 56700 samples in 200 days (<0.6 %). A typical result is shown in Fig. 3 for eight days in April 2012, selected because of wide variation in daily solar radiation. Simulated crop transpiration showed a good fit with measured crop transpiration over the full range of radiation levels. In Fig. 2.3 also the global radiation I_{rad}, status of the lamps f_{on}, and total transmissivity of the cover and screens τ_{tot} (Eq. (2.4)) at these days are shown. Total transmissivity depends on the closure of the shadow screen and the blackout screen. The blackout screen was closed for some hours during night. Then, the transmissivity was very low. However, the closure has no effect on crop transpiration since there is no radiation from the sun during this time. The shadow screen was closed when global radiation exceeded the threshold value set by the grower. This can be seen in the early afternoon of some days with high radiation values when τ_{tot} drops from 0.7 to lower values. The effect of switching on artificial lighting can be seen in the step in crop transpiration around midnight. The correlation coefficient between simulated and measured crop transpiration was 0.86. Average transpiration during night ($I_{rad} < 50\,\mathrm{W m^{-2}}$) was $77\,\mathrm{g m^{-2} h^{-1}}$ for the simulation and $79\,\mathrm{g m^{-2} h^{-1}}$ for the measurement. Average transpiration during day ($I_{rad} > 50\,\mathrm{W m^{-2}}$) was $168\,\mathrm{g m^{-2} h^{-1}}$ for the simulation and $161\,\mathrm{g m^{-2} h^{-1}}$ for the measurement. There can be various reasons for the differences between measured and simulated crop transpiration. While a constant LAI was used for calculation, in practice LAI fluctuates during the year due to crop maintenance and harvesting. Another possible source of error is that the weighing gutter integrates over the measurement interval. Due to the non-linearity with respect to radiation this is not the same as using the average light over the interval as done in the model. Also local moisture differences can play a role. Yet, overall, the crop transpiration model performs very well.

Temperature and humidity

Outcomes of simulations with the model as described in Section 2.2.2 were compared with measured data to assess the usability and performance of the model. Spatial temperature distribution in the greenhouse was evaluated for different periods during the year 2012. The temperature differences between measurement boxes was never larger than 2.0 °C. An example of the spatial distribution of temperature in the greenhouse at 10:00 AM on April 16, 2012 is shown in Fig. 2.4. The standard deviation of each measurement box compared to the mean of the total number of measurement boxes was in the range of 0.4 °C to 0.7 °C, which is less than reported in Opdam et al. (2005) who measured a deviation within 1.0 °C to 1.5 °C from the mean.

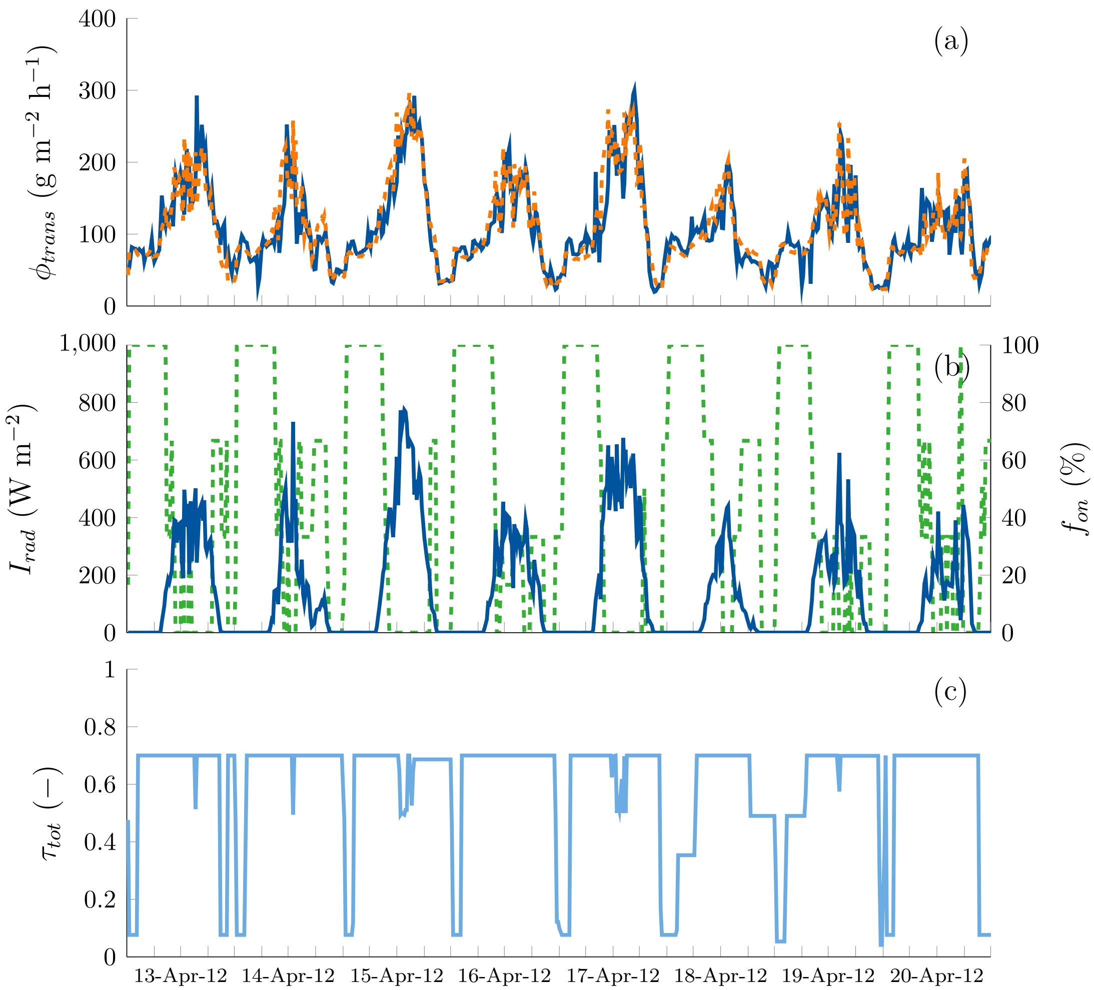


Figure 2.3: (a) Measured (solid line) and simulated (dashed line) crop transpiration (gm^{-2}h^{-1}), (b) global radiation I_{rad} (Wm^{-2}) (solid line) and status of the artificial lighting f_{on} (percent) (dashed line), and (c) total transmissivity τ_{tot} (-) for April 13, 2012 through April 20, 2012.

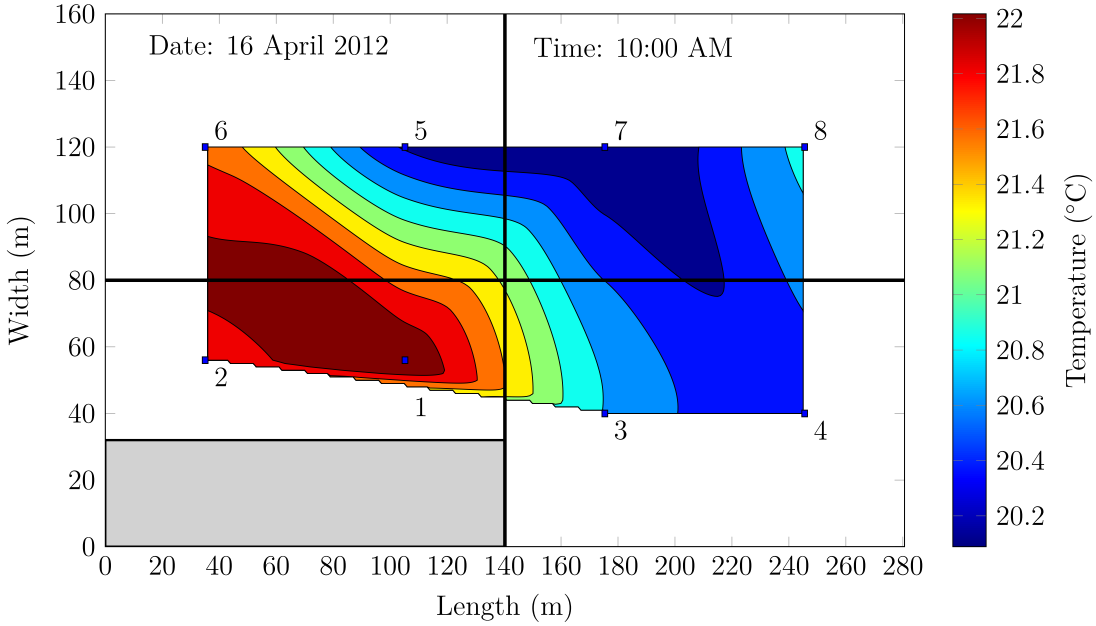


Figure 2.4: Spatial temperature distribution in the greenhouse at 10:00 AM on April 16, 2012. Temperatures were linearly interpolated between the measurement boxes. In the morning, sunrise is at the east side (left) of the greenhouse. This is also the place where the highest temperatures occur in the greenhouse.

Greenhouse air temperature and humidity were simulated for all days in the year 2012. The mean of the 24 hour temperature sums of all days in 2012 was 469 °Chd^{-1} (SD=27 °Chd^{-1} for the measured temperature, and 468 °Chd^{-1} for the simulated temperature. The standard deviation (SD) of the measured temperature sum was 27 °Chd^{-1} and the standard deviation of the simulated temperature sum was 41 °Chd^{-1}. Most of the times the simulation followed the dynamic behaviour of the measurements quite well. A characteristic example is shown in Fig. 2.5.

A quantitative comparison between measured and simulated results over the whole year 2012 is shown in Table 2.1. The correlation coefficient r for temperature was 0.88 , while for the absolute humidity this was 0.77. Relative humidity depends on temperature and absolute humidity. For relative humidity the correlation coefficient was 0.60 , which is lower than for both temperature and absolute humidity, but visual inspection of simulated relative humidity (Fig. 2.5) shows that it follows the measured relative humidity well, although there can be days

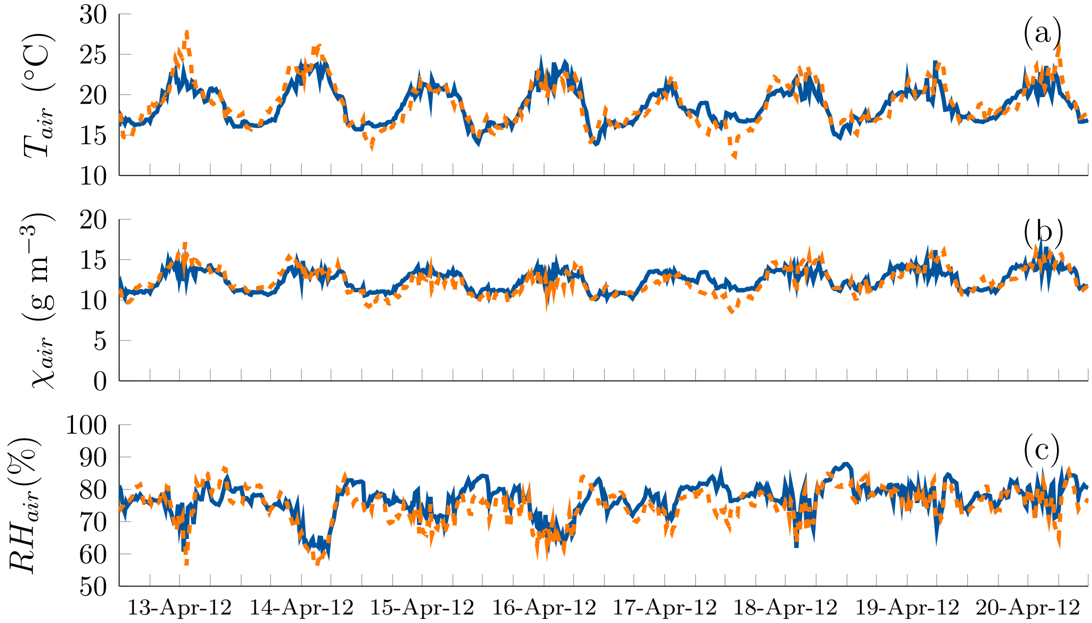


Figure 2.5: (a) Measured (solid line) and simulated (dashed line) air temperature T_{air}, (b) absolute humidity χ_{air}, and (c) relative humidity RH_{air} for 13 through 20 April, 2012.

where the model performance is worse. The Root Mean Square Error (RMSE) of temperature was in the same range as the temperature differences in the spatial distribution (Fig. 2.4). Differences between the simulation and measurements can partly be explained by local temperature and vapour gradients.

Table 2.1: Summary of the results of validation of the greenhouse climate model for 2012. The correlation coefficient r and Root Mean Square Error (RMSE) for greenhouse temperature (T_{air}) and absolute humidity (χ_{air}), and relative humidity (RH_{air}).

	r	RMSE
Temperature	0.88	1.57 °C
Absolute humidity	0.77	1.76 gm^{-3}
Relative humidity	0.60	7.35 %

2.3.2 Optimization

Optimal trajectories for the control inputs (Q_E and g_V) and corresponding temperature and humidity were computed for different days during the year 2012 as described in Section 2.2.4. In this research, the real realised air temperature as measured in the commercial greenhouse was assumed to be the desired temperature. Lower and upper temperature bounds were obtained by smoothing measured indoor temperature and by adding a bandwidth of $\pm 1\,°C$ to the smoothed temperature.

In order to study the effect of the number of collocation points on the optimal energy input, calculation time, and accuracy, the effect of different numbers of collocation points was examined by optimization of the energy input for one day with different numbers of collocation points. The optimal solution was first computed for the smallest number of collocation points, and then, using the obtained solution as new initial guess, the optimal solution was computed for the subsequent number of collocation points.

The optimal energy input for different numbers of collocation points and the calculation time are shown in Fig. 2.6 for 16 April 2012. A range of collocation points, starting from six, with steps of six, until 150 points was used. The calculations were done for three choices of RH_{air}^{max}, to check whether these choices affect the convergence to the optimal solution and the computing time.

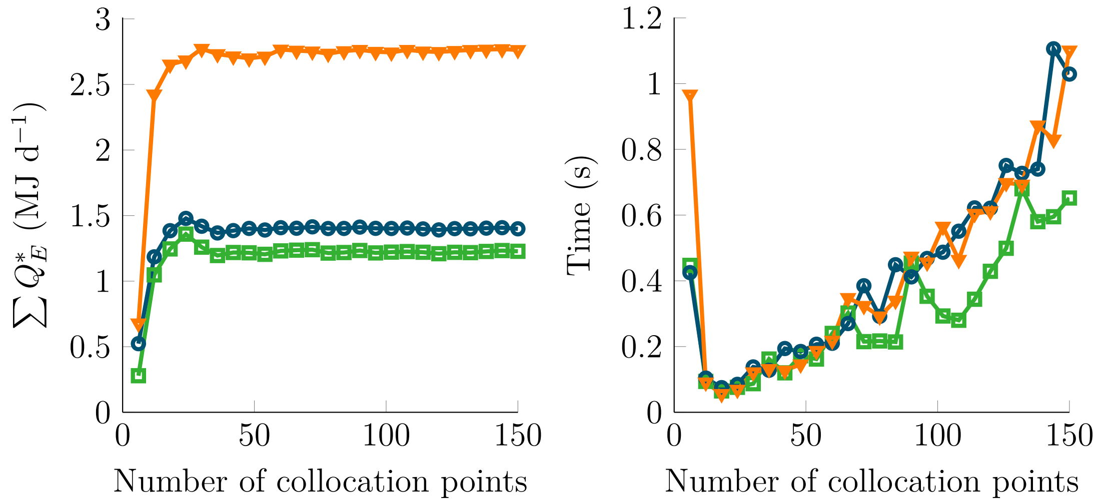


Figure 2.6: Evaluation of the effect of number of collocation points n on the optimal daily energy input $\sum Q_E^*$ (MJd^{-1}) (left) and the effect of the number of collocation points on the calculation time (s) (right) for three different constraints on maximum humidity in the greenhouse ($RH_{air}^{max} = 90\,\%$, $RH_{air}^{max} = 85\,\%$, and $RH_{air}^{max} = 80\,\%$) for 16 April, 2012. The temperature bounds were defined as the smoothed realised temperature in the greenhouse $\pm$ 1 °C.

For a low number of collocation points, the optimal daily energy input $\sum Q_E^*$ first increases because the data and bounds are only defined at the collocation points. Faster changes in for example outdoor weather are therefore averaged out, and not taken into account. This leads to optimal solutions that are not optimal if a higher number of collocation points is chosen. After 24 collocation points, the optimal energy input stabilizes. Calculation time increases for all of the three situations as the number of collocation points increases. A lower value of RH_{air}^{max} leads to slightly higher calculation times. The calculation time to obtain the first optimal solution (n=6) was relatively high.

To exclude the influence of the number of collocation points on the optimal energy input, the minimum number of collocation points used for the remaining calculations was 48. In (Fig. 2.6), left, the optimal energy input remains constant after 48 collocation points. 48 collocation points correspond to a time interval of 30 minutes, suggesting that fluctuations of the greenhouse variables within a scale of 30 minutes are irrelevant. For the given day, and given settings, the optimal daily energy input was about 2.7 MJm^{-2}d^{-1} for $RH_{air}^{max} = 80\,\%$ and about 1.2 MJm^{-2}d^{-1} for $RH_{air}^{max} = 90\,\%$.

Optimal temperature and humidity trajectories were calculated for twelve days in 2012, one day in each month. For these days, the optimal daily energy input $\sum Q_E^*$ and the optimal heat loss due to ventilation $\sum Q_{vent}^*$ are shown in Table 2.2. In this table also the average outdoor day and night temperature, and the average global radiation during the day (light) period are shown, to give some characteristic data of these days. To compare these results with the real situation in the rose greenhouse operated by the grower, calculated energy fluxes (based on measurements) of the pipe rail heating, heat exchangers and natural ventilation are also given. Pipe rail heating was used on all analyzed days. The heat exchangers are used on nine of the twelve days to heat, and on four of the twelve days to cool. An important reason to use the heat exchangers for cooling instead of natural ventilation in real life is to have higher CO_2 levels inside the greenhouse. This cannot be captured in the current study, as the analysis including CO_2 was left for further research. At 16 April, 2012, the grower used the heat exchangers to heat the greenhouse air for some periods during the night and to cool for one period in the afternoon. In the optimal situation, lowest energy input Q_E^* of the twelve days was $0.39\,\mathrm{MJm^{-2}d^{-1}}$ at 16 August, 2012, which was the warmest day. The difference between the grower and the optimal result can be explained by the fact that pipe rail heating was used for the whole day, and cooling with the heat exchangers was applied at the same time. Highest energy input was $6.22\,\mathrm{MJm^{-2}d^{-1}}$ at 16 January, 2012, which was the coldest day of the twelve days. Besides that, 16 January was a bright day, so direct radiation contributed to heating the greenhouse during day. Because of the low outside temperatures, ventilation windows were closed as much as possible in the optimal situation.

Table 2.2: Optimal energy fluxes $\sum Q_E^*$ and $\sum Q_{vent}^*$ (MJm^{-2}d^{-1}), average outdoor air temperature during night $\overline{T}_{out,night}$ and during day $\overline{T}_{out,day}$ (°C), average global radiation during day $\overline{I}_{rad,day}$ (Wm^{-2}), and light sum $\sum I_{rad}$ (MJm^{-2}d^{-1}) for 12 days in 2012. Day time is defined as ($I_{rad} > 50\,\mathrm{Wm}^{-2}$). Also the calculated fluxes prior to optimization (calculated from measured data, based on operation of the greenhouse by the grower) $\sum Q_{pipe}$, $\sum Q_{he,heat}$, $\sum Q_{he,cool}$, $\sum Q_{vent}$, and $\sum Q_{E,grower}$ (MJm^{-2}d^{-1}) are given. The bounds were defined as $\Delta T = \pm\ 1\,°\mathrm{C}$ around the smoothed measured indoor temperature and $RH_{air}^{max} = 85\,\%$.

	16-Jan	16-Feb	16-Mar	16-Apr	16-May	16-Jun	15-Jul	16-Aug	16-Sep	16-Oct	16-Nov	16-Dec
$\overline{T}_{out,night}$	0.1	5.2	8.6	4.7	7.2	14.9	13.9	17.9	14.2	10.6	3.9	7.3
$\overline{T}_{out,day}$	2.4	6.9	9.2	6.9	9.6	17.4	15.6	20.8	17.1	13.2	4.4	7.5
$\overline{I}_{rad,day}$	195	108	211	430	426	431	332	318	234	250	69	73
$\sum I_{rad}$	4.98	3.31	6.88	18.51	21.19	20.42	16.97	14.14	8.99	6.93	1.29	1.03
Calculated fluxes resulting from operating by the grower												
$\sum Q_{pipe}$	3.62	3.94	4.04	4.62	3.35	2.84	3.51	3.80	3.84	4.42	2.82	2.28
$\sum Q_{he,heat}$	3.81	4.82	3.26	0.63	3.57	0.44	0.00	0.00	0.00	1.73	5.57	3.71
$\sum Q_{he,cool}$	0.00	0.00	0.00	0.22	0.00	4.97	2.48	7.87	0.00	0.00	0.00	0.00
$\sum Q_{vent}$	2.49	6.49	5.02	6.25	9.37	4.35	3.86	3.25	4.31	4.98	4.50	4.25
$\sum Q_{E,grower}$	7.43	8.76	7.30	5.47	6.92	8.25	5.99	11.67	3.84	6.15	8.39	5.99
Optimal solution												
$\sum Q_E^*$	6.22	3.13	2.69	1.91	1.71	2.11	1.84	0.39	1.59	1.55	4.54	3.58
$\sum Q_{vent}^*$	0.13	0.88	2.46	3.90	4.82	7.16	5.43	3.32	4.41	3.60	0.00	1.26

The energy input of the strategy resulting from the optimization procedure ($\sum Q_E^*$) was, at all studied days, lower compared to the strategy resulting from the grower $\sum Q_{E_grower}$ ($\sum Q_{pipe}$+$\sum Q_{he,heat}$+$\sum Q_{he,cool}$). At days with lower outside temperatures, part of the energy saving in the optimal situation is realised by less natural ventilation. At those days where the grower used the heat exchangers for cooling, no cooling was used in the optimal solution, but more natural ventilation and less heating was applied. Also the bounds on temperature, which allow lower and higher temperatures compared to the realised air temperature, contributed to the energy saving in the optimal situation. The mean 24 hour temperature sum of the twelve days was 462 °Chd^{-1} (SD=21 °Chd^{-1}) as resulting from growers operation, and 448 °Chd^{-1} (SD=29 °Chd^{-1}) obtained from the optimal situation. Comparative temperature sums indicate comparative conditions for crop growth and development. The mean time that RH_{air} was higher than 80 % was 10.4 h (SD=8.8 h), while in the optimal situation this was 16.0 h (SD=6.1 h). Since CO_2 is not taken into account in the optimization and only twelve days were analyzed it is not completely fair to compare the energy consumption in the optimal situation with the realised situation by the grower. However, this study indicates that a substantial energy saving can be achieved by minimizing the total energy input.

Overall the potential of energy saving with these settings, as a combination of minimizing the energy input and the definition of lower and upper temperature bounds and an upper humidity bound was on average 62 % for the twelve days shown in Table 2.2.

The optimal temperature and humidity trajectories and optimal control trajectories for 16 March, 2012 are shown in Fig. 2.7 and for 16 April, 2012 in Fig. 2.8. The optimal temperature trajectory at 16 March is as much as possible on the lower allowable bound since the outside temperature and radiation on this day were not very high. Bringing the temperature up would require extra heating, which is not desired. During night, heating is applied such that RH_{air} does not exceed the upper humidity constraint. RH_{air} is lower during day time due to the higher temperatures in the greenhouse and the air exchange with outside air due to ventilation. RH_{air} increases again in the early evening due to lower temperature bounds and a lower ventilation flux. At 16 March (Fig. 2.7), outside temperature was higher than at 16 April (Fig. 2.8), but radiation levels were lower. Because of the higher radiation levels at 16 April, Q_E^* was lower and more ventilation was applied.

The temperature at 16 March is almost on the lower bound, where one would expect optimal temperature to be on the upper bound. In the optimal solution, ventilation is applied between midday and late afternoon. This is necessary in order not to violate the upper temperature boundary in the late afternoon. Simulations with no ventilation confirmed this result. With no ventilation, simulation showed that air temperature rises above 40 °C. For both days the maximum ventilation capacity was not limiting.

At 16 April (Fig. 2.8) the difference in energy use is mainly caused by the higher relative humidity that is allowed in the optimal situation. Greenhouse air temperature was on the lower temperature bound during night. During day time, temperature fluctuates between the upper and lower bound because of the fluctuating outdoor radiation and opening and closure of the shadow screen. The grower applied some active cooling around 17 hour, while no cooling is used in the optimal result.

The effect of varying the temperature and humidity bounds on the optimal solution was studied by minimizing the energy input with different constraints for 16 April, 2012. Three different temperature bandwidths (± 1 °C, ± 2 °C and ± 3 °C) and two different values for RH_{air}^{max} (80 % and 90 %) were used. In Fig. 2.9 the optimal energy input $\sum Q_E^*$ and the energy release due to natural ventilation $\sum Q_{vent}^*$, which is associated with the specific ventilation g_V, are shown.

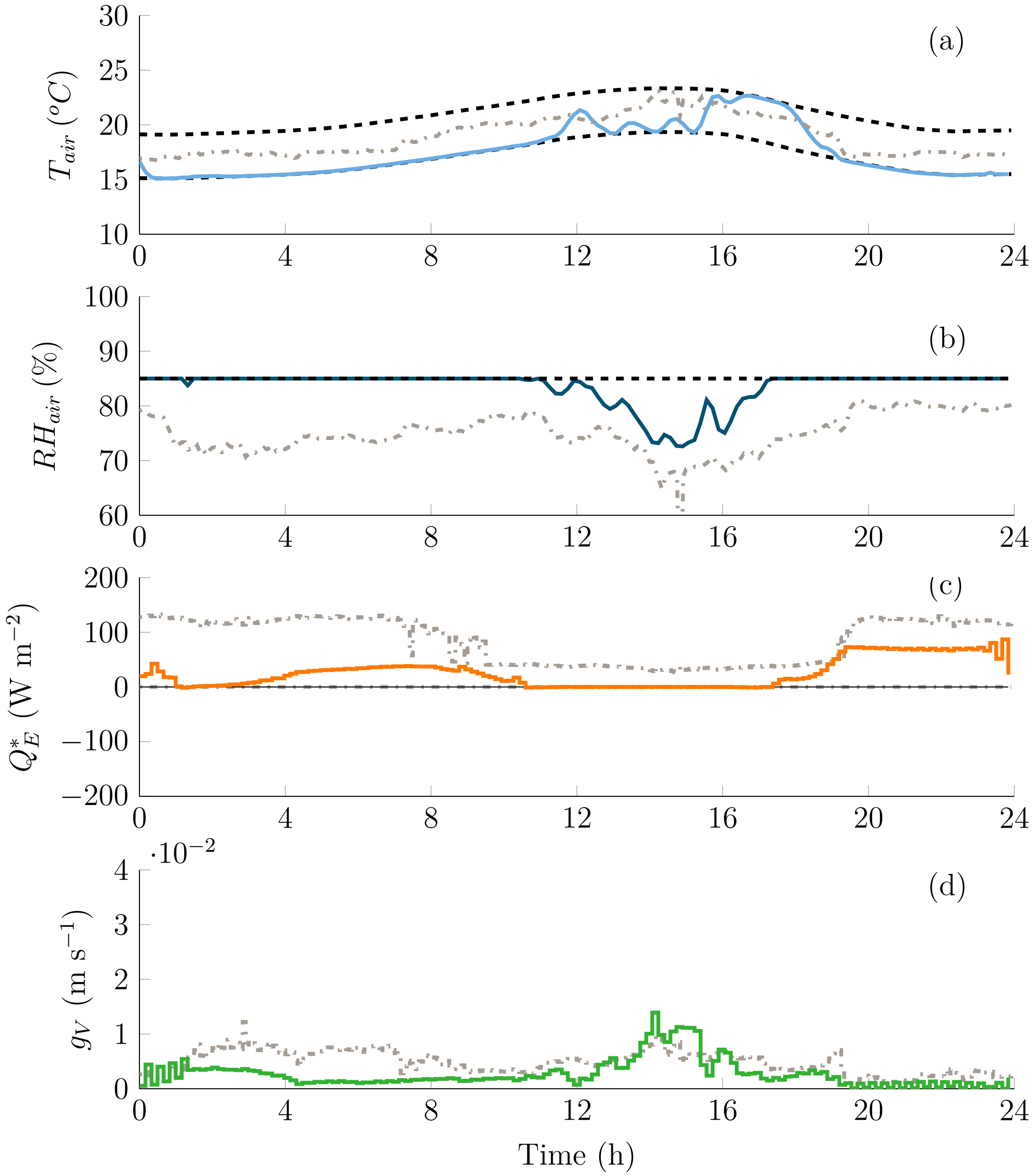


Figure 2.7: Optimal temperature T^*_{air} (a) and relative humidity RH^*_{air} (b) and corresponding optimal control inputs Q^*_E (Wm^{-2}) (c) and specific ventilation g^*_V (ms^{-1}) (d) for 16 March, 2012. The dashed lines are the bounds for temperature and humidity, and defined as $\Delta T = \pm\ 1\,°\mathrm{C}$ and $RH^{max}_{air} = 85\,\%$. The dashed-dotted lines are the realised trajectories by the grower.

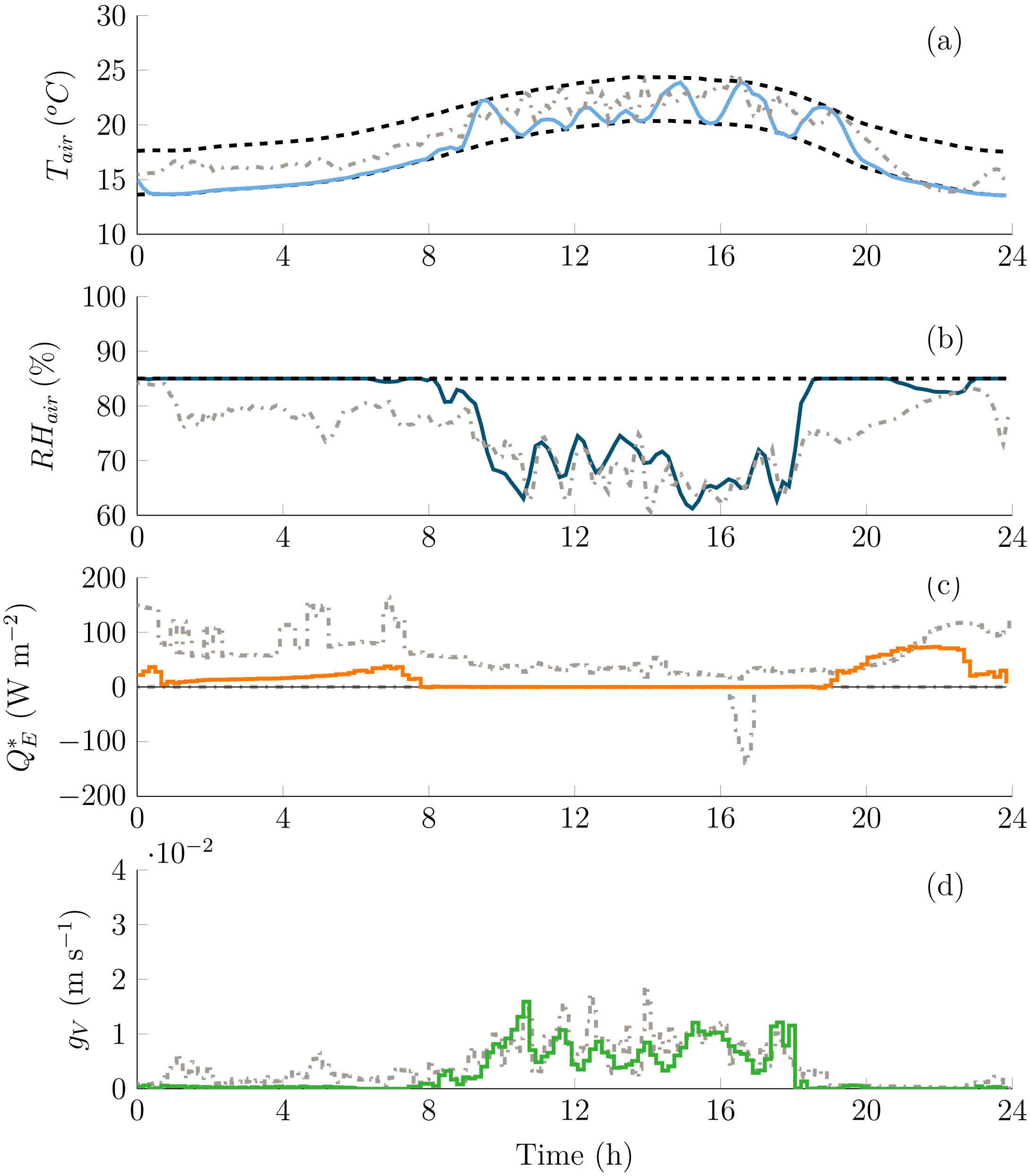


Figure 2.8: Optimal temperature T^*_{air} (a) and relative humidity RH^*_{air} (b) and corresponding optimal control inputs Q^*_E (Wm^{-2}) (c) and specific ventilation g^*_V (ms^{-1}) (d) for 16 April, 2012. The dashed lines are the bounds for temperature and humidity, and defined as $\Delta T = \pm\ 1\,°\mathrm{C}$ and $RH^{max}_{air} = 85\,\%$. The dashed-dotted lines are the realised trajectories by the grower.

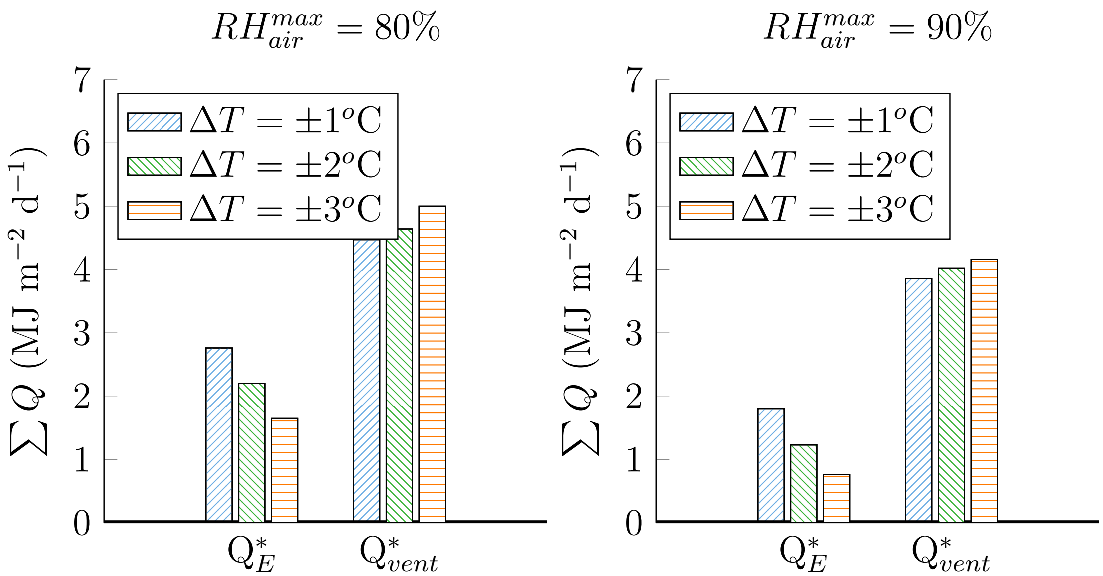


Figure 2.9: Minimal energy input $\sum Q_E^*$ and heat loss due to ventilation $\sum Q_{vent}^*$ for three different temperature bounds ΔT (± 1 °C, ± 2 °C and ± 3 °C) and two different upper bounds for relative humidity RH_{air}^{max} (80 % and 90 %) for 16 April, 2012. The energy input was calculated as the integral of the absolute energy input to account for both heating and cooling.

Relaxing the temperature bounds decreases the total energy input $\sum Q_E^*$ to the greenhouse (Fig. 2.9). Note that at this day no active cooling was used. All energy and vapour removal was done via ventilation. As the temperature bounds are relaxed, lower temperatures are allowed in the greenhouse, thus also less energy is needed to heat the greenhouse and to stay between the bounds. When the temperature bounds are lower, the optimal temperature is also more on the lower bounds, therefore, RH_{air} becomes higher without any dehumidification or ventilation. In order not to exceed RH_{air}^{max} more ventilation is needed. Greenhouse air temperature drops as a result of ventilation, and thus more heating is needed not to exceed the lower temperature bound.

The upper bound on relative humidity RH_{air}^{max} has large influence on the energy input. The higher relative humidity levels are allowed, the lower the amount of energy is needed. For lower RH_{air}^{max} more energy is released via natural ventilation because of dehumidification purposes.

2.4 Discussion

2.4.1 The model

In the literature different methods of modelling greenhouse climate have been described. To compare our model performance with the model performance of other authors the same measure of performance must be used. Even if similar performance indicators were available, also the location of the greenhouse, the type of greenhouse, the crop species, the available equipment in the greenhouse, the weather conditions, and simulation period need to be comparable. These factors make it hard to compare different greenhouse climate models with each other. Some examples of other greenhouse climate models and their performance are discussed here. The simulation model presented by Du et al. (2012) showed a simulation error on greenhouse temperature of 1.5 °C. They compared simulations and measurements for a period of 5 days. Baptista et al. (2010) adapted and validated a climate model for unheated greenhouses with a tomato crop in a mild winter climate region and found an overall RMSE for temperature of 1.6 °C and an overall RMSE of 7 % for the relative humidity. These values are in the same range as the values found in this research. El Ghoumari et al. (2005) found temperature differences in the range of ± 2 °C. In most of the literature the performance measures were in the same range as the performance measures found here, but none of them performed an analysis of the measured and simulated data for one whole year with very different weather circumstances in a commercial scale greenhouse, as was done here. Also, proper validation of crop transpiration against a long time series of weighing gutter data is unique, and showed very good performance.

2.4.2 Optimization

The optimization duration was chosen to be one full day. Given the five minute measurements from the greenhouse there are 288 measurements per day. It was previously shown by Van Henten and Bontsema (2008) that "for an open-loop optimal control problem concerning the realization of an average temperature during a fixed period of one day using a minimum amount of energy with full a-priory knowledge of the outdoor weather, a resolution of the heating profile between half an hour and one hour suffices to produce accurate results in terms of energy conservation". This seems to be confirmed by our analysis of the effect of the number of collocation points on the optimization.

Boundaries for allowable greenhouse air temperature and humidity were chosen based on realised greenhouse air temperature. The results confirm that allowing a wider bandwidth saves energy, which was also stated by (Dieleman and Hemming, 2011) who state that using lower and upper temperature bounds would be more energy-efficient than following a temperature set-point. However, measured greenhouse temperature trajectories vary day by day. Hence, in practice, the target pattern that should be set for each day is not exactly known. Moreover, in on-line application, it can not be assumed that the expected weather is known. Based on a forecast and his experience, the grower must set the target and the bounds. It is also possible for the grower to change the bounds during the day if needed. A new optimal solution can then be calculated and implemented.

The reported energy saving potential of relaxing the bounds assumes that deviating from the grower's trajectory is acceptable and not detrimental to the crop. As was argued before, the realization of the trajectories depends upon the actual weather, which cannot be exactly known to grower in advance. This means that it cannot be assumed that the realised trajectories are exactly matching the grower's believe on what is good for the crop, and from this it can be argued that deviations towards the bounds are probably no problem. On the humidity side, when choosing the maximum bound for relative humidity it is important that there is enough crop transpiration to ensure crop quality and there is no risk of condensation on crop parts. Taking the latter into account would require good insight in spatial distributions within the greenhouse, and a model of condensation on parts of the crop, which is beyond the scope of the current study, but which should make us careful in reporting exact energy savings. As for the temperature, staying on the lower bound for a long time alters the temperature integral, and could, when prolonged, disturb the balanced growth of the crop. However, with the current methodology the grower remains in control, and can adjust the bounds if needed when looking at the crop behaviour.

Heating and ventilation or active cooling at the same time did not occur in the optimization, while in practice growers often use a minimum pipe temperature or minimum window opening. This is done for other reasons than temperature or humidity control, for example to control air circulation in the greenhouse. However, minimum pipe temperature or minimum window opening can be implemented in the optimization procedure as well by adding additional constraints on heating or ventilation. The methodology as described in this paper can also be used by growers to get more insight in the effect of a lower minimum pipe temperature or lower bounds on the relative humidity. Whether to use the pipe rail heating or heat exchangers for heating, or natural ventilation or heat exchangers for cooling was not studied in this research, but in the second part of this research that focuses on the optimal scheduling of the equipment. If CO_2 is included in the optimization, this is going to play a role too. The numbers on energy saving will then also change, however, this can be higher or lower, depending on the desired CO_2 levels, available CO_2, and outside weather conditions. The method we present in this paper will remain valid.

2.5 Conclusions

A novel method was presented and evaluated to minimize the energy input to a modern greenhouse, instead of the use of full-fledged optimal control as outlined in Van Straten et al. (2010). Lower and upper bounds were introduced to specify the greenhouse air temperature and humidity in order to stay as close as possible to growers daily practice. The grower is given the lead in defining bounds. By doing so, no crop production models and market prices are needed, making this approach more suited for implementation in practice.

A dynamic model of greenhouse air temperature and humidity was developed, which was validated using measurements from a commercial greenhouse. A good agreement with reality was obtained (RMSE for T_{air} is 1.57 °C and RMSE for χ_{air} is 1.76 $\mathrm{g\,m^{-3}}$). The crop transpiration model was validated separately, and performed very well year round. It was shown that optimal control techniques can be used to minimize the total energy input to the greenhouse, while keeping greenhouse air temperature and humidity within desired bounds. A substantial potential energy-saving was shown for twelve days in 2012, which is related to the definition of lower and upper bounds, less natural ventilation at colder days, and more natural ventilation and less heating at warmer days. The effect of changing the bounds could be clearly demonstrated. Relaxing the temperature and humidity bounds decreases the energy input to the greenhouse, which is of great interest to growers. The growers will need to take the effect of these settings on the development and production of the crop into account.

2.6 Acknowledgements

We would gratefully thank HortiMaX B.V., Boonekamp Roses B.V., and Lek Habo Groep B.V. for the useful discussions and for providing their data. This research is funded by the Dutch Technology Foundation STW, which is part of the Netherlands Organisation for Scientific Research (NWO), and the Ministry of Economic Affairs.

Appendix

2.A Parameters and constants

Table 2.3: Parameters and constants used in the dynamic model.

Parameter	Description	Value
α_{cov}	heat transfer coefficient of the cover	$5\,\mathrm{Wm^{-2}C^{-1}}$
α_{pipe}	heat transfer coefficient of the pipe rail heating system[1]	$5\,\mathrm{Wm^{-2}C^{-1}}$
η	ratio of electric energy from lamps transformed into heat	$0.75\,-$
τ_{cov}	transmittance of the cover	$0.7\,-$
τ_{scr}	transmittance of the shadow screen	$0.3\,-$
τ_{scr2}	transmittance of the black-out screen	$0.99\,-$
c_{cap}	heat capacity of the greenhouse[2]	$30\,000\,\mathrm{JC^{-1}m^{-2}}$
r_b	boundary layer resistance	$150\,\mathrm{sm^{-1}}$
P_E	electrical power of lamps	$111.4\,\mathrm{Wm^{-2}}$
Constant	**Description**	**Value**
$C_{p,air}$	specific heat of air	$4000\,\mathrm{Jkg^{-1}C^{-1}}$
ρ_{air}	density of air	$1.225\,\mathrm{kgm^{-3}}$
L	energy needed to evaporate water	$2450\,\mathrm{kJkg^{-1}}$

[1]This parameter was missing in the published paper.
[2]The value in the published paper was not correct.

3

Optimal control of greenhouse climate using minimal energy and grower defined bounds

P.J.M. van Beveren
J. Bontsema
G. van Straten
E.J. van Henten

Published as Van Beveren, P. J. M., Bontsema, J., Van Straten, G., & Van Henten, E. J. (2015). Minimal heating and cooling in a modern rose greenhouse. Applied Energy, 137, 97 109. doi.org/10.1016/j.apenergy.2014.09.083

Abstract

Saving energy in greenhouses is an important issue for growers. Here, we present a method to minimize the total energy that is required to heat and cool a greenhouse. Using this method, the grower can define bounds for temperature, humidity, CO_2 concentration, and the maximum amount of CO_2 available. Given these settings, optimal control techniques can be used to minimize energy input. To do this, an existing greenhouse climate model for temperature and humidity was expanded to include a CO_2 balance. Heating, cooling, the amount of natural ventilation, and the injection of industrial CO_2 were used as control variables.

Standard optimization settings were defined in order to compare the grower's strategy with the optimal solution. This optimization resulted in a theoretical 47 % reduction in heating, 15 % reduction in cooling, and 10 % reduction in CO_2 injection for the year 2012. The optimal control does not need to maintain a minimum pipe temperature, in contrast to current practice. When the minimum pipe temperature strategy of the grower was implemented, heating and CO_2 were reduced by 28 % and 10 % respectively.

We also analyzed the effect of different bounds on optimal energy input. We found that as more freedom is given to the climate variables, the higher the potential energy savings. However, in practice the grower is in charge of defining the bounds. Thus, the potential energy savings critically depend on the choice of these bounds. This effect was analyzed by varying the bounds. However, because the effect can be demonstrated to the grower, the outcome has value to the grower with respect to decision making, an option that is not currently available in practice today.

3.1 Introduction

Greenhouse crop production in temperate climates for example, in the Netherlands is a major consumer of fossil fuels. Together, growers and the Dutch government have established targets for reducing the use of fossil fuels and CO_2 emissions by the year 2020 (Van der Valk and Van der Poll, 2007). Reducing energy consumption by greenhouses is beneficial for both growers and society. The total combined area of modern greenhouses in the Netherlands is 9500 ha (LEI Wageningen UR, 2015), worldwide, greenhouses cover approximately 750.000 ha. Given that the trend in greenhouse horticultural practices is moving towards more advanced equipment, the need for more advanced control in order to reduce energy consumption will also become increasingly important.

The primary climate variables that can be controlled in a greenhouse include temperature, humidity, CO_2 concentration, and light intensity at the plant level. Many studies have investigated the available technologies for controlling the greenhouse climate variables that are important for greenhouse crop production. An overview of different approaches for greenhouse climate control is provided by Rodríguez et al. (2015b). Also Bakker et al. (1995); Von Zabeltitz (2010) and ASHRAE (2011) provide an overview of the technologies available for controlling the indoor climate and design considerations when constructing a greenhouse. The actuators for greenhouse climate control are usually controlled by the greenhouse process control computer. Those control systems are developed rather detached from general building control and are a domain on their own. The majority of control rules in the process control computer are heuristic rules based on the experience of the growers and suppliers (Kamp and Timmerman, 1996; Berenguel et al., 2003; Van Straten, 1999). To achieve the desired greenhouse climate the grower can use many setting (Rodríguez et al., 2015a). The grower defines and adapts these settings in the process control computer based on his/her observations of the crop status, and based on his/her experience (Van Straten et al., 2000); in addition, the grower uses weather predictions, specific crop knowledge, production planning and product price forecasts.

Several approaches have been suggested for increasing automation of these processes. For example, Seginer et al. (1996) proposed mimicking an expert greenhouse grower by monitoring the actions of the expert grower, thereby extracting more objective knowledge from collected data using a neural-net. However, collecting data using a neural net requires an extremely large amount of data. Other authors proposed optimal control in order to maximize profit (Van Henten et al., 1997; Seginer and Ioslovich, 1998; Pohlheim and Heißner, 1999; Van Straten et al., 2002; Van Ooteghem et al., 2005; Rodriguez et al., 2008; Ioslovich et al., 2009). Gutman et al. (1993) minimized heating costs by exploiting deviations allowed from the standard blueprints expressed in temperature sums and, based on perfect weather predictions. Chalabi et al. (1996) presented a strategy to minimize energy consumption (rather than costs), using steady-state energy balance and daily weather forecasts.

Incrocci et al. (2008) proposed that optimal CO_2 concentration in the greenhouse can be based on an economic evaluation. To maintain a given CO_2 concentration within the greenhouse, the supply must balance the assimilated CO_2 flux with CO_2 flux to the outside air due to ventilation. Linker et al. (1998) optimized greenhouse operation and in particular CO_2 control, using a neural network. Most of these approaches used crop models and prices of the harvested product.

Despite their clear advantages, to the best of our knowledge, none of the optimal control approaches published to date are currently being applied in modern process control computers. Below is a list of some possible reasons for this lack of use.

- A lack of reliable crop production models for the wide range of crops and species grown in horticultural practice.
- Limited trust of growers and doubts regarding the quality of crop models, and a lack of experimentally demonstrated advantages (Van Straten, 1999).
- The need to leave part of the decision making freedom in the hands of the grower (Van Straten et al., 2000).
- The best approach to any model-based control strategy will require feedback of the crop state (Van Henten, 1994; Day, 1998; Van Henten and Bontsema, 2009). In addition, suitable on-line plant measurements are lacking.
- Accurate predictions of market prices are not currently available.

To overcome the aforementioned obstructions and to implement optimal control techniques in practice, we propose a method that circumvents the need for crop models yet still minimizes energy consumption. This method focuses on minimizing energy input to the greenhouse while obeying grower defined bounds for greenhouse air temperature, humidity, and CO_2 concentration. Thus, the responsibility for the crop yield and hence, income is left in the hands of the grower while the cost side is tackled by minimizing the resource input. Although optimizing inputs by satisfying set bounds may be common in other industries (Camacho and

Bordons, 2012), it is a relatively new concept in the greenhouse community (except for the abovementioned partial approaches, which focus solely on one aspect). The formulation of the optimal control problem allows for settings that growers are familiar with (e.g. minimum pipe temperature) to be easily taken into account in the optimization process. Minimizing energy input to the greenhouse with a dynamic energy balance was presented previously by Van Beveren et al. (2013) and later expanded to include a humidity balance (Van Beveren et al., 2015a). Here, we expand this process further by including a dynamic CO_2 balance. The addition of the dynamic CO_2 balance provides a truly integrated approach that takes all major aspects of greenhouse climate control into account, which has not been done before. This is important, given the trade-off between natural ventilation and the injection of industrial CO_2 , which occurs in a greenhouse with active cooling. Optimization was performed for one full year and compared with data measured from a commercial greenhouse.

In the method presented here, the grower defines the desired climate by temporally varying the upper and lower bounds on the climate variables. The principal idea is to exploit the dynamics of the ambient conditions as much as possible under given constraints with minimal energy input to the greenhouse. The advantage of this method is that it requires only a crop transpiration model for the humidity balance and a relatively simple assimilation model for the CO_2 balance, rather than crop models that include crop production. The grower weighs the expected yield and costs and then makes decisions regarding the bounds based on minimal energy input. Moreover, by varying the bounds the grower can gain further insight into the effects of his/her choices regarding the expected total energy input and CO_2 injection.

3.2 Materials and Methods

3.2.1 The greenhouse

The data used in this study were collected in a 40 709 m^2 Venlo-type greenhouse in Bleiswijk, the Netherlands (52 °N, 4.5 °E) (Fig. 3.1, right). Eave height was 6.4 m and ridge height was 7.2 m. The roof angle was 23°. The spans were equipped with 2020 ventilation windows 1.35 m × 1.67 m in size. A movable shadow screen (XLS 13 F Ultra) with 70 % light transmission was used, and a blackout screen was also present. In addition, the greenhouse was equipped with 4536 1000 W SON-T lamps (110 Wm^{-2}) for providing artificial lighting. A pipe rail heating system was installed, consisting of 1.1 m[pipe]m^{-2}. For each 80 m^2 area of greenhouse, one air-to-water heat exchanger (OPAC-106) was available and could be used to heat, cool, and dehumidify the greenhouse air. The greenhouse was connected to the OCAP (organic CO_2 for assimilation by plants) network in the Netherlands, which transports industrial CO_2 to growers. The maximum CO_2 injection capacity was $1200\,\mathrm{kgh^{-1}}$. Two separate Avalanche+ rose cultivars were grown on a substrate (rockwool) in separate sections of the greenhouse.

3.2.2 Dynamic model of greenhouse climate

In this approach, greenhouse climate is defined in terms of temperature (T_{air}), absolute humidity (χ_{air}), and the carbon dioxide concentration in the greenhouse air ($CO_{2,air}$). To minimize energy input to the greenhouse with optimal control techniques, a model of the greenhouse climate is needed. Therefore, the dynamic model for temperature (Eq. (3.1)) and absolute humidity (Eq. (3.2)) of greenhouse air published by Van Beveren et al. (2013) was expanded to include dynamic CO_2 mass balance (Eq. (3.3)). The latter is needed to study the utilization of the active cooling system in the greenhouse. The use of the cooling system reduces the ventilation requirement, thereby increasing utilization of the injected CO_2 . This results in either higher potential CO_2 levels in the greenhouse or a reduced CO_2 requirement. Controls for light levels in the greenhouse were considered to be set by the grower. The air in the greenhouse was assumed to be homogeneous. A first-principles model approach was used in order to gain insight into the physical processes that are related to the greenhouse climate. The model uses parameters that are relatively easy to obtain when studying other greenhouses. In order to achieve optimization, for computational reasons it is also beneficial to work with simple models.

Greenhouse air temperature is influenced by the following heat fluxes: incoming radiation (Q_{sun}), heat losses through the cover (Q_{cover}), transpiration by the crop (Q_{trans}), artificial lighting (Q_{lamps}), natural ventilation (Q_{vent}), cooling ($Q_{he,cool}$) and heating ($Q_{he,heat}$) by the heat exchangers, and heating by the pipe rail system (Q_{pipe}, in $\mathrm{Wm^{-2}}$). The absolute humidity of greenhouse air is influenced by the following vapor fluxes: crop transpiration (ϕ_{trans}), condensation on the cover (ϕ_{cov}), condensation in the heat exchangers due to cooling (ϕ_{he}), and vapor exchange with outside air by natural ventilation (ϕ_{vent} in $\mathrm{gm^{-2}s^{-1}}$). The calculation of fluxes in the energy and vapor balance, as published by Van Beveren et al. (2015a), were largely based on Van Henten (1994); Stanghellini and De Jong (1995); De Zwart (1996); Van Ooteghem (2007b); Van Henten and Bontsema (2009); Vanthoor (2011). Energy and vapor exchange with outside air were calculated using the natural ventilation model published by De Jong (1990). This approach yields the following equations for air temperature and humidity:

$$\frac{dT_{air}}{dt} = \frac{1}{c_{cap}}(Q_{sun} - Q_{cov} - Q_{trans} + Q_{lamp} \\ -Q_{vent} + Q_{he,heat} - Q_{he,cool} + Q_{pipe}) \quad (^{\circ}\mathrm{Cs}^{-1}) \tag{3.1}$$

$$\frac{d\chi_{air}}{dt} = \frac{1}{h}\left(\phi_{trans} - \phi_{cov} - \phi_{he} - \phi_{vent}\right) \quad (\mathrm{gm}^{-3}\mathrm{s}^{-1}) \tag{3.2}$$

The CO_2 model is based on the work of De Zwart (1996); Van Ooteghem (2007b); Stanghellini et al. (2011). The CO_2 mass balance is described as:

$$\frac{dCO_{2,air}}{dt} = \frac{1}{h}\left(\phi_{c,inj} - \phi_{c,ass} - \phi_{c,vent}\right) \quad (\mathrm{gm}^{-3}\mathrm{s}^{-1}) \tag{3.3}$$

where h is the average height of the greenhouse, $\phi_{c,inj}$ is the injection of pure industrial CO_2 to the greenhouse, $\phi_{c,ass}$ is the assimilation of CO_2 by the crop, and $\phi_{c,vent}$ is the CO_2 exchange with outside air due to ventilation. Fluxes in the CO_2 balance are described in more detail in the following sections.

CO_2 obtained from an external industrial source ($\phi_{c,inj}$) was injected into the greenhouse. Injection data were available from the process control computer to validate the model and to compare with the grower's operation of the greenhouse.

The original assimilation model of Nederhoff and Vegter (1994) was later simplified by Stanghellini et al. (2011) to achieve a two-variable model that reproduces the trend and the level of the complex model. In this model (Eq. (3.4)), assimilation is a function of radiation at the plant level ($I_{rad,plant}$ in Wm^{-2}) and CO_2 concentration (in gm^{-3}). The model of Nederhoff and Vegter (1994) gives parameters for tomato, cucumber, and sweet pepper, but not for rose. In the simplified model, the maximum assimilation rate of a tomato crop is $2.2 \cdot 10^{-3}$ $\mathrm{gm}^{-2}\mathrm{s}^{-1}$. A model of photosynthesis for rose (*Rosa hybrida L.*) was presented by Kim and Lieth (2001, 2003). This model has more parameters than the model of Stanghellini et al. (2011) and is based on measurements from a specific species of rose. Although the model of Stanghellini et al. (2011) does not include photorespiration, simulations using both models yielded similar performance; therefore, the simplified model of Stanghellini et al. (2011) was used without further calibration.

$$\phi_{c,ass} = 2.2 \cdot 10^{-3} \frac{1}{1 + \frac{0.42}{CO_{2,air}}} \left(1 - e^{-0.003 I_{rad,plant}}\right) \quad (\mathrm{gm^{-2}s^{-1}}) \tag{3.4}$$

Exchange of CO_2 with outside air due to natural ventilation was described as:

$$\phi_{c,vent} = g_V \left(CO_{2,air} - CO_{2,out}\right) \quad (\mathrm{gm^{-2}s^{-1}}) \tag{3.5}$$

where g_V is the specific ventilation (in $\mathrm{m^3m^{-2}s^{-1}}$), $CO_{2,air}$ is the carbon dioxide concentration of indoor air (in ($\mathrm{gm^{-3}}$)) and $CO_{2,out}$ is the carbon dioxide concentration of outside air. Specific ventilation (g_V) is a function of window opening, indoor and outside temperature, and wind speed and was calculated using the ventilation model presented by De Jong (1990).

3.2.3 Data collection

Data collected at 5 minute time intervals from the HortiMaX® process control computer in the greenhouse during the entire year of 2012. Temperature and humidity were measured using eight measurement boxes (Fig. 3.1, left), with two boxes in each of the four compartments. CO_2 was measured at two locations in the greenhouse. To compare the simulation results with the measurements, the box values were averaged to yield the spatial mean. Differences between the separate temperature, humidity, and CO_2 measurements were analyzed by comparing the mean absolute error (MAE, Eq. (3.6)) between the average and individual sensors and the correlation coefficient between the average and individual sensors in order to test the consistency of the measurements.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid \tag{3.6}$$

In this equation, $\hat{y}_i$ is the simulated value at time i, y_i is the measured value at time i, and n is the number of measurements (Wallach et al., 2014).

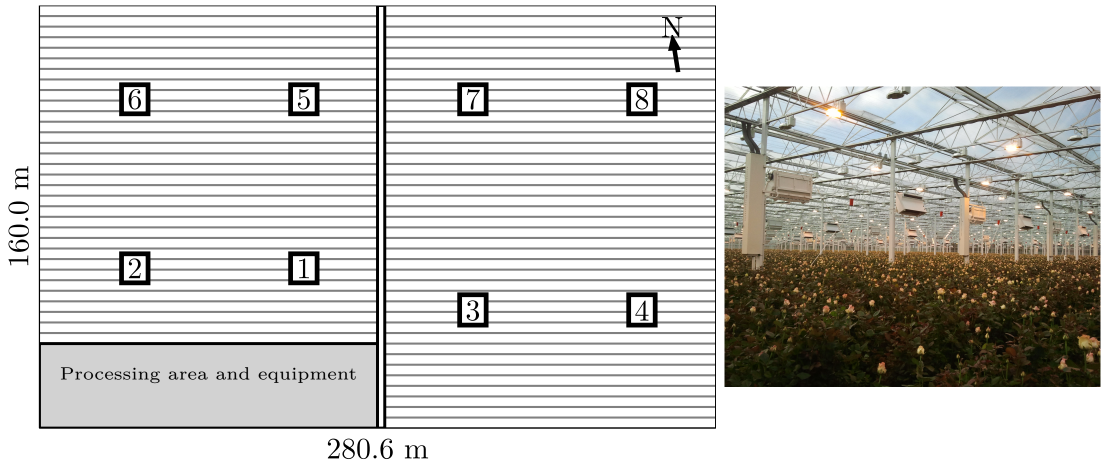


Figure 3.1: Floor plan of the greenhouse with the locations of the eight measurement boxes for temperature and humidity (left) and a photo of the greenhouse interior (right).

The mean (and standard deviation, SD) MAE between the average and individual temperature sensors was 0.31 °C (0.31 °C). The mean correlation coefficient between the individual sensors was 0.98 on average. The mean (SD) MAE of the relative humidity, was 1.3 % (0.4 %). The mean correlation coefficient between the relative humidity (RH) sensors was 0.94 for the entire year. MAE (SD) between the two CO_2 sensors was 88.4(80) ppm. The correlation coefficient between the two CO_2 measurements was 0.86, which means that considerable differences were occasionally measured between the sensors.

The following outside weather conditions were measured: solar radiation, temperature, wind speed, relative humidity, and CO_2 concentration. Because no outside CO_2 sensor was installed at this greenhouse, we used CO_2 measurements obtained from the Wageningen UR Greenhouse Horticulture Research Station, which is located approximately four kilometers from the rose greenhouse. All other outside weather conditions were measured using a HortiMaX® weather station.

The crop transpiration model, a modification of the model presented by Stanghellini (2010), was validated using data from the HortiMaX® Prodrain® weighing gutter system presented in Van Beveren et al. (2015a).

3.2.4 Formulation of the optimal control problem

Four control variables were defined in order to maintain temperature, humidity, and CO_2 concentration between the grower-defined bounds while minimizing total energy input to the greenhouse. In contrast with Van Beveren et al. (2015a), total energy input was divided into heating and cooling, and a control variable for the injection of CO_2 was added to the optimization.

The first control variable was the energy input to the greenhouse ($Q_{E,heat}$). This can be in the form of heating with the pipe rail heating system or heating with the water-to-air heat exchangers. The second control variable was the energy extracted from the greenhouse by active cooling ($Q_{E,cool}$). Active cooling can be performed solely using heat exchangers. The reason for separating these two energy inputs is because it should be possible to supply both heat and cooling at the same time. This follows from horticultural practice in which ventilation is applied to remove water vapor while at the same time heat is applied in order to maintain a desired temperature. This approach also allows for the implementation of a minimum pipe temperature in the greenhouse. The third control variable was the specific ventilation (g_V), which is related to opening of ventilation windows. The amount of air exchange between inside- and outside air influences the temperature, humidity, and CO_2 concentration of the greenhouse air. The fourth control variable was the injection of industrial CO_2 ($\phi_{c,inj}$) into the greenhouse.

The optimization problem was formulated as a dynamic optimal control problem. Given the model, the initial conditions $T_{air}(0)$, $\chi_{air}(0)$, and $CO_{2,air}(0)$, the external inputs, and the constraints on the climate variables and control inputs, the optimal control trajectory that minimizes total energy input over time can be obtained by minimizing the following functional J:

$$\min_{Q_{E,heat},Q_{E,cool},g_V,\phi_{c,inj}} J(Q_{E,heat}, Q_{E,cool}, g_V, \phi_{c,inj}) = \int_{t_0}^{t_f} \left(Q_{E,heat}^2 + Q_{E,cool}^2\right) \, dt \tag{3.7}$$

where t_0 is the initial time and t_f the final time.

The bounds on the climate variables were defined as

$$T_{air}^{min}(t) \leq T_{air}(t) \leq T_{air}^{max}(t), \tag{3.8}$$

$$RH_{air}(t) \leq RH_{air}^{max}(t), \tag{3.9}$$

$$CO_{2,air}^{min}(t) \leq CO_{2,air}(t) \leq CO_{2,air}^{max}(t) \tag{3.10}$$

where $T_{air}^{min}(t)$ and $T_{air}^{max}(t)$ were the lower and upper temperature bounds, $RH_{air}^{max}(t)$ was the upper bound for relative humidity, and $CO_{2,air}^{min}$ and $CO_{2,air}^{max}$ the lower and upper bounds for CO_2 .

The control variables were constrained by the following control inequality constraints:

$$Q_{E,heat}^{min}(t) \leq Q_{E,heat}(t) \leq Q_{E,heat}^{max}(t) \tag{3.11}$$

$$-Q_{E,cool}^{min}(t) \leq Q_{E,cool}(t) \leq Q_{E,cool}^{max}(t) \tag{3.12}$$

$$g_V^{min}(t) \leq g_V(t) \leq g_V^{max}(t) \tag{3.13}$$

$$0 \leq \phi_{c,inj}(t) \leq \phi_{c,inj}^{max}(t) \tag{3.14}$$

$$\int_{t_0}^{t_f} \Phi_{c,inj} dt \ \leq \phi_{c,inj}^{max,day} \tag{3.15}$$

where $Q_{E,heat}^{max}$ was the maximum heating capacity and $Q_{E,cool}^{min}$ was the maximum cooling capacity. The minimum specific ventilation (g_V^{min}) was equal to the leakage ventilation, and g_V^{max} was equal to the specific ventilation at 100 % window opening of both wind and leeward side windows, and thus changed over time. Once the required g_V was obtained from the optimization, the ventilation model was used to obtain the required window opening at the prevailing wind speed. $\phi_{c,inj}^{max}$ was the maximum CO_2 injection rate, and $\Phi_{c,inj}^{max,day}$ was the maximum amount of CO_2 that could be injected per day.

To compare the optimization results with the grower's operation of the greenhouse, we first defined a trajectory of the climate variables. Next, for the optimization, bounds were defined as listed in Table 3.1. The choice was guided by what would be considered realistic in practice. In addition, realistic equipment capacities were defined in order to be able to compare with the grower's strategy. Energy use based on the grower's operation was calculated using the controls captured from the greenhouse process control computer and calculated with the model equations as described above.

Table 3.1: Standard settings of the bounds for optimization.

Symbol	Description	Value	Unit
$T_{air}^{min}(t)$	Lower temperature bound	$\overline{T}'_{air,meas}(t) - 0.5°C$	°C
$T_{air}^{max}(t)$	Upper temperature bound	$\overline{T}'_{air,meas}(t) + 0.5°C$	°C
$RH_{air}^{max}(t)$	Upper RH bound	$\max RH_{air,meas}(t)$	%
$CO_{2,air}^{min}(t)$	Lower CO_2 bound	$0.97 \cdot \overline{CO}'_{2,air,meas}(t)$	gm^{-3}
$CO_{2,air}^{max}(t)$	Upper CO_2 bound	2000 ppm	gm^{-3}
$Q_{E,heat}^{max}(t)$	Maximal heating capacity	200	Wm^{-2}
$Q_{E,cool}^{min}(t)$	Maximal cooling capacity	200	Wm^{-2}
$\phi_{c,inj}^{max}(t)$	Maximal CO_2 injection capacity	1200	kgh^{-1}
$\Phi_{c,inj}^{max,day}$	Total amount of CO_2 available per day	$\int \phi_{c,inj,meas} dt$	$gm^{-3}d^{-1}$

As temperature bounds, a deviation of 0.5 °C around the smoothed realized temperature was chosen. Smoothing was performed using a moving average filter with a span of 36 measurements, which corresponds to a time span of 3 hours. The upper bound for RH was defined as a constant value per day according to the highest measured RH on that day. The lower bound for CO_2 was defined as 97 % of the smoothed, measured CO_2 concentration in the greenhouse. The upper boundary was chosen as a fixed value of 2000 ppm in order to prevent damage to the crop.

The maximum heating and cooling capacity were fixed at 200 Wm^{-2}. For the standard situation, the minimum heating capacity $Q_{E,heat}^{min}$ and minimal cooling capacity $Q_{E,cool}^{max}$ were set to zero. The maximum injection capacity with standard settings was 1200 kgh^{-1}, which corresponds to 33 $gm^{-2}h^{-1}$.

For the total amount of CO_2 available per day, the total amount of CO_2 that was injected by the grower was used as the upper bound.

To implement minimum pipe temperature as often used in practice a lower bound for the minimum heating capacity ($Q_{E,heat}^{min}$) was set to the pipe temperature that the grower used at that time in the greenhouse (a measured time series). The lower bound for heating was calculated as:

$$Q_{E,heat}^{min} = \alpha_{pipe} \left(T_{pipe,min} - T_{air}\right) \quad (Wm^{-2}). \tag{3.16}$$

Here, α_{pipe} is the heat transfer coefficient of the heating pipes (in Wm^{-2}).

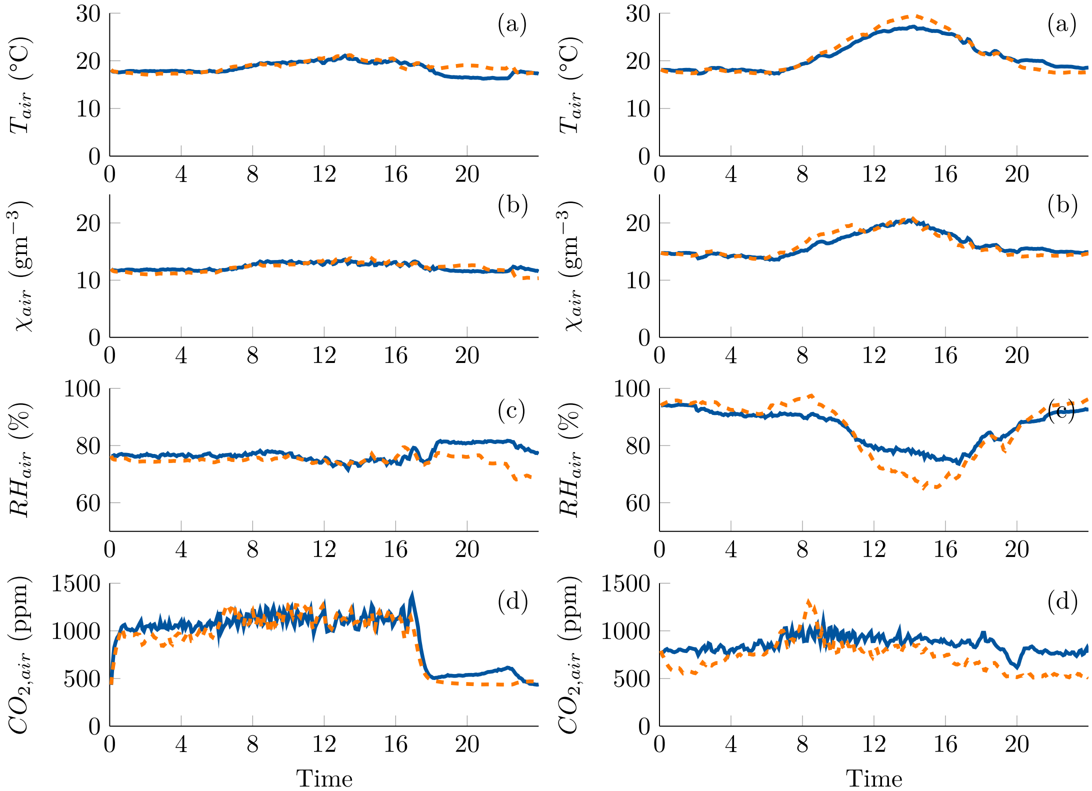
The optimal control problem was solved using PROPT - Matlab Optimal Control Software (Rutquist and Edvall, 2010). PROPT uses a collocation method to solve optimal control problems; thus, the solution takes the form of a polynomial that satisfies the differential algebraic equations and path constraints at the collocation points (Edvall and Goran, 2009). The input data were interpolated between the collocation points, and an optimization horizon of one day was used. Data processing, model building, validation, and optimal control formulation with PROPT were performed using Matlab (version 7, MathWorks Inc., Natick, MA).

3.3 Results

3.3.1 Model performance

Figs. 3.2a and 3.2b show the measured and simulated greenhouse air temperature (T_{air}), absolute humidity (χ_{air}), relative humidity (RH_{air}), and CO_2 concentration ($CO_{2,air}$) on a cold (February 18, 2012) and on a warm day (July 23, 2012). On the cold day in February, mean outside temperature was 7.1 °C, and mean global radiation was 103 Wm^{-2} during the light period; on the warm day, mean outside temperature was 18.3 °C and mean global radiation was 437 Wm^{-2}.

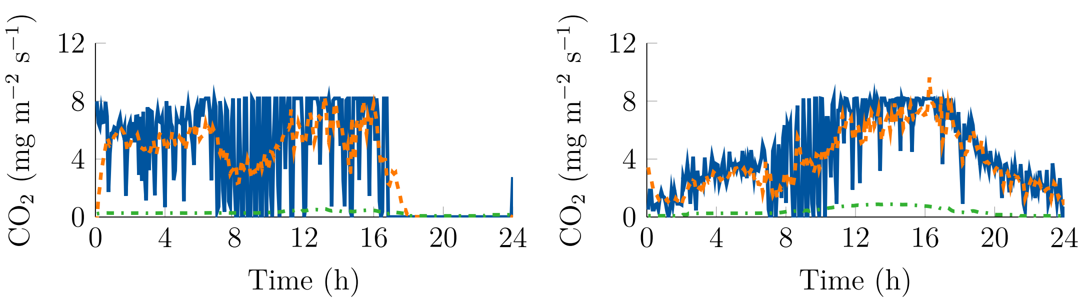
The simulated values were quite similar to the values measured on these two days. The largest differences were observed in the simulated CO_2 concentration and in the estimate of relative humidity, which is a function of both temperature and absolute humidity. This difference is due to the dependence of the CO_2 balance on the ventilation model and on the measurement of CO_2 injection. The different fluxes in the CO_2 balance are shown in Figs. 3.3a and 3.3b for the cold and warm days in 2012. The principal factors that influence ambient CO_2 concentration are ventilation and CO_2 injection. Fig. 3.3 shows that the injection of CO_2 is for the most part needed in order to compensate for CO_2 losses due to ventilation. Compared to the two other fluxes, the assimilation of CO_2 has a relatively small impact on CO_2 balance. For the cold and warm days (i.e. February 18 and July 23), assimilation comprised 7 % and 9 %, respectively, of the total CO_2 usage (ventilation + assimilation). Higher assimilation rates are expected during the summer due to higher light levels in the greenhouse.



(a) 18 February, 2012

(b) 23 July, 2012

Figure 3.2: Measured (—) and simulated (- - -) T_{air} (a), χ_{air} (b), RH_{air} (c), CO_2 concentration (d) for 18 February (a) and 23 July (b), 2012.



(a) 18 February, 2012

(b) 23 July, 2012

Figure 3.3: CO_2 injection (—), ventilation (- - -), and assimilation flux (-·-) for 18 February (a) and 23 July, 2012 (b).

The model was validated for the entire year of 2012. To identify possible differences in performance over time, the model's performance was assessed for each month. The monthly correlation coefficient (r) and Root Mean Square Error ($RMSE$, Eq. (3.17)) for the three climate variables are summarized in Table 3.2. The table shows the results for an open-loop simulation for the whole year at once. There was no update of the states with measurement data. The simulation result (temperature, humidity, and CO_2 concentration were compared with the average spatial indoor climate for each time step (5 min).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \tag{3.17}$$

In this equation, $\hat{y}_i$ is the simulated value at time i, y_i is the measured value at time i, and n is the number of measurements Wallach et al. (2014).

Table 3.2: Correlation coefficient r and Root Mean Square Error $RMSE$ of measured and simulated greenhouse air temperature, relative humidity, and CO_2 concentration per month and for the whole year 2012.

r	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Tot	Unit
T_{air}	0.65	0.72	0.85	0.84	0.92	0.92	0.94	0.96	0.92	0.79	0.71	0.69	0.89	–
RH_{air}	0.32	-0.33	0.58	0.79	0.71	0.59	0.66	0.73	0.75	0.76	0.77	0.57	0.54	–
$CO_{2,air}$	0.49	0.62	0.78	0.73	0.82	0.84	0.75	0.80	0.68	0.75	0.79	0.58	0.75	–
$RMSE$	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Tot	Unit
T_{air}	1.20	1.64	1.38	1.32	1.26	1.26	1.19	1.11	1.06	1.14	1.16	1.34	1.26	°C
RH_{air}	6.2	14.8	4.3	3.4	6.3	7.4	8.6	6.7	9.0	5.1	6.5	8.4	7.7	%
$CO_{2,air}$	219	288	159	167	153	153	178	170	213	158	190	237	194	ppm

Correlation was highest between the measured and simulated temperature values. With respect to RH, a negative correlation was observed in February. At the beginning of this month, the outside temperature was below zero; in contrast, in all other months the differential between inside and outside temperature was smaller than in the beginning February. The correlation was stronger for the three climate variables in the summer period than in the winter period.

The $RMSE$ for temperature was approximately 1.2 °C for the entire year; $RMSE$ for temperature was higher in February. A higher RMSE was also observed in February with respect to RH and CO_2. $RMSE$ for RH was lowest the months of March and April. With respect to CO_2 , the differences between measured and simulated values were relatively high. A visual inspection of the simulation results for the entire year revealed that some days had a near perfect match between measured and simulated values. These days were distributed throughout the entire year and usually lasted for a few days.

3.3.2 Optimization results

Fig. 3.4 shows the optimization results for June 16, 2012 using the standard settings defined in Table 3.1. This date was chosen because it is a typical example of a situation in which CO_2 is a limiting factor and active cooling was used (both by the grower and in the optimal situation). CO_2 was considered a limiting factor because all available CO_2 was used in the optimal case.

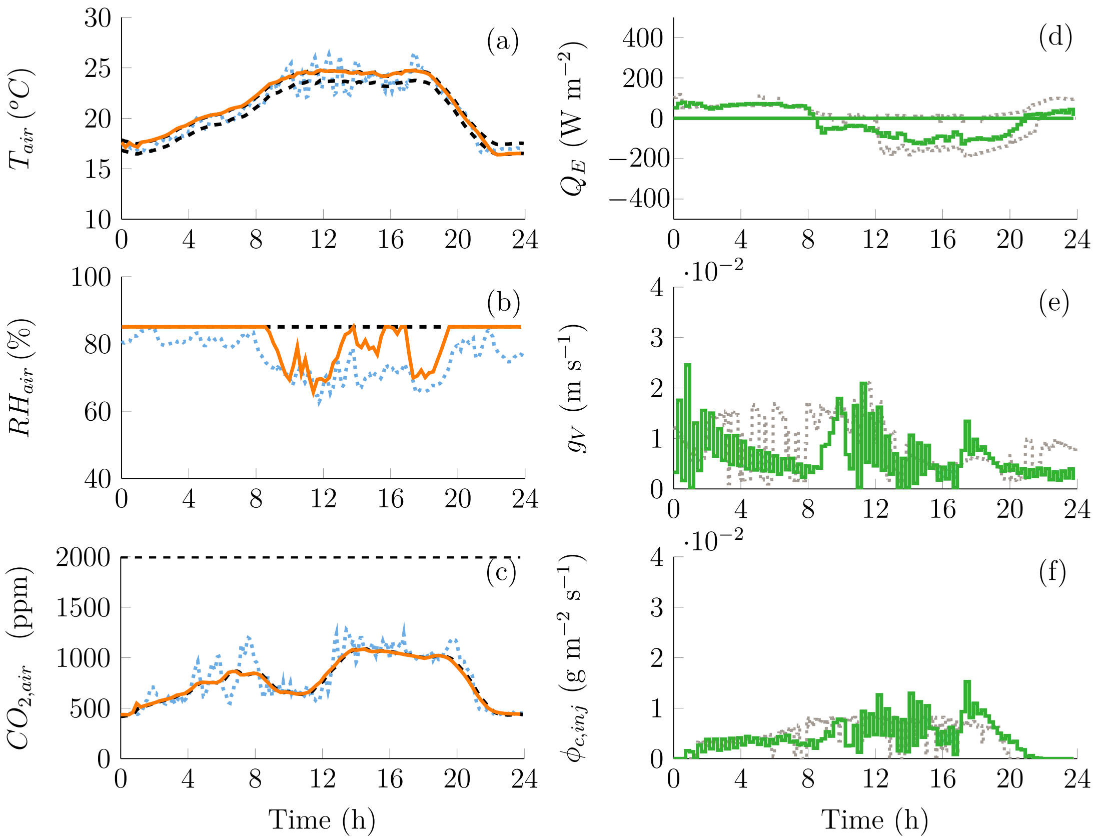


Figure 3.4: Optimal states (——) and optimal control trajectories (——) for June 16, 2012 with standard settings. The dashed black lines are the bounds of the states. The realized climate variables (——) and the control trajectories resulting from grower's operation (——) are also shown.

The temperature sum for the realized situation by the grower and the optimal situation on June 16, 2012 was 504 °Ch and 511 °Ch, respectively. Using the chosen standard settings, the temperature sum was always similar to the realized temperature sum by the grower. This ensures comparable plant growth and development. The maximum allowed RH in the greenhouse was 85 %. RH was kept at the upper bound during the night and was lower during the day. The amount of CO_2 injected by the grower and in the optimal situation was $355\,\mathrm{gm^{-2}d^{-1}}$in both cases; thus, all available CO_2 was used. In the optimal situation, CO_2 was at the lower bound at all times. Although higher CO_2 concentrations are allowed, they are not favorable, as only a limited amount of CO_2 is available; thus, the amounts of heating and active cooling are minimized at the same time. Although, higher CO_2 levels can be achieved in the greenhouse, additional active cooling is needed.

The minimal energy input (heating and cooling) on June 16, 2012 was 5.71 $\mathrm{MJm^{-2}d^{-1}}$; minimal energy input was $2.15\,\mathrm{MJm^{-2}d^{-1}}$ and $3.54\,\mathrm{MJm^{-2}d^{-1}}$ for heating and cooling, respectively. Heating and active cooling resulting from the grower's operation was $8.25\,\mathrm{MJm^{-2}d^{-1}}$; $3.28\,\mathrm{MJm^{-2}d^{-1}}$ and $4.97\,\mathrm{MJm^{-2}d^{-1}}$ was due to heating and cooling, respectively. The net energy (i.e. heating minus cooling) that was extracted from the greenhouse was $1.39\,\mathrm{MJm^{-2}d^{-1}}$ for the optimal situation and $1.69\,\mathrm{MJm^{-2}d^{-1}}$ for the grower's situation. The energy fluxes due to artificial lighting, radiation, and heat loss through the cover were similar to the fluxes realized when following the grower's strategy. The energy flux due to transpiration was slightly lower in the optimal case, likely due to differences in temperature and humidity. Natural ventilation was higher in the optimal situation. However, in the optimal situation, active cooling was applied in order to retain CO_2 in the greenhouse and to maintain the desired CO_2 levels. Therefore, less heating was applied in the greenhouse in the optimal situation. This difference was due primarily to the lower heating beginning at 9 pm. From midnight till 8 am, heating was virtually the same in both situations. Compared to the grower's situation, in the optimal situation, active cooling began earlier and less natural ventilation was applied between 8 am and 12 pm than in the grower situation. The amount of active cooling was just sufficient to maintain temperature at the upper bound. Because of the active cooling, less CO_2 was injected between 8 am and 12 pm.

Based on the realized greenhouse air temperature (shown as the blue line in Fig. 3.3a), we conclude that the chosen bandwidth of the smoothed temperature (±0.5 °C) during the night was also realized by the grower, whereas the grower allowed higher fluctuations in indoor temperature during the day. Because, a larger bandwidth would allow the temperature to be higher, less cooling would be needed, thereby saving. The daily optimization results with standard settings for the entire year of 2012 are shown in Fig. 3.5. Within 2012, optimal conditions were not achieved in 78 days (21 % of the year); the majority of these days were during the summer. For these days, the calculated energy fluxes from the grower were used as the optimal result. We observed a correlation between days with poor simulation performance and days with no optimal solution, particularly when RH was considered. The average $RMSE$ between the simulation and measurements of RH was 6 % for days with an optimal solution, compared to 8 % for days in which no optimal solution was obtained.

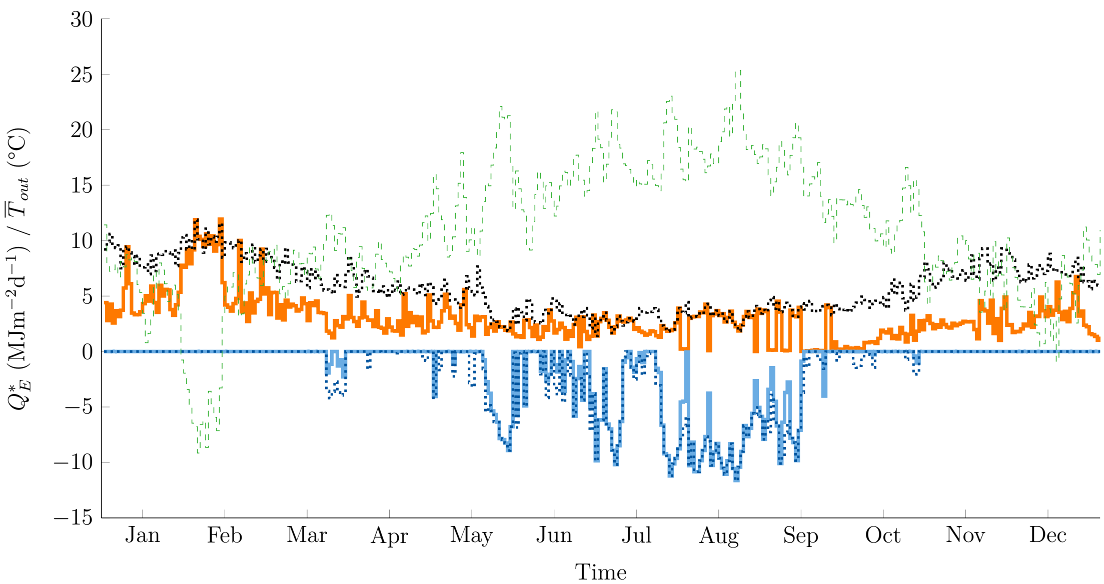


Figure 3.5: Results of daily optimization with standard settings for the year 2012. Optimal heating (—), optimal cooling (—), heating grower (······), cooling grower (······), and mean outside temperature(- - -).

In 2012, the optimal input of heat and cold was lower than the heat and cold input resulting from the grower's operation. On the days in which the outside temperature was <0 °C, energy input was similar to the energy input obtained by the grower. Active cooling was applied on the same days in the optimal case as when the grower used active cooling. However, the grower applied active cooling ($Q_{he,cool}$ < 0.5 MJm^{-2}d^{-1}) on 127 days compared to 105 days in the optimal situation. In addition, the amount of cooling was lower in the optimal situation.

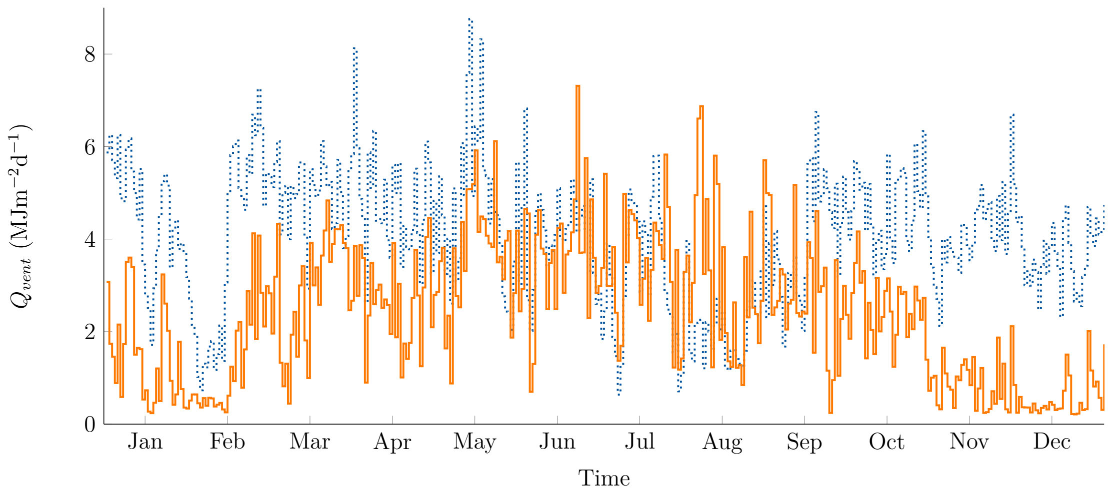


Figure 3.6: Daily optimal ventilation (——) and ventilation of the grower (······) Q_{vent} (MJm^{-2}d^{-1}) for 2012.

The total amounts of heating, cooling, and CO_2 injection in the optimal situation and based on the grower's operation are summarized in Table 3.3. In the optimal case, 47 % less heating, 15 % less cooling, and 10 % less CO_2 was supplied to the greenhouse.

Table 3.3: Total heating, cooling, and CO_2 injection of the grower, the optimal situation with standard settings, and the optimal situation with minimum pipe temperature as used by the grower for 2012.

	Heating GJm^{-2}y^{-1}	Cooling GJm^{-2}y^{-1}	CO_2 injection kgm^{-2}y^{-1}
Grower	2.08	0.71	95.4
Opt standard settings	1.10	0.60	85.7
Opt minimum pipe	1.49	0.71	85.9

In the optimal situation, less CO_2 was supplied to the greenhouse in order to meet the CO_2 constraints (Table 3.3). The primary cause for this is the lower daily ventilation flux in the optimal situation compared to the situation calculated based on the grower's operation (Fig. 3.6). In the optimal situation, daily ventilation was higher during some of the summer days; on these days, less heating and cooling was applied in the optimal situation, and temperature and humidity constraints were met by a combination of active cooling and natural ventilation. The energy input during the cold period in February was similar between the optimal situation and the grower's strategy. Compared to the optimal situation, less ventilation was used in the grower's strategy; thus, less CO_2 was injected into the greenhouse.

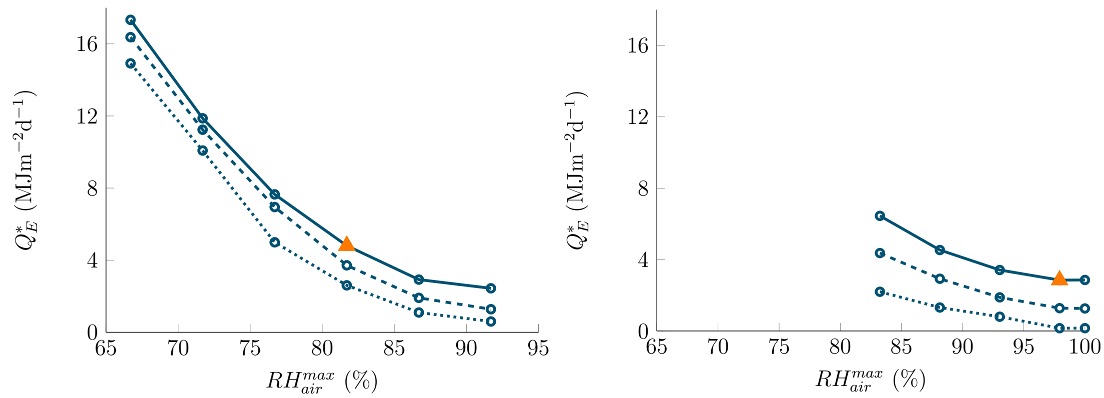
We also studied optimal heating and cooling for the case with a minimum pipe temperature. Minimum pipe temperature was similar between the optimal situation and the grower's strategy. Two reasons to use a minimum pipe temperature in practice are to create air movement through the canopy and to prevent of condensation on the leaves and fruit (Teitel et al., 1999). For 59 days (16 % of the year), no optimal solution was found with the optimization settings used (all days were during warm period of the year); for these days we used the data obtained from the grower. Compared to the grower's strategy, optimal heating and cooling was 28 % lower and optimal cooling was 1 % higher, respectively (Table 3.3). Due to the minimum pipe temperature, more heat was delivered to the greenhouse, and greenhouse air temperature was closer to or matched the upper bound. Therefore, more ventilation and active cooling was applied in the optimal situation with minimum pipe temperature. Active cooling was used on 136 days. The CO_2 needed on a yearly basis was similar to the situation using standard settings.

3.3.3 Analysis of optimization settings

Effect of temperature and humidity bounds

Next, we analyzed the effects of the lower and upper temperature bounds, as well as the upper bound for the relative humidity (RH_{air}), on optimal energy input. The following temperature deviations (ΔT) were used: 0.5 °C (standard case), 2.0 °C, and 3.5 °C. A deviation of 0.5 °C means that the temperature is permitted to be either 0.5 °C above or below the smoothed measured indoor temperature. The range for RH_{air}^{max} was −15 % to 10 % in increments of 5 %, according to the highest measured RH_{air}. This analysis was performed for both February 18 and June 16.

The energy input needed to meet the constraints with standard settings for February 18, 2012 was 4.8 $\mathrm{MJm^{-2}d^{-1}}$ (Fig. 3.7a). It therefore follows from the analysis that expanding the permissible temperature range will result in a lower energy input. Maintaining lower RH levels in the greenhouse increased energy input due additional heating and ventilation needed to maintain temperature between the bounds and to remove vapor from the air via natural ventilation. Similar results were obtained for June 16 (Fig. 3.7b).

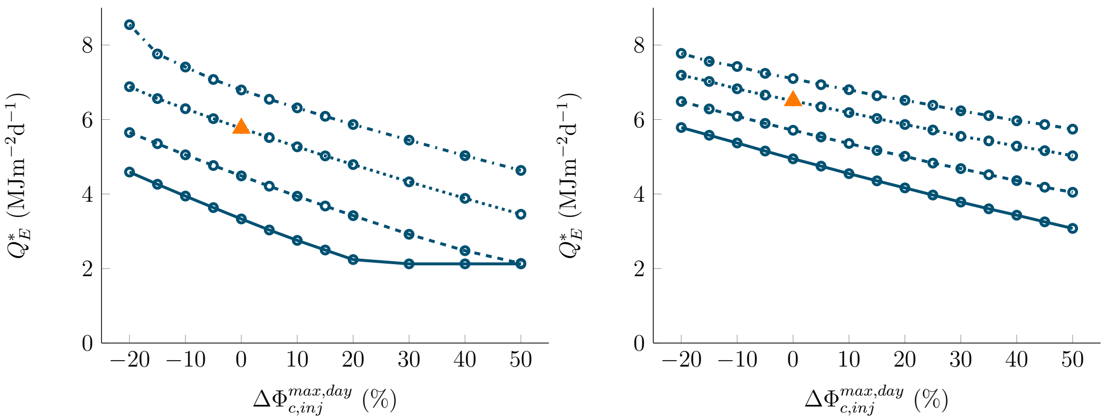


(a) 18 February, 2012 (b) 16 June, 2012

Figure 3.7: Optimal energy input Q_E^* for different temperature and humidity bounds for 18 February, 2012 (a) and 16 June, 2012 (b). Values for ΔT_{air} were 0.5 °C ( ), 2.0 °C ( ), and 3.5 °C ( ). All other settings were standard settings. ▲ is optimization with standard settings.

Effect of CO_2 bounds

Next, we analyzed the effect of the lower bound for $CO_{2,air}$ and the total amount of CO_2 available per day $\Phi_{c,inj}^{max,day}$ on optimal energy input. This analysis was performed for June 16 and September 4. June 16, 2012 was a cloudier day with high radiation levels (average radiation was 431 Wm^{-2}), and the mean outdoor temperature during the light period was 17.4 °C. September 4, 2012 was a bright day; mean outdoor temperature during the light period was 21.0 °C, and average radiation was 437 Wm^{-2}. Active cooling was used by the grower on both days. The results of optimizing using four different levels of the lower bound ($CO_{2,air}^{min}$) are shown in Fig. 3.8. The data from February 18 were not included in the analysis, as no active cooling was applied on this day, and CO_2 did not limit energy input. Therefore, small changes in the CO_2 bounds had no effect on the energy input. For the entire year of 2012, all available CO_2 was used on 282 days (77 % of the year). The days in which CO_2 was not a limiting factor occurred in the spring and in the winter.



(a) 16 June, 2012

(b) 4 September, 2012

Figure 3.8: Optimal energy input Q_E^* for different lower CO_2 bounds ($CO_{2,air}^{min}$) and available CO_2 ($\Phi_{c,inj}^{max,day}$) for 16 June, 2012 (a) and 4 September, 2012 (b). Values for $CO_{2,air}^{min}$ were the standard settings −20 % (), −13 % (), −3 % (), and 7 % (). All other settings were standard optimization settings. is optimization with standard settings.

On both June 16 (Fig. 3.8a) and September 4 (Fig. 3.8b), the total amount of available CO_2 had a strong effect on minimal energy input. Specifically, when $\Phi_{c,inj}^{max,day}$ was reduced, optimal energy input (Q_E^*) was higher. Thus, less CO_2 was available, and in order to maintain the desired CO_2 concentration, the windows must be closed more to prevent CO_2 loss to the environment. On the other hand, when $\Phi_{c,inj}^{max,day}$ was higher, energy input was lower. This will not be the case in situations in which CO_2 is not a limiting factor and when energy input is needed in order to meet the temperature and humidity constraints. This situation was the case on June 16, in which >20 % extra CO_2 was available during the day. Changing the lower CO_2 bound ($CO_{2,air}^{min}$) from the standard settings to lower values (i.e. when the CO_2 concentration can be lower) reduces energy input (and vice versa). In this situation, the ventilation windows can be more open, and less active cooling (which costs energy) is needed in order to meet all constraints.

3.4 Discussion

The optimization method presented here has the advantage that it does not require any crop production models or price forecasts. Thus, one of the most important factors determining actual energy input in this method is the grower who defines the bounds. Defining the bounds based on the current status and the needs of the crop remains a task for the grower, and these need not to be the most economic and/or energy-efficient. Nevertheless, the formulation of the optimal control problem that we proposed has practical implementation, as it can save energy while ensuring the grower's desired yield. In addition, settings can be made easily within the grower's comfort zone, including minimum pipe temperature and minimum ventilation. Minimum pipe temperature and minimum ventilation can be included in the optimization by changing the bounds of Eq. (3.11) and Eq. (3.13), respectively. After optimization, the effect of these bounds on energy input becomes clear and can be presented to the grower so that he/she can learn and make decisions based on a variety of scenarios.

The accuracy of both the model and the measurements clearly influences the outcome of the optimization. Therefore, good model performance is important for achieving optimal control in practice. Some of the factors that can influence model performance, include the accuracy and consistency of the measured data and incidental spatial differences due to factors such as unrecorded operational activities and/or unrecorded intervention by people. CO_2 concentration was measured at only two locations in the greenhouse, whereas temperature and humidity were measured at eight locations. Moreover, differences were measured between the various sensors (see Section 3.3.1); these differences were similar to the differences reported by Bontsema et al. (2011), who studied the effect of inaccurate measurements on energy consumption within a greenhouse. With respect to the climate within a greenhouse, spatial differences can be horizontal and/or vertical. Opdam et al. (2005) noted that the largest temperature differences are due to the position of the sun. In addition, measuring the outdoor weather and control inputs can influence energy input and these measures can have inaccuracies. The sensitivity of the model and the optimization procedure with respect to these potential errors are currently being studied.

In the optimization procedure, active cooling with heat exchangers was used when there was a cooling demand and when the total amount of available CO_2 was limited. When more CO_2 was available, active cooling could be reduced in order to save energy. However, CO_2 has its own costs and benefits. For example, higher CO_2 levels can affect production. In addition, having more CO_2 available means that active cooling can only be reduced if all constraints are satisfied. To prevent extreme temperatures, more natural ventilation can be used, resulting in more CO_2 being emitted into the environment, which could also be a goal to be minimized in light of the objectives to reduce greenhouse gas emissions.

In the current study, minimizing energy input provided less energy savings than in our previous study (Van Beveren et al., 2015a). In the current study, an entire year was analyzed with constraints on temperature, humidity, and CO_2 concentration; in our previous study, we analyzed only 16 days distributed throughout the year, and we examined only temperature and humidity. Thus, the addition of CO_2 balance maximum CO_2 available per day forces the system to increase the use of active cooling. This situation applied to many days in which the grower used active cooling, and this matched the optimal situation. This difference resulted in higher energy input compared to our previous study. Nevertheless, a clear reduction in both energy and CO_2 input was observed using standard settings. How do these figures compare with other figures reported with respect to energy saving climate control? Other researchers used optimal control techniques to manage greenhouse climate and found energy savings that ranged from 8 % (Tap, 2000) to 52 % (Van Ooteghem, 2007b). Thus, the current results are consistent with previous research. Moreover, recent practical experiments reported high potential energy savings. For example, De Zwart (2014) recently reported that energy savings can be as high as 24 % for a tomato crop without affecting crop growth. In addition, Kempkes et al. (2014) reported that using a double glass cover, implementing new growing strategies, and using a dehumidification system can yield energy savings of up to 60 % without affecting the production levels.

To realize these potential energy savings, practical implementation is needed. In the climate control system of most modern greenhouses, growers can specify many settings in the process control computer; however, the resulting greenhouse climate and the consequences with respect to energy use are not always evident to the grower. The optimization procedure proposed here can help growers by providing more insight into their decision-making process with respect to energy management. However, once the optimal energy strategy has been determined, the calculated energy demand must be supplied to the greenhouse. Therefore, the next logical step is to determine which equipment can be used to meet this energy demand in the most economical manner. This can be done a posteriori, and the grower can learn from alternative strategies that could be followed, rather than depending solely on his/her own historical data. This would represent the first step towards creating a fully automated system in which the grower has merely a supervisory role, and it would help define long-term goals. This first step is important for successful implementation and to help the grower build trust in the outcome of these kinds of systems (Van Straten et al., 2000). An intermediate step would be to predict the optimal trajectories one day in advance. For such a prediction, the weather forecast for the next day is needed, and an additional tool would be needed to determine the greenhouse climate based on the grower's actual settings.

3.5 Conclusion

Here, we present an optimization framework for minimizing energy input in greenhouses; this novel framework takes into account temperature, humidity, and CO_2 concentration. We also validated a model incorporating temperature, humidity, and CO_2 concentration using data collected for one full year from a 4 ha commercial greenhouse. Using standard settings, heating and cooling were potentially reduced by 47 % and 15 %, respectively. Even after incorporating the grower's minimum pipe temperature, heating was still reduced by 28 % (under these conditions, cooling was unchanged). In both cases, total CO_2 injection was reduced by 10 %. Furthermore, the results revealed that active cooling was used on days in which CO_2 was a limiting factor. Finally, changing the bounds can have potential effects on both energy and CO_2 input, and these effects can be demonstrated to the grower.

3.6 Acknowledgements

We thank HortiMaX B.V., Lek Habo Groep B.V., and M. Boonekamp for useful discussions and for sharing their data. Language editing of a near-final draft of the paper was provided by C.F. Barrett.

4

Optimal utilization of a boiler, combined heat and power installation, and heat buffers in horticultural greenhouses

P.J.M. van Beveren
J. Bontsema
G. van Straten
E.J. van Henten

Published as Van Beveren, P. J. M., Bontsema, J., Van Straten, G., & Van Henten, E. J. (2019). Optimal utilization of a boiler, combined heat and power installation, and heat buffers in horticultural greenhouses. Computers and Electronics in Agriculture, 162, 1035–1048. doi.org/10.1016/j.compag.2019.05.040

Abstract

In the daily operation of a greenhouse, decisions must be made about the best deployment of equipment for generating heat and electricity. The purpose of this paper is two-fold: 1) To demonstrate the feasibility and flexibility of an optimal control framework for allocating heat and electricity demand to available equipment, by application to two different configurations used in practice. 2) To show that for a given energy and electricity demand benefit can be obtained by minimizing costs during resource allocation.

The allocation problem is formulated as an optimal control problem, with a pre-defined heat and electricity demand pattern as constraints. Two simplified, yet realistic, configurations are presented, one with a boiler and heat buffer, and a second one with an additional combined heat and power generator (CHP) and a second heat buffer.

A direct comparison with the grower is possible on those days where the other equipment that was at the grower's disposal was not used (63 days in the available 2012 data set). On those days overall costs savings of 20 % were obtained. This shows that a given heat demand does not come with a fixed price to pay. Rather, benefits can be obtained by determining the utilization of the equipment by dynamic optimization. It also appears that prior knowledge of gas and electricity prices in combination with dynamic optimization has a high potential for cost savings in horticultural practice. To determine the factors influencing the outcome, different sensitivities to the optimization result were analyzed.

4.1 Introduction

Greenhouses to produce vegetables, flowers, and ornamentals require heating in colder periods. High-tech greenhouses in temperate climates, like the Netherlands and Belgium (Van Den Bulck et al., 2013), consume large amounts of fossil energy. The quest for energy saving in modern greenhouse horticulture (Van der Valk and Van der Poll, 2007) has led to investments in a wide variety of equipment. In daily operation, decisions about the best deployment of this equipment must be made. This operation is complex due to varying heat and cooling demands, and varying prices of gas and electricity and calls for effective control schemes to support the grower in this process. In current greenhouse practice the equipment is controlled by different controllers that operate based on a set of pre-defined rules. Depending on the configuration the set of rules is tailor-made. Supervision of the operation is done by the grower. If necessary the grower can overrule the controller manually.

In order to reduce the energy consumption of greenhouses a two-stage approach for optimal management of energy resources was introduced in Van Beveren et al. (2015a,b). This approach decouples greenhouse climate and the generation from the required energy input (Fig. 4.1). The first stage minimizes the energy input to the greenhouse for a pre-defined set of bounds to specify the desired greenhouse climate. The second stage, described in this paper, minimizes the energy costs of realizing the required energy profile (obtained from the first stage) using the available equipment. The motivation is that this approach does not rely on a complex crop model, but rather uses the grower's experience and knowledge.

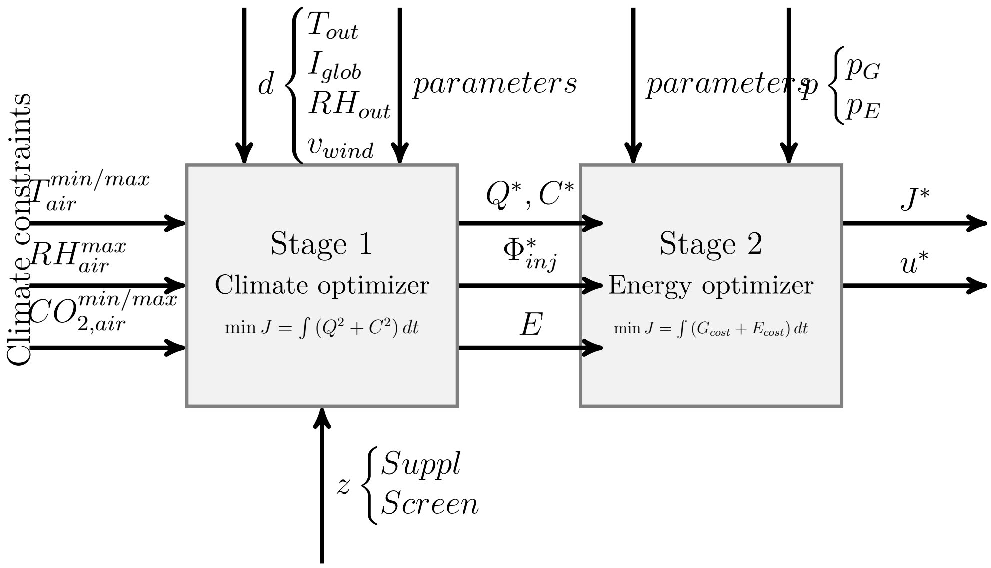


Figure 4.1: Overview of the 2-stage approach. The climate optimization needs the climate constraints (set by the grower), outdoor climate measurements d, controls from the greenhouse z (here supplementary lighting $Suppl$ and screen position $Screen$), and greenhouse parameters. The results of stage one are the optimal heat profile Q^*, optimal cooling profile C^*, the CO_2 injection pattern Φ_{inj}^* and, electricity need of the greenhouse E. Those are fed into the energy optimizer. Here, the prices p of gas p_G and electricity p_E and parameters of the equipment are needed. The results of the optimization in stage 2 are the optimal controls u^* such as the power of the CHP and boiler, and heat fluxes to the buffers, that lead to the optimal value of the goal function J^*.

Control is closely kin to dynamic optimization. Optimization of energy systems in greenhouse horticulture was studied before (e.g. Van Willigenburg et al. (2000); Tap (2000); Van Ooteghem (2007b); Bozchalui and Cañizares (2014); Husmann and Tantau (2001); Vanthoor (2011); Seginer et al. (2018)), but the focus was mainly on greenhouse climate management and control. In those studies, a crop model is needed, and the operation of equipment is an integral part of the optimization and does often not comply with current practice. There are far less studies about the deployment, operation and control of all equipment that generate and store warm water (used for heating) and cold water (used for cooling) for greenhouses. Molenaar et al. (2007) presented optimization of the energy costs for a closed greenhouse using a given heat, cold and electricity demand for a typical year. The problem was solved with linear programming techniques by discretizing the model equations to an hourly time basis. However, the optimization results in Molenaar et al. (2007) were not compared with data from practice. Different energy management strategies for commercial greenhouse are summarized in Vadiee and Martin (2012, 2014). Here, the focus was not on optimization of an existing energy system, but more on the configuration and choice of different materials and equipment to improve the energy conservation of the greenhouse.

Applications of various optimization techniques and analyses of energy systems with a wide variety of equipment in similar configurations are present in other fields. For instance, applications of CHP systems and thermal storage can be found, among others, for residential buildings in Haeseldonckx et al. (2007); Schütz et al. (2015); Fuentes-Cortés et al. (2015); Ren et al. (2008), for a hospital in (Vanhoudt et al., 2011), university campus (Pagliarini and Rainieri, 2010; Chandan et al., 2012), and industrial power plants (Mitra et al., 2013). These studies minimize total energy costs for heating and cooling based on a specified heat and cold demand. An overview of optimization techniques for thermal energy storage control of mainly office buildings, commercial buildings, and university campuses was published in Ooka and Ikeda (2015); Cho et al. (2014). Greenhouses differ from the aforementioned buildings because of different heat and electricity demands, originating from different processes and requirements and a stronger thermal coupling to the outdoor climate. Furthermore, the greenhouse industry in the Netherlands is characterized by a wide deployment of CHP systems. In 2011, for instance, a total of about 3000 MW of electrical power was installed on a total area of 10 300 ha. Part of the electricity was used for lighting, but most of the electricity was sold to the public grid (Vermeulen, 2014). CHP systems are advantageous for greenhouse horticulture since the heat, electricity, and CO_2 can all be used in the greenhouse. Furthermore, these installations are important in balancing the national power grid.

The purpose of this paper is two-fold: 1) The wide variety of configurations of equipment requires a formulation that is flexible in terms of type and number of equipment. Therefore, a framework for managing heat and electricity producing equipment, based on optimal control is desired. This is offered by an optimal control method that is presented here. The objective is to study the feasibility and flexibility of the method. 2) To show that for a given energy and electricity demand that satisfies minimum overall energy use, further benefit can be obtained by minimizing costs during resource allocation. If the sources and prices are fixed, there is a fixed price to pay for energy. However, the freedom to achieve further benefits is, in principle, in the possibility to shift the mix of sources to fulfill the heat and electricity demand, and the exploitation of time variation in energy market prices. In order to investigate this question, ideally an optimized energy profile, as developed in(Van Beveren et al., 2015a) would be the best starting point. In this paper the starting point is different. Instead of an optimized profile, actual energy profiles as realized by the grower on days where the configuration coincides with the one in Fig. 4.3 are used. The motivation for this choice is that in this way a comparison with real data is possible, thus increasing the credibility of the results. The formulation and demonstration of an optimization method for energy equipment utilization applied to the horticultural greenhouse and compared to real data is novel.

In this paper we demonstrate the generality of the optimization method with two commercially used configurations of equipment: 1) A system with a heat demand from a greenhouse equipped with a boiler and a single high temperature heat buffer. This case serves as a demonstration to test and evaluate the optimization method. 2) A system with a boiler, CHP, and two buffers; one for high temperature heat storage and one for low temperature heat storage. We compare the optimization results with real heat and electricity data from a commercial full-scale greenhouse in the Netherlands.

4.2 Materials and methods

For 2012, greenhouse climate and energy data (five-minute time interval) were obtained from the greenhouse process control computer of a 4 ha commercial rose greenhouse in Bleiswijk, The Netherlands (see Van Beveren et al. (2015a,b) for more details). The recorded data were obtained from different sensors and actuators in the greenhouse. These measurements are standard in modern greenhouses.

In addition, a time series with real gas and electricity prices (15-minute time interval) was obtained via the electricity and gas supplying company of the grower. This makes it possible to compare the optimal scenarios with the grower's operation. In the Netherlands, electricity generated from horticultural CHP installations is partly used for artificial lighting, but mostly sold to the national power grid (Vermeulen and Van der Lans, 2011). Growers in the Netherlands have the possibility to trade electricity on different markets that operate on different time scales. The greenhouse in this study traded electricity on the so-called unbalance market only. On this market, prices fluctuate every 15 minutes. Although rare, a negative electricity price can occur, meaning that the grower gets paid for using electricity.

All data were collected for the whole year of 2012. However, in the real system of the actual greenhouse there was additional equipment, such as a heat pump and aquifer, which are not considered in this study. Therefore, we could only compare the days where the configuration of the actual greenhouse was congruent with the configuration of the optimization. There are, altogether, 63 days for which the configuration was congruent with that of the grower, as explained in more detail in Section 4.B.

A general optimal control formulation defines the optimization problem in a flexible and generic manner. The optimal control problem in this paper was solved using Tomlab optimization software (Edvall and Goran, 2009) in Matlab (version 7, The MathWorks Inc., Natick, USA) on a PC with core i5 CPU 660 3.33 GHz,4 GB RAM and Windows 7 x64 installed. "Tomlab is a general-purpose development, modeling, and optimal control environment in Matlab for research, teaching, practical solution of optimization problems" (Holmstrom et al., 2010).

Tomlab requires the definition of the number of collocation points to solve the optimization problem (Edvall and Goran, 2009). All optimizations were done using a sequence of collocation points, starting from 24 collocation points per day. When an optimal solution was obtained, the result served as the initial guess for the next optimization with a higher number of collocation points. This procedure was repeated for 48, 96 and 144 collocation points per day. The raw data were re-sampled to the number of collocation points needed for the optimization. It was found that the result converged with the number of collocation points, and that the step from 96 to 144 points hardly gave further improvement, so 144 points are enough. The reported CPU times were recorded using 144 collocation points per day.

4.2.1 Case 1: Demonstration of the optimal control method with configuration of boiler and buffer

System configuration

The first configuration considered in this work consists of a boiler and a high temperature buffer (HT) (Fig. 4.2). The heat demand from the greenhouse (Q_{des} = $Q_{HT,grh}$) as a function of time is assumed to be known. This constraint follows from the two-stage approach described in Van Beveren et al. (2015b,a), but could also have another pre-defined pattern. The heat demand of the greenhouse depends among other things largely on the desired greenhouse climate and the outside weather. The boiler in this example has a maximum capacity ($Q_{HT,boil}^{max}$) of 3 MW (75 Wm^{-2}). When the boiler is active it should be on for at least 80 % of capacity. In addition, the number of switching instances should be reduced (Fransen, 2015). Both constraints have been implemented for reasons of efficiency and minimal wear of the boiler.

The buffer had a maximal capacity of 3.1 MJm^{-2}. The heat flux from or to this buffer is defined as $Q_{HT,buf}$. From a physical point of view a heat flux should be considered as positive. From this perspective, two heat fluxes would have to be introduced: one for loading and one for unloading of the buffer. With such a formulation the optimal control method does not preclude the possibility of simultaneously loading and unloading. This is unwanted and in practice not possible. Therefore, here, the problem is reformulated such that the heat flux from or to the buffer is either negative (loading the buffer with heat) or positive (unloading the buffer). This definition ensures that loading and unloading of the buffer cannot occur at the same time. The total heat flux to the greenhouse (Q_{des}) is determined by the sum of the heat flux coming from the boiler ($Q_{HT,boil}$) and the heat flux coming from, or going to the heat buffer ($Q_{HT,buf}$). The properties of the heat buffer are given in Table 4.1.

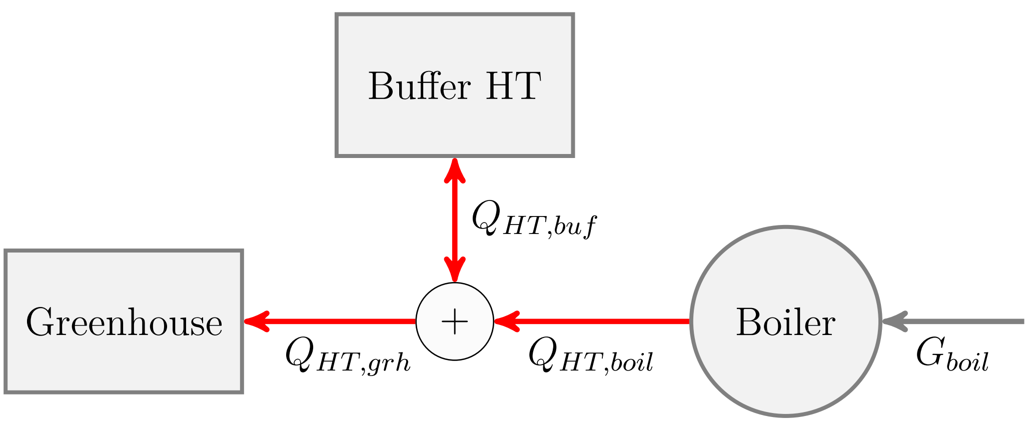


Figure 4.2: Schematic overview of the system configuration using a boiler and buffer. Colors of the arrows: high temperature heat fluxes (—) and gas flux (—).

In this configuration it is assumed that CO_2 coming from the boiler is not used for CO_2 enrichment of the greenhouse. This is the practice for a growing number of greenhouses in the Netherlands that use CO_2 from industrial sources distributed via a pipe network maintained by the company OCAP (Organic Carbon dioxide for Assimilation of Plants). However, the use of exhaust CO_2 from the boiler for CO_2 enrichment can easily be included in the optimal control formulation due to its generic nature.

Formulation of the optimization problem

The energy content of the buffer is described by:

$$\frac{dH_{HT,buf}(t)}{dt} = -Q_{HT,buf}(t), \tag{4.1}$$

with the known initial high temperature heat (HT) in the buffer from the grower ($H_{HT,grower}$),

$$H_{HT,buf}(t_0) = H_{HT,grower}(t_0). \tag{4.2}$$

In the sequel, for easier readability, the explicit time dependency of the variables is dropped from the notation where the dependency is evident.

The amount of heat delivered by the boiler ($Q_{HT,boil}$) and buffer ($Q_{HT,buf}$) at each moment in time is equal to the heat demand of the greenhouse (Q_{des}) (Eq. (4.3)). Eq. (4.3) acts as a constraint in the optimization.

$$Q_{HT,boil} + Q_{HT,buf} = Q_{des} \tag{4.3}$$

No losses from the buffer are assumed in order to keep the formulation as simple as possible. Due to their nature, all fluxes have non-negativity constraints, except for the buffer flux, since it can be positive or negative as explained before. The buffer flux is constrained by:

$$Q^{min}_{HT,buf}(t) \leq Q_{HT,buf}(t) \leq Q^{max}_{HT,buf}(t), \tag{4.4}$$

where $Q^{min}_{HT,buf} = -Q^{max}_{HT,buf}$. The buffer state has the following state constraint:

$$0 \leq H_{HT,buf}(t) \leq H^{max}_{HT,buf}(t). \tag{4.5}$$

In order to cope with the operation range of the boiler, a zero-or-range constraint was introduced (Hansen and Huge, 1989). This range constraint is represented in the optimal control problem with the following definition:

$$Q_{HT,boil} - Q_{HT,boil}^{max} b_{boil} \leq 0 \tag{4.6}$$
$$Q_{HT,boil} - r_{boil} Q_{HT,boil}^{max} b_{boil} \geq 0 \tag{4.7}$$
$$Q_{HT,boil} \geq 0 \tag{4.8}$$

where Eq. (4.8) is a trivial constraint on the heat flux from the boiler, which can only be positive. Eq. (4.6) and Eq. (4.7) give the following constraint for $b_{boil} = 0$: $Q_{HT,boil} = 0$. For $b_{boil} = 1$, the constraint is $r_{boil}^{min} Q_{HT,boil}^{max} \leq Q_{HT,boil} \leq Q_{HT,boil}^{max}$. The value of r_{boil}^{min} was 0.8.

The selected control variables are:

$$u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} = \begin{bmatrix} Q_{HT,boil} \\ Q_{HT,buf} \\ b_{boil} \end{bmatrix}, b_{boil} \in \{0, 1\}. \tag{4.9}$$

Then, the goal is to find the optimal control $u^*(t)$, $t_0 \leq t \leq t_f$ that minimizes the cost function in Eq. (4.10) which is the total gas cost of the boiler for the given time evolution of the gas price (p_G) in €m^{-3} (Eq. (4.11)). The optimization period can be any period in this formulation. When time periods longer than 24 hour are taken, the gas price varies over time.

$$\min_u J = \min_u \int_{t_0}^{t_f} \left(p_G G_{boil}(u) \right) \, \mathrm{d}t, \tag{4.10}$$

$$p_G(t), t_0 \leq t \leq t_f. \tag{4.11}$$

The amount of gas used by the boiler (G_{boil}) is proportional to the amount of heat produced by the boiler:

$$G_{boil} = \frac{Q_{HT,boil}}{\eta_{boil} \cdot S} \tag{4.12}$$

The parameters for the optimization in Section 4.2.1 are listed in Table 4.1.

Switching the boiler on and off too frequently should be avoided in order to save maintenance costs (Fransen, 2015). This kind of requirements can be implemented in the optimal control formulation by adding a penalty accounting for the number of switching moments to the goal function:

$$\widetilde{J} = \int p_G G_{boil} + 10^{-3} \dot{Q}^2_{HT,boil} \mathrm{d}t. \tag{4.13}$$

The penalty parameter (1×10^{-3}) is hard to assess a priori and was therefore chosen empirically to obtain a realistic switching behavior.

Experiments

Three experiments were performed with this configuration to demonstrate the optimization procedure and to demonstrate the performance of the optimizations with different initial buffer fill status (f_0). The first two experiments were performed with goal function (Eq. (4.10)), to test the effect of the initial buffer status on the performance. In the third experiment the effect of the buffer switch restriction according to Eq. (4.13) was investigated.

4.2.2 Case 2: Optimization of a configuration with boiler, CHP, and buffers and comparison with real data

System configuration

The second configuration consisted of a boiler, combined heat and power installation (CHP), and two heat buffers (Fig. 4.3). The main reason to have a boiler installed next to the CHP is to serve as a back-up for heat production in case the CHP cannot run because of maintenance or repair. The CHP has a maximum thermal capacity (Q^{max}_{chp}) of 2520 kW (62 W m^{-2}); of which 70 % of the heat is at a high temperature, and 30 % at a low temperature. The former is gained from the exhaust gas condenser. The thermal efficiency of the CHP ($\eta_{Q,chp}$) is 0.46 and the electrical efficiency ($\eta_{E,chp}$) is 0.37. Thus, the maximum electricity production is 2060 kW (51 W m^{-2}). The thermal and electrical efficiency of the CHP were assumed to be constant for the operating range that was used, which is reasonable in view of the restricted operation range between 0.85 and 1. The thermal and electrical efficiencies are obtained from the supplier and are in line with the values reported in (Vermeulen, 2014). Electricity from the CHP is either used in the greenhouse for artificial lighting (E_{des}) or sold to the public electricity grid (E_{sell}). Electricity can also be bought from the grid (E_{buy}).

High temperature heat from the boiler or CHP can be stored in the high temperature buffer ($H_{HT,buf}$) or directly go to the greenhouse. Low temperature heat (LT) can be stored in the low temperature heat buffer ($H_{LT,buf}$) or directly go to the greenhouse. High temperature heating of the greenhouse air is done with the pipe rail heating system and low temperature heating is done with heat exchangers above the crop. In the analysis, we assume that there is no difference between applying greenhouse heating with heating pipes or with heat exchangers.

As explained in Section 4.2.1, the heat fluxes to or from the buffers ($Q_{HT,buf}$, $Q_{LT,buf}$) are positive (unloading of the buffer), negative (loading of the buffer), or zero. In Figs. 4.2 and 4.3 this is indicated by the two-sided arrows.

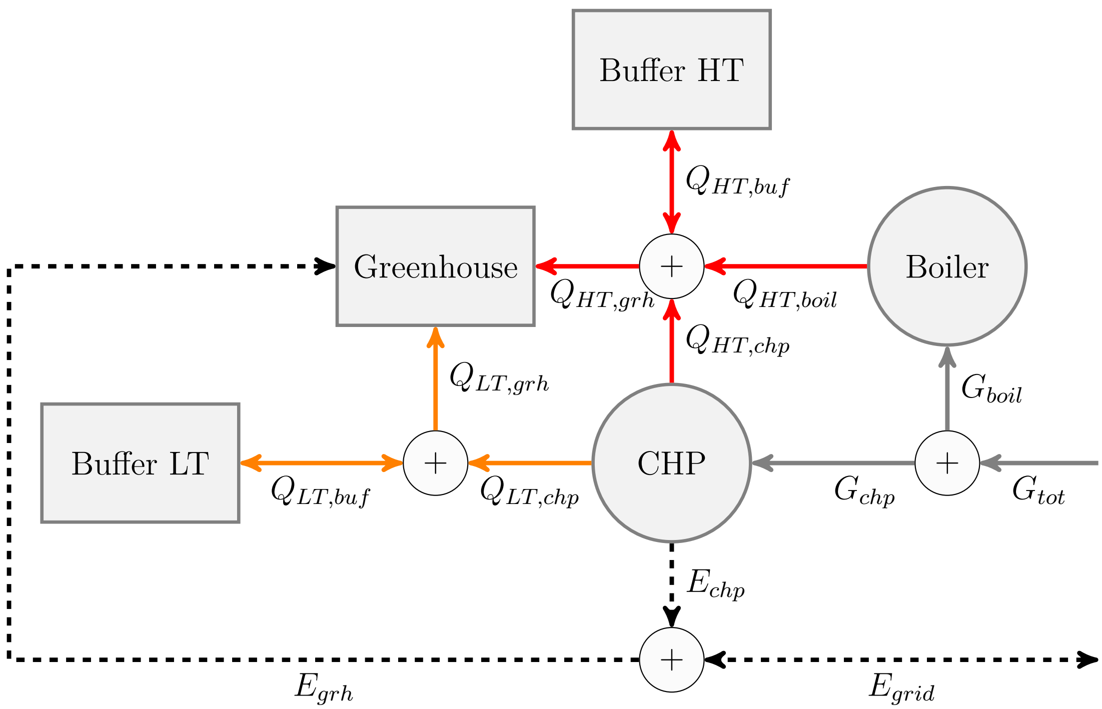


Figure 4.3: Schematic overview of the system configuration using boiler, CHP, and buffers. Colors of the arrows: high temperature heat fluxes (—), low temperature heat fluxes (—) gas fluxes (—), and electricity fluxes (- - -).

Formulation of the optimization problem

The energy content of the high temperature buffer (H_{HT}) is described by Eq. (4.1) and the energy content of the low temperature heat buffer (H_{LT}) is described by

Eq. (4.14). The energy content of the low temperature buffer depends only on the low temperature buffer flux ($Q_{LT,buf}$). Again, no losses from the buffer are assumed. However, the effect of this assumption was investigated. Therefore, Eq. (4.1) and Eq. (4.14) were extended as described in Section 4.C according to the numbers given in (Van Steekelenburg et al., 2011).

$$\frac{dH_{LT,buf}}{dt} = -Q_{LT,buf} \tag{4.14}$$

To ensure fair comparison between grower and optimization, the heat withdrawn or stored in the buffer over the day must be considered. Therefore, in the optimization the initial and final fill status are taken like the values obtained from the data of the grower. This leads to the following initial and terminal state constraints:

$$H_{HT,buf}(t_0) = H_{HT,grower}(t_0), \tag{4.15}$$
$$H_{LT,buf}(t_0) = H_{LT,grower}(t_0), \tag{4.16}$$
$$H_{HT,buf}(t_f) = H_{HT,grower}(t_f), \tag{4.17}$$
$$H_{LT,buf}(t_f) = H_{LT,grower}(t_f). \tag{4.18}$$

The buffers have state constraints that represent the minimum and maximum storage capacity:

$$0 \leq H_{HT,buf}(t) \leq H_{HT,buf}^{max}(t), \tag{4.19}$$
$$0 \leq H_{LT,buf}(t) \leq H_{LT,buf}^{max}(t). \tag{4.20}$$

The total heat demand from the greenhouse can be satisfied by the boiler, high temperature buffer, low temperature buffer, directly from the CHP, or a combination of those. The sum of these fluxes must be equal to heat demand from the greenhouse (Q_{des}).

$$Q_{HT,boil} + Q_{HT,chp} + Q_{LT,chp} + Q_{HT,buf} + Q_{LT,buf} = Q_{des} \tag{4.21}$$

The heat demand from the greenhouse in this paper is obtained from the realized controls (see Section 4.B). In the final two-stage approach the heat demand will be obtained by minimization of the energy input of the greenhouse as explained and calculated in Van Beveren et al. (2015a,b).

The electricity demand (E_{des}) is taken equal to the electricity consumption of the artificial lighting in the greenhouse. It can be delivered by the CHP (E_{chp}) or by the grid (E_{grid}):

$$E_{chp} + E_{grid} = E_{des}. \tag{4.22}$$

If the CHP produces more electricity than E_{des}, the electricity is sold to the grid (E_{grid}). E_{grid} is positive if electricity is bought from the grid and negative if sold to the grid. The cost of electricity generated by the CHP is already accounted in the gas price.

The CHP has a similar constraint as the boiler and must operate in a certain power range. Therefore, just like the zero-or-range constraint for the boiler (Section 4.2.1), another zero-or-range constraint has been implemented for the CHP. This introduces next to b_{boil} another boolean control variable (b_{chp}). The lower bound of the operating range of the CHP (r_{chp}^{min}) was determined from the data of the grower to be 0.85.

In summary, the problem is subject to the following inequality control constraints (similar as in Section 4.2.1),

$$Q_{HT,boil} - Q_{HT,boil}^{max} b_{boil} \leq 0, \tag{4.23}$$

$$Q_{HT,boil} - r_{boil} Q_{HT,boil}^{max} b_{boil} \geq 0, \tag{4.24}$$

$$Q_{HT,boil} \geq 0, \tag{4.25}$$

$$Q_{chp} - Q_{chp}^{max} b_{chp} \leq 0, \tag{4.26}$$

$$Q_{chp} - r_{chp} Q_{chp}^{max} b_{chp} \geq 0, \tag{4.27}$$

$$Q_{chp} \geq 0, \tag{4.28}$$

$$b_{boil}, b_{chp} \in \{0, 1\}, \tag{4.29}$$

$$Q_{HT,buf}^{min}(t) \leq Q_{HT,buf}(t) \leq Q_{HT,buf}^{max}(t), \tag{4.30}$$

$$Q_{HT,buf}^{min}(t) \leq Q_{HT,buf}(t) \leq Q_{HT,buf}^{max}(t), \tag{4.31}$$

In Eqs. (4.30) and (4.31) $Q^{min}_{buf,HT} = -Q^{max}_{buf,HT}$, and $Q^{min}_{buf,LT} = -Q^{max}_{buf,LT}$, since it was assumed that the minimum and maximum fluxes of loading and unloading are equal.

The amount of gas used by the CHP (G_{chp}) is proportional to the amount of heat produced by the CHP:

$$G_{chp} = \frac{Q_{chp}}{\eta_{Q,chp} S} \tag{4.32}$$

where the total efficiency of the CHP $\eta_{chp} = 0.83$ was determined from data from the grower's gas meter and power data. The electricity production by the CHP is calculated as:

$$E_{chp} = \frac{\eta_{E,chp}}{\eta_{Q,chp}} Q_{chp}. \tag{4.33}$$

The ratio between $\eta_{E,chp}$ and $\eta_{Q,chp}$ was obtained from the power data of the CHP from a full year based on five minute data. A constant value of 0.81 was found.

For this configuration of equipment, the control variables are:

$$u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \\ u_6 \end{bmatrix} = \begin{bmatrix} Q_{HT,boil} \\ Q_{HT,chp} \\ Q_{HT,buf} \\ Q_{LT,buf} \\ b_{boil} \\ b_{chp} \end{bmatrix}, b_{boil}, b_{chp} \in \{0, 1\}. \tag{4.34}$$

Then, the goal function minimizing the total costs of buying gas, and buying or selling electricity - representing the revenues as negative costs - for the given time evolution of the gas and electricity price (Eq. (4.36) and Eq. (4.37)) is:

$$\min_u J = \min_u \int_{t_0}^{t_f} \left(p_G G_{tot} + p_E E_{grid}\right) \, \mathrm{d}t, \tag{4.35}$$

$$p_G(t), t_0 \leq t \leq t_f, \tag{4.36}$$

$$p_E(t), t_0 \leq t \leq t_f, \tag{4.37}$$

$$G_{tot} = G_{boil} + G_{chp}. \tag{4.38}$$

And E_{grid} is given through Eqs. (4.21), (4.22) and (4.33) by:

$$E_{grid} = E_{des} - \frac{\eta_{E_{chp}}}{\eta_{Q_chp}} \cdot (Q_{des} - Q_{HT,boil} - Q_{HT,buf} - Q_{LT,buf}) \tag{4.39}$$

Contrary to Eq. (4.13), no penalty was added for frequent on/off switching of the boiler and CHP in the standard optimization runs. However, different penalty values were tested. On most days, the control was not affected by the penalty. On some days, there was a slight reduction of the number of switching events per day (i.e. six instead of seven switching events per day). The total energy costs were not influenced.

The optimization was performed over a full day period. The parameters for the optimization in Section 4.2.2 are listed in Table 4.1. The CPU time for the optimization over a day varied between 1 and 48 s, with a mean value of 6 s and a standard deviation of 7 s.

Table 4.1: Parameters for optimization of system with boiler, CHP, and buffer in Section 4.2.2.

Symbol	Description	Value	Unit
A	Greenhouse area	40 709	m^2 [grh]
$H_{HT,buf}^{max}$	Heat storage capacity buffer HT	3.14×10^6	Jm^{-2} [grh]
$H_{LT,buf}^{max}$	Heat storage capacity buffer LT	1.05×10^6	Jm^{-2} [grh]
$Q_{HT,buf}^{max}$	Maximal heat flux to buffer HT	150	Wm^{-2} [grh]
$Q_{LT,buf}^{max}$	Maximal heat flux to buffer LT	150	Wm^{-2} [grh]
$-$	Installed boiler capacity in the greenhouse	2×10^6	W
$-$	Installed CHP capacity in the greenhouse	2.52×10^6	W
$Q_{HT,boil}^{max}$	Maximum boiler thermal flux	49	Wm^{-2}[grh]
Q_{chp}^{max}	Maximum CHP thermal flux	62	Wm^{-2}[grh]
r_{boil}^{min}	Minumum of the range for operating the boiler	0.8	$-$
r_{chp}^{min}	Minumum of the range for operating the CHP	0.85	$-$
S	Combustion heat of natural gas	35.17×10^6	Jm^{-3} [gas]
η_{boil}	Boiler efficiency	0.94	-
$\eta_{Q,chp}$	Thermal efficiency CHP	0.46	-
$\eta_{E,chp}$	Electrical efficiency CHP	0.37	-

Experiments

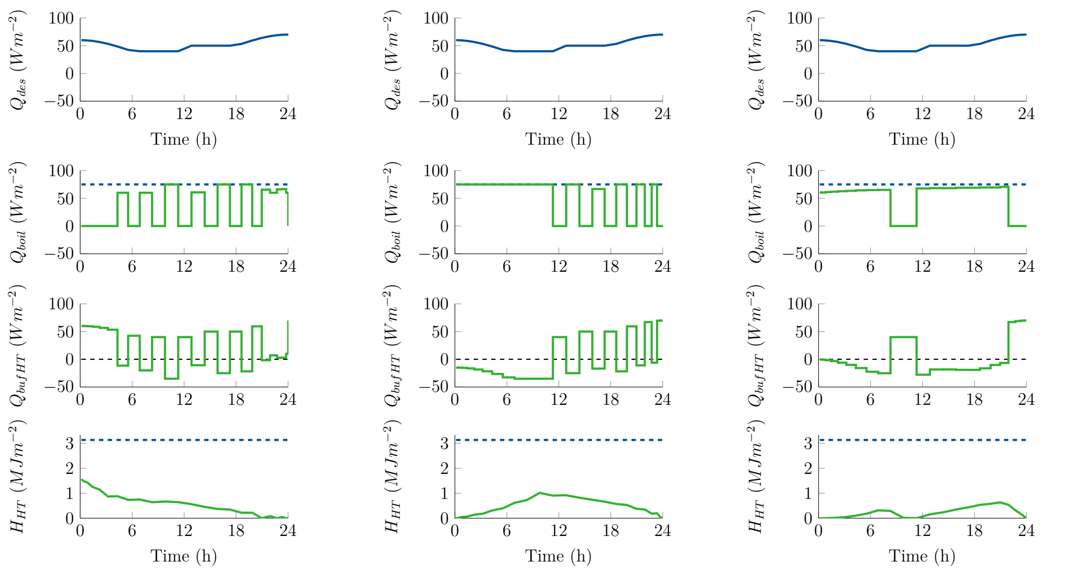
Various scenarios were analyzed to assess the optimization for the configuration with boiler, CHP, and buffers all using the desired heat pattern as calculated with the procedure explained in Section 4.B. In the first scenario fixed prices for gas and electricity were used.

The second scenario was to perform the optimization with real heat and electricity demand patterns. In order to determine the factors that influenced the costs most heavily, the effect of the buffer filling terminal constraints and the sensitivity for the desired heat and electricity pattern was analyzed. In order to study the sensitivity of the optimization result to the final buffer fill status, the final buffer fill status for the high temperature buffer was changed by 10 %. Furthermore, the heat and electricity demand, calculated from the grower's operation, as well as the prices of electricity and gas were varied by 10 %. Apart from changing the electricity price with a fixed percentage, additional scenarios were analyzed with randomly modified prices. For each value of the electricity price (time series) the price was modified by picking a random value (uniform discrete distribution) from a pre-defined interval. After obtaining the random modification factors, the values where normalized, such that the mean percentage of change was zero. A range of $-10\,\%$ to $10\,\%$, and a range of $-50\,\%$ to $50\,\%$ were used and repeated five times. Lastly, the effect of extending the buffer models with a heat loss factor was investigated.

4.3 Results

4.3.1 Case 1: Demonstration of the optimal control method with configuration of boiler and buffer

The result of optimizing the utilization of the boiler and buffer is shown in Fig. 4.4 for three different scenarios using the same artificial heat demand profile. The gas price was fixed at 0.34 €m^{-3} for the three presented scenarios.



(a) $f_0 = 0.5$ (b) $f_0 = 0$ (c) $\tilde{J} = \int p_G G_{boil} + 10^{-3}\dot{Q}^2_{HT,boil}\,\mathrm{d}t$

Figure 4.4: Desired heat profile of the greenhouse (top row), optimal control of the boiler (second row), optimal buffer flux (third row), and corresponding heat stored in the buffer (bottom row).

In Fig. 4.4a the result of minimizing the gas cost with an initial buffer fill status (f_0) of 0.5 is shown. The buffer is empty at the end of the optimization period (Fig. 4.4a). This is the expected result since the goal is to minimize the total gas cost. The effect of the zero-or-range constraint (Section 4.2.1) can be seen in Fig. 4.4a. When the boiler is active, it is active between 60 and 75 Wm^{-2} (i.e. between 80 and 100 % of full capacity). The surplus of heat is stored in the buffer as indicated by the negative buffer flux ($Q_{HT,buf}$) during these periods. When the boiler is not active, the greenhouse is heated using heat from the buffer. At 22 h the boiler is active for 90 % and some heat is coming from the buffer in order to empty it completely. The total gas cost for this day was 1186 € for the whole greenhouse, and therefore equal to 2.92×10^{-2} €m^{-2}.

When the initial buffer fill status is zero (Fig. 4.4b), the only heat source available for heating the greenhouse is the boiler. The first half of the day the boiler is active, and the surplus heat is stored in the buffer. The second half of the day the buffer and boiler are active in such a way that the buffer is empty again at the end of the optimization period. The total gas cost for this day were 4.54×10^{-2} €m^{-2}, which is higher than in the previous case because no 'free' heat was available in the buffer at the start.

In order to reduce the switching behavior of the boiler, a penalty on the switching of the control was implemented by replacing the goal function with Eq. (4.13) as described in Section 4.2.1.

Because the value of the goal functions is different, a direct comparison is not possible, but when we compare the gas costs component, it appears that the total gas costs remain the same. This reveals that there are several buffer control solutions for the optimization with the original goal function, meaning that the control solution found in Fig. 4.4b is not unique. In fact, by adding the penalty, the solution is forced to the quieter operation of Fig. 4.4c, without additional costs.

4.3.2 Case 2: Optimization of a configuration with boiler, CHP, and buffers and comparison with real data

Optimization with fixed prices

The desired heat and electricity demand profile to be delivered to the greenhouse and prices for November 1, 2012 are shown in Fig. 4.5a and b, respectively. The electricity demand is the electricity consumption of the lamps for artificial lighting in the greenhouse. The maximum capacity of the lamps was 112.5 $\mathrm{Wm^{-2}}$. The heat demand (Fig. 4.5a) was higher during the period when the lamps were off. The buffer fill status at beginning and end were fixed at the observed values.

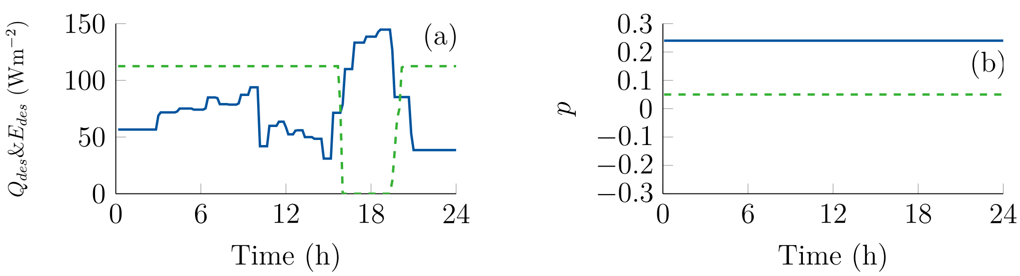


Figure 4.5: Desired heat (solid) and electricity demand (dashed) (a), and gas price (solid, €$\mathrm{m^{-3}}$) and electricity price (dashed, €$\mathrm{kWh^{-1}}$) (b) for November 1, 2012 with fixed prices for gas and electricity.

Fig. 4.6 shows the results for November 1, 2012 with a fixed gas price of 0.24 €$\mathrm{m^{-3}}$ and a fixed electricity price of 0.014×10^{-6} €$\mathrm{J^{-1}}$ (0.05 €$\mathrm{kWh^{-1}}$) (equal to the mean prices for the whole year 2012). Heat fluxes of the boiler and CHP, the buffers, and the energy content of the buffers are shown in Fig. 4.6a, b, and c for the optimal situation and in Fig. 4.6d, e, and f for the grower's operation.

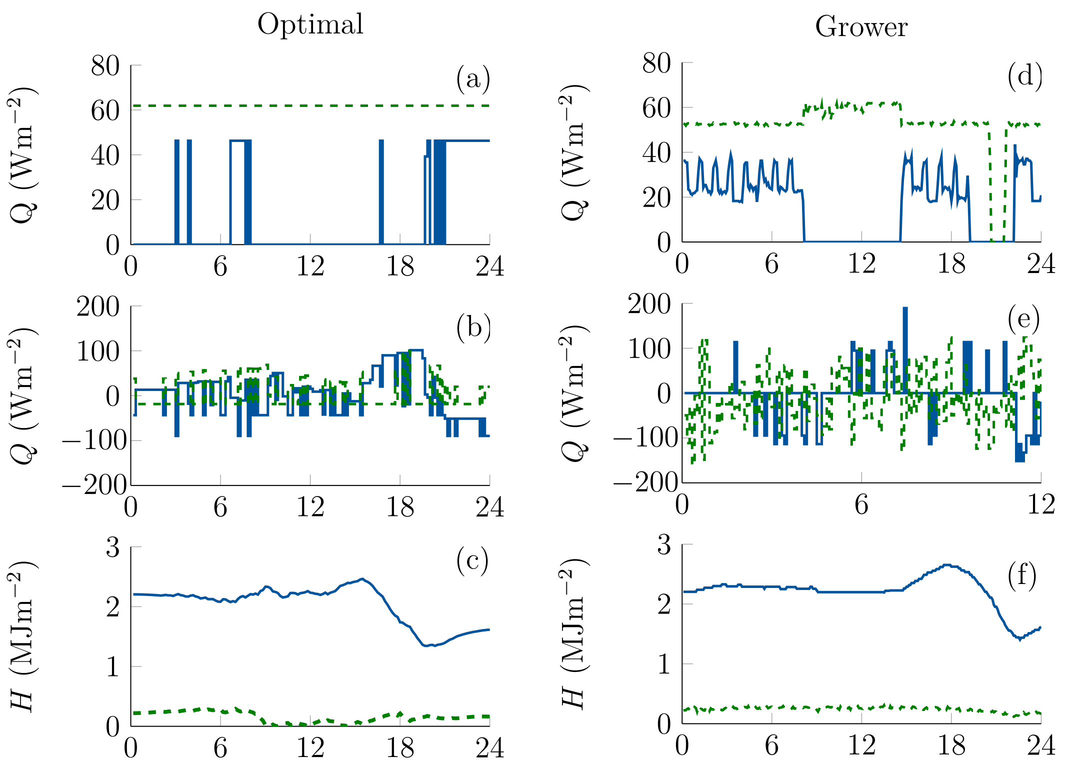


Figure 4.6: Optimal (a) and grower's operation (d) of operating the boiler (solid) and CHP (dashed), for the optimal scenario (b) and grower's operation (e), and energy content of the high (solid) and low temperature (dashed) buffers for the optimal scenario (c) and grower's operation (f) for November 1, 2012 with fixed prices for gas and electricity.

The total costs in the optimal scenario were 0.11 €m^{-2}, while in the grower's scenario this would have been 0.12 €m^{-2} (using the same fixed prices). In the optimal scenario the CHP was always running, producing 5.3 MJm^{-2}, while the grower produced 4.5 MJm^{-2} with the CHP. The remaining heat demand was produced by the boiler.

The optimization with fixed prices was also performed for a summer day (July 13, 2012) with a lower electricity and heat demand profile (not shown). The total costs were 0.037 €m^{-2}, while in the grower's scenario this would have been 0.040 €m^{-2}. The CHP was used to produce all heat in both cases. However, the moments when the CHP was on were different. Less electricity was bought from the grid, and more electricity was sold to the grid in the optimal scenario.

For both days, it appears that varying the level of the gas and electricity prices affected the total costs but did not affect the amount of heat and electricity produced.

Optimization with real, time variant, prices

Optimization results

Two days were selected in order to demonstrate the grower's operation of the system and of the optimized operation. The first selected day was July 13, 2012, which was a day with a relatively low electricity demand. The second day was October 9, 2012, which was a day with a higher electricity demand. The heat and electricity demand and prices for July 13, 2012 are shown in Fig. 4.7a and b, respectively. The heat and electricity demand and prices for October 9, 2012 are shown in Fig. 4.9a and b, respectively.

Heat fluxes of the boiler and CHP, heat fluxes of the buffers, and the energy content of the buffers are shown in Fig. 4.8a, b, and c for the optimal situation, and Fig. 4.8d, e, and f for the grower's operation.

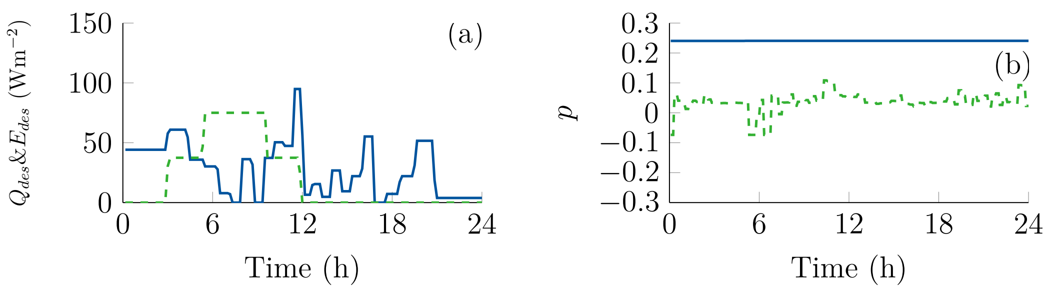


Figure 4.7: Desired heat (solid) and electricity (dashed) demand (a), and gas (solid, €m^{-3}) and electricity price (dashed, €kWh^{-1}) (b) for July 13, 2012.

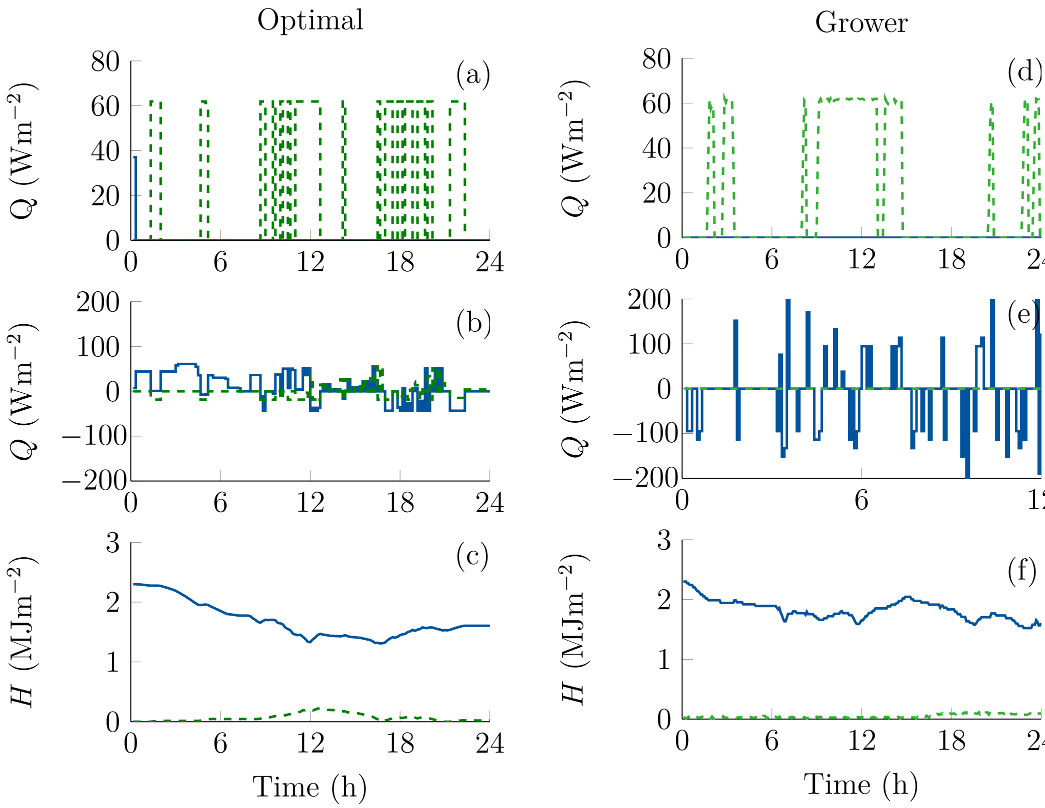


Figure 4.8: Optimal (a) and grower's operation (d) of operating the boiler (solid) and CHP (dashed), high (solid) and low temperature (dashed) buffer fluxes for the optimal scenario (b) and grower's operation (e), and energy content of the high (solid) and low temperature (dashed) buffers for the optimal scenario (c) and grower's operation (f) for July 13, 2012.

The breakdown of heat and electricity production for the selected days is summarized in Table 4.2. For July 13, 2012 the boiler was not used in both the optimal and grower's scenario. All heat was produced by the CHP. The total amount of heat produced by the CHP was slightly higher in the optimal scenario. More electricity was sold to the grid, while a similar amount of electricity was bought from the grid. The total costs for buying the electricity were lower and the total revenues from selling electricity were higher in the optimized scenario compared to the grower's operation. It can be seen that between the fixed initial and final values, that are identical for both optimization and grower, the time pattern of the energy content of the buffers ($H_{buf,HT}$ and $H_{buf,LT}$) were quite similar in both scenarios.

For October 9, 2012, the boiler was used in the optimal scenario but not by the grower. In the optimized scenario the CHP was used less. More electricity was bought from the grid to fulfill the electricity demand. Therefore, the electricity costs were slightly higher than in the grower's scenario, but this was more than compensated by the lower expenditure for gas.

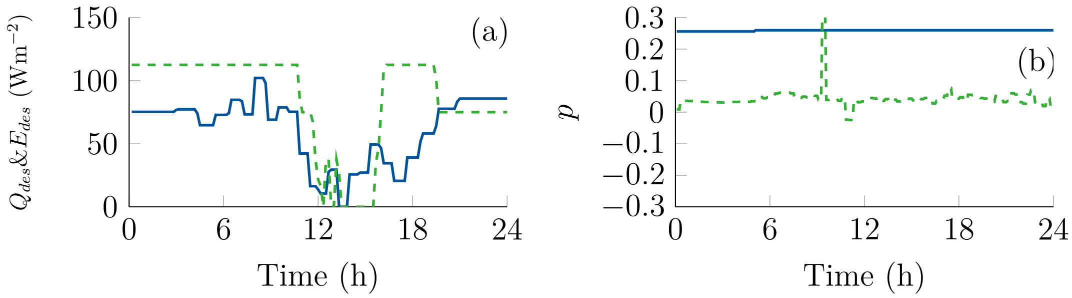


Figure 4.9: Desired heat (solid) and electricity (dashed) demand (a), and gas price (solid, €m^{-3}) and electricity price (dashed, €kWh^{-1}) (b) for October 9, 2012.

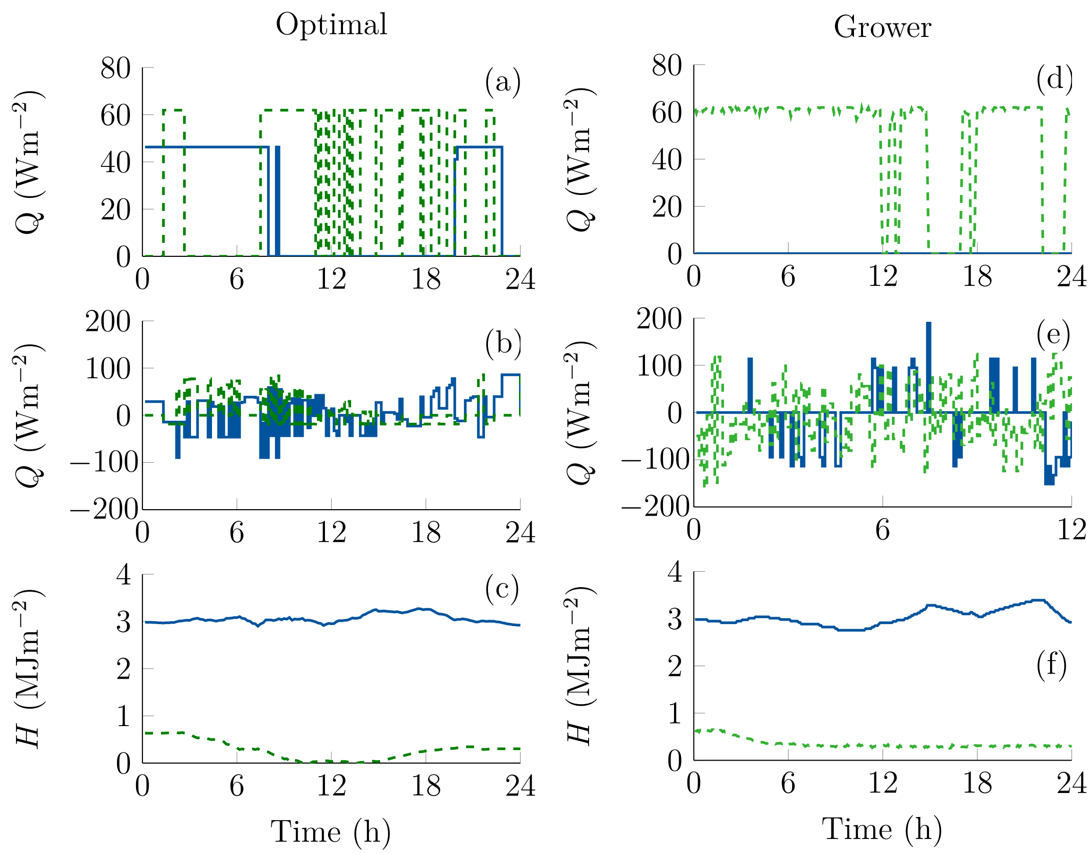


Figure 4.10: Optimal (a) and grower's operation (d) of operating the boiler (solid) and CHP (dashed), high (solid) and low temperature (dashed) buffer fluxes for the optimal scenario (b) and grower's operation (e), and energy content of the high (solid) and low temperature (dashed) buffers for the optimal scenario (c) and grower's operation (f) for October 9, 2012.

The boiler was utilized, such that the heat demand at each time is delivered and the constraints on the filling of the buffers at the end of the optimization period were fulfilled.

There is a slight difference in heat and electricity produced between the optimal scenario and the scenario of the grower (Table 4.2). This is because of noise in the assessment of the energy content of the buffers in the data of the grower (Section 4.B). The heat profile sometimes showed negative values (Section 4.B) since in the current set up it is not possible to take cooling needs into account; they were set to zero. For days with no negative values in Q_{des}, the total produced heat and electricity in the optimal scenario and grower's scenario were equal (not shown).

Table 4.2: Performance indicators calculated from grower's operation of the greenhouse and optimization for two example days: July 13, 2012 and October 9, 2012.

Symbol	July 13, 2012 Optimal	July 13, 2012 Grower	October 9, 2012 Optimal	October 9, 2012 Grower	Unit
			Energy		
$\int Q^{tot}_{HT,boil}$	0.00	0.00	1.29	0.00	MJm^{-2}
$\int Q^{tot}_{chp}$	1.69	1.64	3.00	4.22	MJm^{-2}
$\int E_{buy}$	1.72	1.74	5.06	4.14	MJm^{-2}
$\int E_{sell}$	0.91	0.67	0.55	0.38	MJm^{-2}
			Costs of energy		
$\int G_{tot}$	0.025	0.025	0.058	0.070	€m^{-2}
$\int E_{buy}$	0.007	0.008	0.057	0.051	€m^{-2}
$\int E_{sell}$	-0.015	-0.009	-0.007	-0.005	€m^{-2}
J	0.018	0.025	0.114	0.116	€m^{-2}

The optimization results for the 63 days where the configuration was congruent with that of the grower, are summarized in Fig. 4.11.

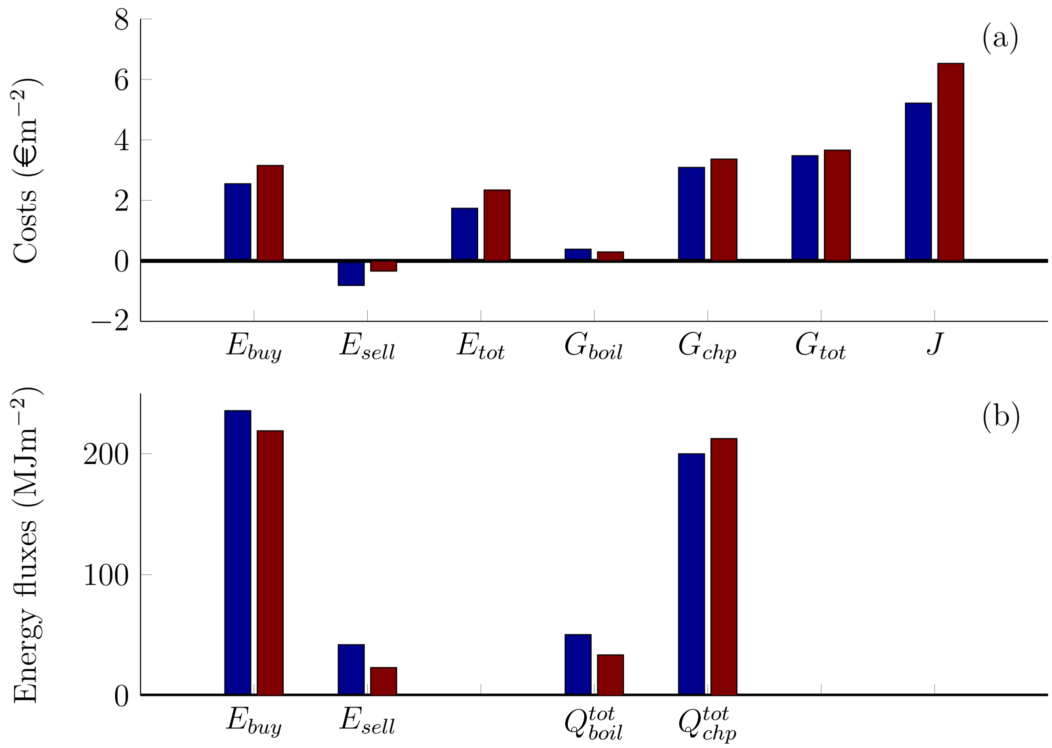


Figure 4.11: Energy costs (a) and total energy fluxes (b) of the grower's scenario (red) and the optimal scenario (blue) for 63 days in 2012.

The cumulative cost function value (J^*) on those 63 days was 20 % lower in the optimal scenario compared to the costs of the grower. This is mostly explained by the lower costs for buying electricity from the grid E_{buy} (−19 %) and the higher benefits from selling electricity to the grid E_{sell} (140 %). The optimization can make use of the prior and full knowledge of the prices over the optimization horizon, in contrast to the grower. The costs for gas vary much less over time than the costs for electricity, therefore, the difference between the total costs for gas differs much less (5 %) between the optimal scenario and the grower's scenario.

A comparison of energy consumption and utilization of equipment for the analyzed days is shown in Fig. 4.11b. In the optimal scenario the amount of heat coming from the boiler is higher than in the grower's scenario. The boiler only produces heat but has a higher efficiency for heat production than the CHP. This means that less natural gas must be bought to produce the same amount of heat. Another difference between the optimal scenario and the grower is that more electricity is sold to the grid and more electricity is bought from the grid.

Fig. 4.12 shows the difference of the total costs between the grower and the optimized scenario for all 63 days considered. The optimal cost function value is lower on all 63 days than the costs of the grower.

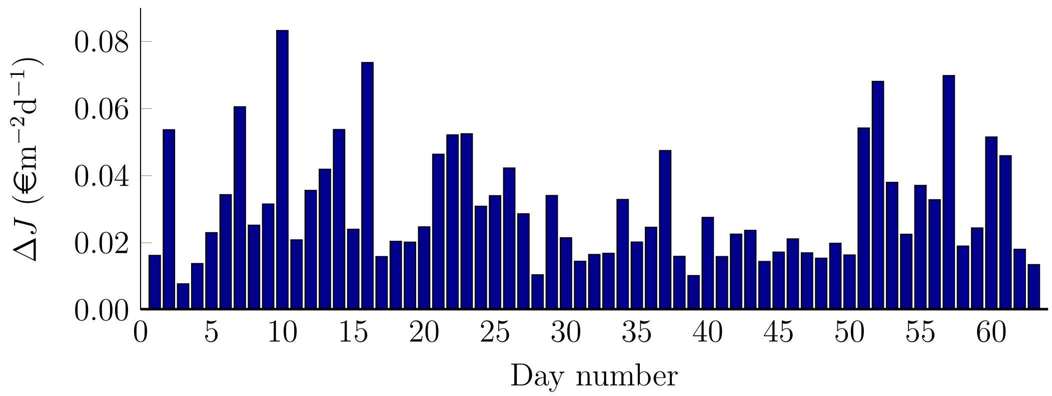


Figure 4.12: Difference in the cost function value of the grower's scenario and the optimized scenario (J_{grower} - $J_{optimal}$) for all analyzed days in 2012. See Section 4.B for the corresponding dates and day numbers.

Sensitivity analysis

The results of the single parameter sensitivity analysis (Section 4.2.2) on the final buffer fill status (H_{HT}), desired heat demand (Q_{des}) and desired electricity demand (E_{des}) are shown in Table 4.3.

A lower total buffer fill status of the high temperature buffer at the end of the optimization period of 10 % led to a lower gas use of 0.7 m^{3}m^{-2} and lower total costs of 0.11 €m^{-2}. A higher terminal buffer fill status led to higher gas use and costs. The total extra costs for the extra gas are relatively low because more electricity was produced that was sold to the grid. This means that a higher heat demand does not necessary lead to higher costs when the surplus electricity is sold for a price that is high enough. The same holds for overall lower and higher desired heat profile. The difference in total costs are relatively low. The costs and gas use for the case with 10 % lower heat demand were about the same as in the standard scenario.

Table 4.3: Effect of final buffer fill status, desired heat demand, desired electricity demand, and prices of electricity and gas on the goal function (J^*) and optimal gas use (G^*_{tot}) over the selected 63 days.

#	Standard scenario	New scenario	$\sum J^*$ €m^{-2}	$\sum \int G^*_{tot}$ m^{3}m^{-2}
1	$H_{HT,buf}(t_f) = H_{HT,grower}(t_f)$		5.22	13.9
2	$H_{HT,buf}(t_f) = H_{HT,grower}(t_f)$	$H_{HT,buf}(t_f) \geq H_{HT,grower}(t_f)$	5.22	13.9
3	$H_{HT,buf}(t_f) = H_{HT,grower}(t_f)$	$H_{HT,buf}(t_f) \geq 0.9 \cdot H_{HT,grower}(t_f)$	5.11	13.2
4	$H_{HT,buf}(t_f) = H_{HT,grower}(t_f)$	$H_{HT,buf}(t_f) \geq 1.1 \cdot H_{HT,grower}(t_f)$	5.32	14.5
5	$Q_{des}(t)$	$0.9 \cdot Q_{des}(t)$	5.04	12.8
6	$Q_{des}(t)$	$1.1 \cdot Q_{des}(t)$	5.41	14.9
7	$E_{des}(t)$	$0.9 \cdot E_{des}(t)$	4.69	13.9
8	$E_{des}(t)$	$1.1 \cdot E_{des}(t)$	5.74	13.9
9	$p_G(t)$	$0.9 \cdot p_G(t)$	4.86	14.4
10	$p_G(t)$	$1.1 \cdot p_G(t)$	5.56	13.3
11	$p_E(t)$	$0.9 \cdot p_E(t)$	5.03	13.3
12	$p_E(t)$	$1.1 \cdot p_E(t)$	5.38	14.4
13	$a = 0\,\%$	$a = 1\,\%$	5.24	14.0
14	$a = 0\,\%$	$a = 2\,\%$	5.26	14.0

The total gas use was similar when the electricity demand profile was varied because more electricity was bought from the grid when the electricity demand was higher than the electricity production of the CHP. The total costs were much more sensitive to the electricity demand than the heat demand for the analyzed days.

Lowering the gas price always by 10 % led to lower energy costs and higher gas use. This is because, compared to the standard scenario, there were more moments with electricity demand from the greenhouse for which it was cheaper to generate the electricity with the CHP instead of buying the electricity from the grid. Also, the costs of producing electricity when sold to the grid was lower. Higher electricity prices also lead to higher gas use, for the same reasons, but the total energy costs become somewhat higher. Lower electricity prices led to somewhat lower energy costs and gas use as in the standard scenario.

The effect of a perfect price forecast for electricity was investigated by by random modification of the electricity price at each time with a random percentage from a pre-defined range. The standard deviation of the optimal solutions was 0.0007 € for the interval of −10 % to 10 %, and 0.004 € for the interval of −50 %

to 50 %. This effect is rather small, because the mean percentage of the changed price was zero.

The effect of heat loss from the buffer for 1 % heat loss per day led to an increase of 0.4 % of the total costs for energy. The total costs for scenario 14 in Table 3 were 0.8 % higher than the costs of the standard scenario. The gas use increased proportionally with the heat loss.

4.4 Discussion

4.4.1 Configuration

In this study, optimizations were first performed using a boiler and heat buffer (configuration 1) and secondly using a boiler, CHP, and two different heat buffers (configuration 2). Both configurations occur in Dutch greenhouse horticulture practice. Clearly, in practice, configurations may vary; for instance, in configuration 2, often just one heat buffer is installed. However, the optimal control method is flexible and can easily be adapted to the actual scenario, such as selling heat to the neighboring greenhouse or adding additional equipment.

CO_2 for the enrichment of greenhouse air was not taken into account for the two configurations optimized in this paper. The reason is that in this case an industrial CO_2 source was used. The desired CO_2 concentration or dosing strategy in modern greenhouses depends, among others, on the type of crop, crop development stage, light conditions, and the ventilation rate. However, by virtue of the generic character of the optimization problem this scenario can be accommodated as well, provided that like heat and electricity demand, the CO_2 demand pattern is specified in advance. CO_2 from the boiler is often used directly for CO_2 enrichment (Bailey, 2002). CO_2 from the CHP is also often used but the exhaust gas is mostly cleaned in order to prevent crop damage due to noxious gasses in the exhaust gas. To implement this in the optimization framework, the desired CO_2 must be produced by the boiler or CHP (both with their own efficiency for the production of CO_2) or come from an external CO_2 source. The efficiency or costs of running the exhaust gas cleaner need to be considered in case of a CHP with exhaust gas cleaner.

4.4.2 Optimization

The desired heat and electricity profiles for generating the greenhouse climate were taken equal to those of the grower. These profiles of the grower were calculated from data of power production by the CHP, boiler and buffers stored in the greenhouse process control computer. In the optimization, the amount of heat stored in the buffers depends on the incoming and outgoing heat flux. Heat losses during transportation and storage were neglected, and it was assumed that all heat that was stored in the buffer was regained, which could lead to an underestimation of the true energy consumption of about 0.4 % per percent of heat loss per day as shown in the sensitivity analysis. The available measured buffer data showed very fluctuating behavior (Section 4.B).

More than one buffer control solution is possible if the buffer efficiency is equal to 1, as assumed in the paper, and when the gas price is constant. Even when the efficiency of the buffer is smaller than 1, there can be multiple controls that can deliver the same amount of heat to the greenhouse. However, in that case the total costs will be slightly higher since not all heat that is put in the buffer can be regained.

The costs for electricity and gas found in the optimization were 20 % lower than in the grower's scenario. An important difference is that, in the optimization, the costs of gas and electricity were perfectly known in advance. Differences between the energy fluxes in the optimized and grower's scenario were sometimes small but could result in large differences in the costs because of the strong fluctuations that occurred in the electricity price. Therefore, we emphasize that a reliable prediction of the prices, together with a proper prediction of the heat and electricity demand of the greenhouse would be very valuable for growers. Zaheer-uddin and Zheng (2000) also suggest that it is possible to take advantage of the storage possibilities and electricity prices by allowing the demand of heat and electricity to vary within acceptable limits. This is also in line with the energy savings found by widening the bounds in Van Beveren et al. (2015b).

The presented optimization is an open loop optimization. In the current form, the optimization is performed afterwards and can be used as a tool to analyze the performance and find possibilities for improvement. In order to implement the optimization procedure in the current greenhouse practice as a forecasting tool, a receding horizon optimal control approach would be suitable Tap (2000); Van Straten et al. (2002); Van Ooteghem et al. (2005); Oldewurtel et al. (2012). In that case, a reliable weather forecast and price forecasts for electricity and gas must be available for the horizon of the optimization (e.g. one or a few days). The prediction of outdoor weather is important because the heat and electricity profiles that must be realized depend strongly on the weather conditions.

Also, in practice, the calculation time is an important aspect for implementation. The calculation times found for the optimization with fixed prices were far below the chosen time interval of one hour. Even the longest calculation time of 316 s for three successive days is still shorter than the time interval of one hour. The CPU time for the optimization with real prices were all shorter than one minute. Therefore, we do not expect problems with calculation time in practice. Another aspect for practical implementation is the prevention of frequent switching of the equipment. The current quadratic method did not provide a satisfactory solution, thus, requires further investigation.

In practice, many different configurations and combinations of equipment for heat and cold production and storage occur. This work aimed to be a starting point for optimizing and understanding optimal scheduling of these systems. Therefore, the next logical step would be to expand the optimization framework with other equipment like a heat pump, aquifer storage, cold storage in short term buffers, and cooling machines. Heat and cold storage in aquifers is typically used for long term (seasonal) energy storage. Extension of the optimization framework in such systems requires a solution to handle long term buffering.

Optimizing the configurations as described in this paper for a longer period are expected to decrease the energy use and costs since the buffers can be used more effectively. In case of a longer optimization period, the buffers have more freedom and time to anticipate to the desired heat and electricity profile. This is supported by the results of the sensitivity analysis on the final buffer filling.

If there are no constraints on the buffer capacity and final buffer filling, the cost effectivity of the CHP can be assessed as follows: The boiler has a thermal efficiency of 0.94. To produce 1 MJ of heat, 35.17 m^3 of gas must be burned. As 1 MWh is equivalent to 3600 MJ, the production of 1 MWh of heat with the boiler requires 109 m^3 gas with associated costs of p_G (€m^{-3}) * 109 (m^3). The thermal efficiency of the CHP is 0.46 for heat (Table 4.1). To produce 1 MWh of heat with the CHP, 223 m^3 gas must be burned, so it seems that the costs of 1 MWh CHP heat are p_G (€m^{-3}) * 223 (m^3). However, this comparison is not fair since the CHP also produces electricity. So, the total efficiency (heat + electricity) of the CHP is 0.83. With an efficiency of 0.83, 123 m^3 gas is needed to produce 1 MWh (heat + electricity), whereby, about 45 % is electricity and 55 % is heat. Although it seems that the CHP is not as energy efficient as the boiler, economically the CHP is in general more efficient, provided that the electricity price is high enough. For example, burning 114 m^3 gas produces 0.8 MWh electricity, in this case, the CHP is more cost-effective if the electricity price is larger than 0.14 * p_G.

4.5 Conclusion

Several issues that hamper the application of the flexible dynamic framework for resource allocation in greenhouses have been solved. In particular, zero-or-range constraints were implemented in order to operate the boiler and CHP between a specified range when they are active. In addition, simultaneous loading and unloading of the buffer was prevented by defining the heat flux from and to the buffers as a single flux that can be positive or negative. It was shown that these modifications, together with a powerful numerical tool, ensured the feasibility of the dynamic optimization approach.

The application of open-loop optimization for a realistic greenhouse configuration showed a potential benefit in the order of 20 % as compared to the actual operation of the grower, at least for those days where the configurations were congruent. It shows that a given heat demand does not necessarily come with a fixed price to pay. Rather, using price information in conjunction with dynamic optimization appears to pay off. It underlines that trading and short-term forecasting of gas and electricity prices in combination with dynamic optimization have a high potential for cost savings in horticultural practice. The total energy cost for the studied greenhouse was more sensitive to the electricity demand than to the heating demand.

The benefits of the optimization procedure implemented this way are two-fold: 1) it facilitates the decision on when and how to deploy which piece of equipment, and 2) it provides an economically optimal solution.

The presented framework will be the basis for further development and extension with other equipment for heating and cooling.

4.6 Acknowledgments

The authors thank HortiMaX B.V., Lek Habo Groep B.V., Wageningen U&R Greenhouse Horticulture, and M. Boonekamp for useful discussions and for sharing their data. We thank Agro Energy for supplying the electricity and gas prices for the studied greenhouse. Furthermore, we thank the Dutch Technology Foundation STW, which is part of the Netherlands Organisation for Scientific Research (NWO), and which is partly funded by the Ministry of Economic Affairs for their support. We would also like to thank the reviewers for their efforts to improve the quality of this paper.

Appendices

4.A Nomenclature

Table 4: Nomenclature

Symbol	Description	Unit
a	Buffer heat loss factor	$\%\mathrm{d}^{-1}$
A	Greenhouse area	m^2
b	Boolean control variable	$-$
E	Electricity flux	$\mathrm{Wm}^{-2}[\mathrm{grh}]$
G	Gas flux	$\mathrm{m}^3[\mathrm{gas}]\mathrm{m}^{-2}[\mathrm{grh}]\mathrm{s}^{-1}$
H	Heat content	$\mathrm{Jm}^{-2}[\mathrm{grh}]$
J	Goal function	€$\mathrm{m}^{-2}[\mathrm{grh}]$
p	Price	€
Q	Heat flux	$\mathrm{Wm}^{-2}[\mathrm{grh}]$
r	Range of operation	$-$
S	Heat of combustion	$\mathrm{Jm}^{-3}[\mathrm{gas}]$
t	Time	s
u	Control variable	
α	Buffer heat loss factor	$\%\mathrm{s}^{-1}$
η	Efficiency	$-$
Subscript		
$boil$	Boiler	
buf	Buffer	
buy	Bought from the grid	
chp	Combined heat an power installation	
des	Desired	
E	Electricity	
f	Final	
grh	Greenhouse	
$grower$	Grower	
G	Gas	
$grid$	Public electricity grid	
HT	High Temperature	
LT	Low Temperature	
$load$	Loading	
$optimal$	Optimal	
$sell$	Sold to the grid	
$unload$	Unloading	
Superscript		
min	Minimum	
max	Maximum	
$*$	Optimal	

4.B Derivation of the desired heat profile

In order to compare the optimization results with the operating strategy resulting from grower's operation of the greenhouse, the desired heat and electricity profiles were calculated from the realized production and delivery of heat and electricity as registered by the process control computer at the greenhouse facility (Eq. (40)).

$$\begin{aligned} Q_{des,grower} = Q_{HT,boil} + Q_{chp} - Q_{HT,buf,load} \\ + Q_{HT,buf,unload} - Q_{LT,buf,load} + Q_{LT,buf,unload} \end{aligned} \quad (40)$$

The greenhouse also delivered heat to a neighboring greenhouse ($Q_{buf,ext}$). This heat must also be delivered, so it was assumed to be part of $Q_{des,grower}$.

The five minute data of the buffer fill rate showed rather fluctuating behavior, while the data of the boiler and CHP were less fluctuating and more smooth. The fluctuating behavior was stronger for the low temperature heat buffer than for the high temperature heat buffer. To obtain data that better represent the inertia of the heat buffers, the high frequency was removed by taking hourly mean values for Q_{des} (Fig. 13). A possible explanation for the behavior of the data can be the update interval of the energy content calculation and delays in the system due to the volume of the heating system.

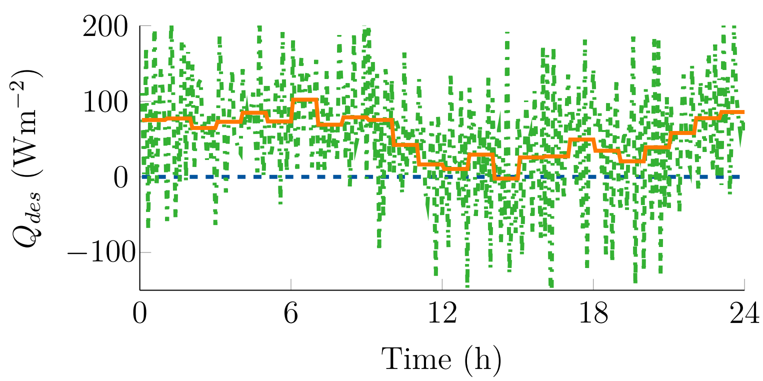


Figure 13: Calculated desired heat pattern using five minute data (· - · -) and hourly means (——) for October 9, 2012

Only days when the heat pump was not used were selected for comparison between the utilization of the equipment by the grower and the optimal scenario because the heat pump and heat buffering in the aquifer are not part of the model and optimization procedure yet. This extension will be considered in future research. In 2012 there were 64 days without heat pump usage. Some data were missing during one of the days, therefore, this day was excluded from the analysis. A list of the selected days is given in Table 5. Within these 63 days, the low temperature heat storage was not used on 17 days. On those days the low temperature heat buffer was used as storage of cold water for greenhouse cooling. In the optimization procedure, this was implemented by adapting the maximum heat storage capacity, namely by setting $H_{LT,buf}^{max} = 0$.

Table 5: Selected days for analysis.

Index	Day of year	Date	Index	Day of year	Date	Index	Day of year	Date
1	24	24-Jan-12	22	198	16-Jul-12	43	279	5-Oct-12
2	44	13-Feb-12	23	199	17-Jul-12	44	280	6-Oct-12
3	62	2-Mar-12	24	200	18-Jul-12	45	282	8-Oct-12
4	65	5-Mar-12	25	201	19-Jul-12	46	283	9-Oct-12
5	70	10-Mar-12	26	255	11-Sep-12	47	284	10-Oct-12
6	97	60-Apr-12	27	256	12-Sep-12	48	286	12-Oct-12
7	105	14-Apr-12	28	257	13-Sep-12	49	287	13-Oct-12
8	106	15-Apr-12	29	260	16-Sep-12	50	290	16-Oct-12
9	124	3-May-12	30	261	17-Sep-12	51	291	17-Oct-12
10	131	10-May-12	31	264	20-Sep-12	52	292	18-Oct-12
11	156	4-Jun-12	32	265	21-Sep-12	53	293	19-Oct-12
12	157	5-Jun-12	33	266	22-Sep-12	54	294	20-Oct-12
13	158	6-Jun-12	34	267	23-Sep-12	55	295	21-Oct-12
14	159	7-Jun-12	35	268	24-Sep-12	56	296	22-Oct-12
15	161	9-Jun-12	36	269	25-Sep-12	57	298	24-Oct-12
16	170	18-Jun-12	37	270	26-Sep-12	58	299	25-Oct-12
17	176	24-Jun-12	38	271	27-Sep-12	59	301	27-Oct-12
18	191	9-Jul-12	39	272	28-Sep-12	60	306	1-Nov-12
19	192	10-Jul-12	40	273	29-Sep-12	61	312	7-Nov-12
20	195	13-Jul-12	41	277	3-Oct-12	62	313	8-Nov-12
21	197	15-Jul-12	42	278	4-Oct-12	63	319	14-Nov-12

4.C Derivation of heat loss factor buffer

The buffer without heat loss is modeled as (Eq. (4.1) and Eq. (4.14)):

$$\frac{dH}{dt} = -Q \tag{41}$$

Suppose the heat loss Q_{loss} is proportional to the heat content:

$$Q_{loss} = -\alpha H \tag{42}$$

Eq. (41) then becomes:

$$\frac{dH}{dt} = -\alpha H - Q \tag{43}$$

Heat loss factors for different buffers used in greenhouse horticulture can be found in (Van Steekelenburg et al., 2011). Suppose the heat loss for 1 day (24 hours) is $a\%$ of the starting energy content. Assume $Q = 0$. Then it follows from Eq. (43) that:

$$H(t_f) = H(t_0)e^{(-\alpha(t_f - t_0))} \tag{44}$$

Since $H(tf) = (1 - 0.01 * a)H(t0)$ it follows that:

$$-\alpha(t_f - t_0) = \ln(1 - 0.01a) \tag{45}$$

From this it follows that with $t_f - t_0 = 24h = 24 \cdot 3600s$, α is given by:

$$\alpha = -(\ln(1 - 0.01a))/(24 \cdot 3600) \tag{46}$$

In this way, the empirically known value of daily heat loss a is replaced by the parameter α, so that the optimization including heat loss can be performed by replacing Eq. (41) by Eq. (43).

5

Optimal utilization of energy equipment in a semi-closed greenhouse

P.J.M. van Beveren
J. Bontsema
A. van 't Ooster
G. van Straten
E.J. van Henten

Published as Van Beveren, P. J. M., Bontsema, J., Van 't Ooster, A., Van Straten, G., & Van Henten, E. J. (2020). Optimal utilization of energy equipment in a semi-closed greenhouse. Computers and Electronics in Agriculture, 179, 105800. doi.org/10.1016/j.compag.2020.105800

Abstract

Increasing variability in energy-saving equipment and systems in the greenhouse industry raises the question of how to best utilize the various equipment in such a setting. The development of adequate solutions for deployment and control of this diversity of equipment has not kept pace with the innovations in the greenhouse industry. In earlier work a two-step dynamic optimization framework was developed, where in step one energy demand for heating and cooling is optimized within the climate constraints set by the grower, and in step two energy costs are minimized of alternative equipment use to satisfy that demand. Here the aims are: 1) to develop step two; 2) to illustrate the potential cost savings of both steps by comparing optimization results with real-life data from one specific grower, as a benchmark.

The energy equipment of a 4 ha semi-closed greenhouse was optimized on a daily basis using dynamic optimization for a period of one year. Predefined heating, cooling, and electricity demand patterns computed from available grower data served as input, together with realized prices for gas and electricity. The installed equipment contained a boiler, a CHP (combined heat and power installation), short term buffers for high and low temperature heat and cold water storage, a heat pump, an aquifer for long term heat and cold storage and cooling towers. Cooling towers are a new element in the field of greenhouse energy optimization.

The results show that cost optimization of the energy system is feasible and beneficial. Energy cost savings of 29 % were obtained for the optimized situation as compared to the real situation at the grower. All available equipment was utilized in the optimal situation. The results show that trading of electricity and short-term forecasting of gas and electricity prices in combination with dynamic optimization has a high potential for cost savings in horticultural practice. Dynamic optimization pointed to a higher share of sustainable energy in the energy budget.

5.1 Introduction

A greenhouse is a permanent glass or plastic covered building for the production of fruits, vegetables, flowers, or ornamentals that has means for controlling the crop environment (Stanghellini et al., 2019). The high energy demand of greenhouses, especially in Northern latitudes, led to the development of the closed greenhouse concept (Opdam et al., 2005; Bakker et al., 2006; Grisey et al., 2011; Vadiee and Martin, 2012, 2013). The main idea of the closed greenhouse is to maximize the utilization of solar energy through seasonal storage (Vadiee and Martin, 2013). It is called closed greenhouse because of the absence of air exchange with outdoor air. Heating, cooling, and dehumidification are needed to maintain temperature and relative humidity (RH) levels within acceptable bounds for plant production (Van Beveren et al., 2015a). Cooling and dehumidification are usually done via heat-exchangers in the greenhouse (Bakker et al., 2006; De Zwart, 2011) as well as low temperature heating. This enables higher CO_2 concentrations in the greenhouse and consequently a higher potential plant production at lower injection rates (Dieleman and Hemming, 2011; Gieling et al., 2011). In a typical summer situation, the surplus heat is stored in the short term (diurnal) buffers or long term (seasonal) storage in underground aquifers (Van 't Ooster et al., 2007). In contrast to the summer situation, warm water from the aquifer heats the greenhouse in periods where no cooling is required. A heat pump increases the temperature of the stored water to a level that is suitable for heating.

The concept of the completely closed greenhouse evolved over the last decade in the direction of the semi-closed greenhouse concept. Semi-closed greenhouses have a smaller cooling capacity than the closed greenhouse and have ventilation windows that are opened when the cooling system has insufficient capacity (Qian et al., 2011). Next to cooling, ventilation is occasionally also needed for dehumidification. The semi-closed greenhouse can save a lot of energy by minimizing the ventilation and storing the surplus heat. In this way, natural gas consumption for heating is minimized. Several studies analyzed the performance of semi-closed greenhouses (De Zwart, 2008; Campen and Kempkes, 2011; Gieling et al., 2011; Qian et al., 2012).

However, the control of closed and semi-closed greenhouses was studied less. Molenaar et al. (2007) optimized by means of linear programming the energy costs of a closed greenhouse for a whole year using an artificially generated heat and electricity demand. Van Ooteghem (2007b) presented a (receding horizon) optimal control formulation for a semi-closed greenhouse with aquifer thermal storage and a boiler. Van Willigenburg et al. (2000) proposed a three time-scale receding horizon optimal control approach to optimize a greenhouse with heat storage tank. In these examples only a limited set of equipment was considered, not fully reflecting the wide range of equipment available to greenhouse industry today. It seems the development of adequate solutions for deployment and control has not kept pace with the rapid adoption of such equipment in greenhouse industry in past years.

Scrutinizing work of Yu et al. (2015) shows that a similar kind of control issues are encountered in air conditioning of buildings using complex heating, cooling and energy storage systems. However, solutions from that application domain cannot be one to one projected on greenhouse practice due to significant differences between greenhouse systems and building systems.

Accounting for the growing complexity of the energy systems installed and fluctuating prices on the energy market, further extend the work presented in Van Beveren et al. (2015a,b, 2019) and addresses the fundamental question on how to best utilize the available equipment. To deal with the complexity of the optimization and control problem, in Van Beveren et al. (2015b, 2019) a two-step optimization paradigm was introduced. The first step consists of minimizing the energy input while realizing a desirable greenhouse climate, as defined by lower and upper temperature, humidity, and CO_2 bounds set by the grower. This step yields patterns for heating, cooling, and CO_2 enrichment (Van Beveren et al., 2015a,b). Then, the second step addresses the optimal scheduling and utilization of the equipment needed to fulfill the required demands calculated in step one and minimizing operating costs (Van Beveren et al., 2019). It is worth noting that in the second optimization step also demand patterns can be used based, in retrospect, on real-life data obtained in a practical greenhouse, thus offering the opportunity to evaluate practical system operation strategies compared to optimized strategies.

The current paper addresses the second optimization step and builds on and extends the work of Van Beveren et al. (2019). The novelty of this paper is threefold. First, while Van Beveren et al. (2019) addressed two simple yet realistic system configurations to build understanding for the optimization problem at hand, the current work addresses a realistic energy system configuration in its full complexity including, besides a boiler, CHP, short term low temperature and high temperature buffers, also a heat pump, aquifer long term energy storage and cooling towers. Addressing the optimal utilization of cooling towers in such an energy system is the second novelty of this work. Optimal control of energy systems for buildings that include cooling towers or cooling machines are presented among others by Kintner-Meyer and Emery (1995); Ma et al. (2009); Pavlov and Olesen (2012). Greenhouse systems with cooling towers have been described by Buchholz et al. (2005); Bakker et al. (2006); Blanco et al. (2014), but to the best of our knowledge optimal control of such an energy system in greenhouse cultivation has not been addressed before. Thirdly, the optimization is evaluated for a full year and compared to operational data of a real greenhouse utilizing this energy system in its full complexity.

This paper is organized as follows. First, the data of the greenhouse and equipment is disclosed (Section 5.2.1), then the formulation of the dynamic optimization problem addressing energy equipment and use is presented (Section 5.2.3). Secondly, in Sections 5.3.1 to 5.3.3 optimal operation of the semi-closed greenhouse is illustrated and compared with practical operation of the studied greenhouse with the realized heating, cooling, and electricity demand of the year 2012. In addition to taking the real demands as a starting point, also the minimized energy demand of the greenhouse (Van Beveren et al., 2015a) was taken as a starting point for optimization of the energy costs (Section 5.3.4). This demonstrates the potential cost saving of application of the optimization procedures in both the stages of energy demand and energy supply optimization.

5.2 Materials and methods

5.2.1 Data

Data was collected from a four-hectare (40 709 m^2) rose producing greenhouse in Bleiswijk, the Netherlands (52 °N, 4.5 °E). Operational data from both the greenhouse process control computer and the energy control system were obtained for the whole year 2012, thus allowing comparison of the optimal control results with practice. The data from the energy control system included temperature measurements and control settings of pumps and valves. Data from both sources had a five-minute sampling interval. The outdoor climate for 2012 is shown in Appendix 5.B. Furthermore, the real dynamic electricity and gas prices for the whole year 2012 were obtained through the energy supplier of the grower (15-minute time interval). In the Netherlands, electricity produced with CHP installations is partly used for artificial lighting but mostly sold to the national power grid (Vermeulen and Van der Lans, 2011). Growers can trade electricity on different markets that operate on different time scales. The greenhouse in this study traded electricity on the so-called unbalance market only. In this market, prices fluctuate every 15 minutes. Although rare, a negative electricity price can occur, meaning that the grower gets paid for using electricity.

5.2.2 Greenhouse description

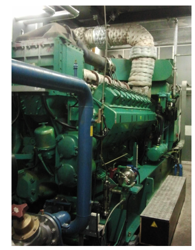
The greenhouse dimensions were 281 m by 160 m, where a part of about 140 m by 32 m were office, equipment and storage space. Eave height was 6.4 m and ridge height was 7.2 m.

The following equipment was present in the greenhouse to control greenhouse climate: 1) pipe rail heating system, 2) ventilation windows, 3) water-to-air heat-exchangers for heating, cooling and dehumidification (OPAC106, De Zwart and Janssen (2010)), 4) supplementary lighting, and 5) energy and shading screens. The heat-exchangers (3) were placed above the crop. In the heat-exchangers cold or warm water was led to a large contact surface to exchange energy with the air. Air was recirculated through the unit by an internal fan. The use of such units is not common in greenhouse industry, yet. Active cooling may result in active dehumidification, so less ventilation is needed and higher CO_2 concentrations can be maintained in the greenhouse.

The available energy equipment to supply the heat and cold were an aquifer storing warm and cold water, heat pump, short term low temperature (LT) buffer and cold water (C) storage, short term high temperature (HT) buffers, boiler, CHP (combined heat and power installation), and cooling towers. Heat was also delivered to the neighboring greenhouse. Photos of the greenhouse and some of the equipment are shown in Fig. 5.1.

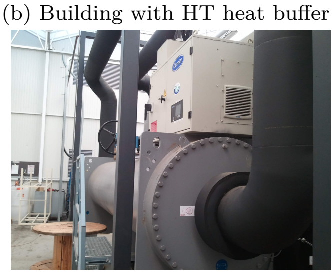
(a) The greenhouse with crop

(b) Building with HT heat buffer



(c) CHP installation

(d) Aquifer pumps



(e) Heat pump

(f) Cooling tower

Figure 5.1: Photos of the greenhouse and equipment.

5.2.3 System configuration

A schematic overview of the system configuration is shown in Fig. 5.2. All symbols are explained in Appendix 5.A.

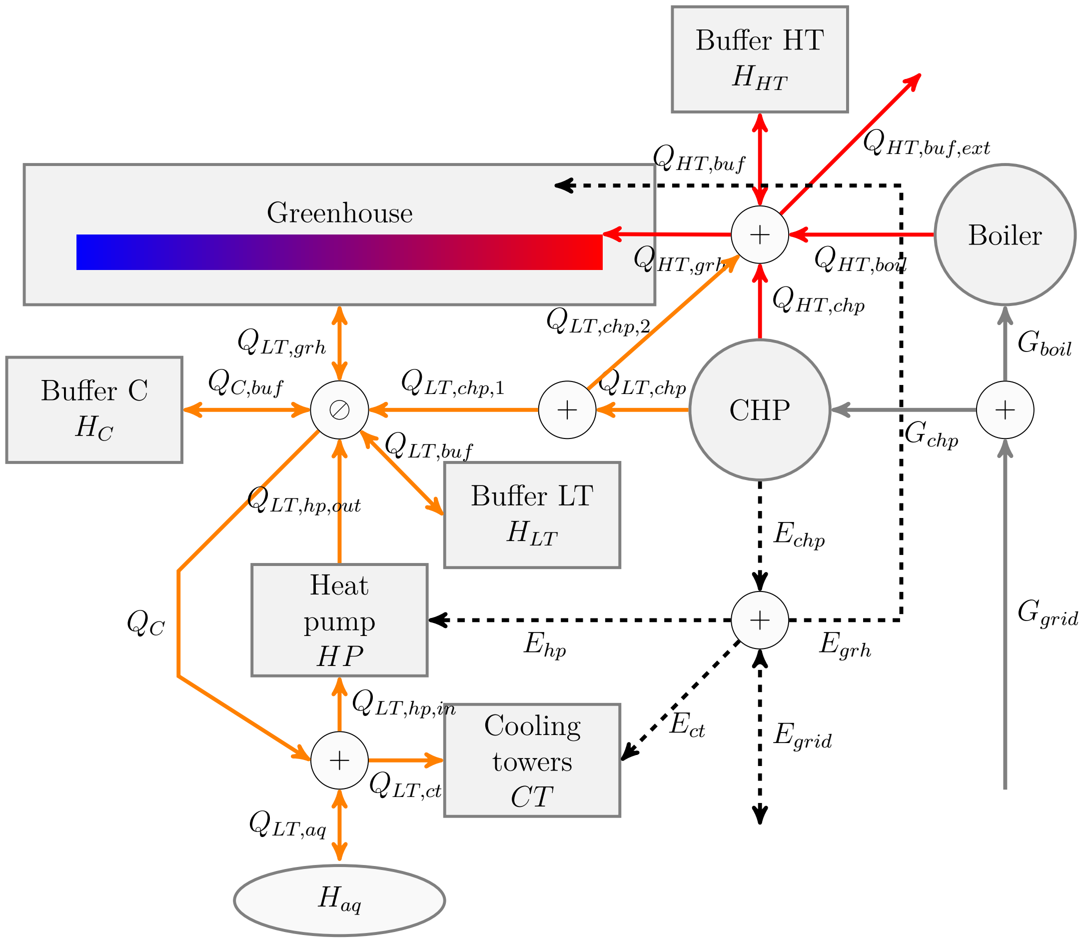


Figure 5.2: System configuration for heating and cooling the greenhouse. High temperature heat fluxes (red line), low temperature heat fluxes (orange line), electricity fluxes (dashed black line) and gas fluxes (grey line) are represented by arrows.

Heating can be applied with the pipe rail heating system under the crop or with the heat-exchangers above the crop. The pipe rail heating system requires high temperature heat (>35 °C). Heating with the heat-exchangers requires low temperature heat (25 °C to 35 °C). Cooling can only be applied with the heat-exchangers.

In greenhouses without or with limited active cooling, the ventilation windows are opened to lower the greenhouse air temperature on warm sunny days. As a consequence, the CO_2 concentration drops under the desired CO_2 level because of limited CO_2 dosing capacity. The advantage of active cooling is that ventilation loss of CO_2 is neutralized, and CO_2 remains available for assimilation which is beneficial for crop production and the environment.

Cooling is not only applied to lower greenhouse air temperature, but also to dehumidify greenhouse air. When using the heat-exchangers for cooling, vapor from the air condensates in the heat-exchanger. Dehumidification of greenhouse air is needed to prevent too high humidity levels in the greenhouse. High humidity levels increase the risk of diseases and fungi threatening crop health (Dieleman and Hemming, 2011). The need for dehumidification does occur more frequent in the late summer and autumn period in the Netherlands. Illuminated rose crops, as grown in the studied greenhouse, require a high number of dehumidification hours due to higher transpiration rates in cold and dark periods (Campen et al., 2003). It was observed in the data from the grower that heating and cooling were sometimes applied at the same time in order to correct both temperature and humidity.

High-temperature heat can either come from the boiler or the CHP. The CHP produces heat, electricity, and carbon dioxide gas (CO_2). Most greenhouses in the Netherlands use a gas-fired boiler combined with a CHP for heating the greenhouse. While burning gas, CO_2 is produced to enrich the greenhouse air. The CO_2 from the CHP was not used in the studied greenhouse. All CO_2 came from a CO_2 distribution network (OCAP, Ros et al. (2014)) in the west of the Netherlands except for a couple of days that OCAP CO_2 was not available. On those days, CO_2 from the boiler was applied. The CHP in the greenhouse was a Cummins QSV 91 G 18 bar with a total thermal capacity of 2.5 MW.

The cold water buffer and low-temperature heat buffer are two large water storages under the greenhouse floor of about 2650 m^3 each. These buffers are so-called 'Klimrek' buffers (Brand et al., 2008), and can either be used as a low-temperature heat storage (25 °C to 35 °C) or as a cold water storage (7 °C to 17 °C). As depicted in Fig. 5.3, buffers were initially employed by the grower as low-temperature heat storage in 2012. After 75 days, one buffer was designated as cold storage and the other as low-temperature buffer. During 16 weeks in summer, both buffers were operated as cold buffers. After this period, one buffer was in use as a low-temperature heat storage again, and finally, both buffers were used as low-temperature heat buffers.

The function of the heat pump is to bring low-temperature water to a higher temperature level, so that it is suitable for heating the greenhouse via the heat-exchangers or for temporary storage in the LT buffer. At the same time, water with a lower temperature (cold water) is leaving the heat pump. The heat pump can also be employed to fill the cold water buffer. Alternatively, the heat pump cools the warm water coming from the greenhouse or buffer. The produced cold water is then stored for later use. This is a typical summer situation.

The heat pump installed in the greenhouse was an electrical Carrier Evergreen Chiller 19XR with refrigerant type R-134a. The maximum thermal power of the heat pump was 2.5 MW. The COP (coefficient of performance) of the heat pump was determined from measured data as 5.5 (SD=1.0).

An aquifer is a water-bearing sand layer to store warm or cold water. The aquifer used at the greenhouse consisted of four cold wells and four warm wells. The mean (measured) temperature of the water on the cold side of the aquifer was 10.7 °C (SD=4.0 °C) and the mean (measured) temperature of the water on the warm side of the aquifer was 20.6 °C (SD=4.8 °C).

The cooling towers were installed to fulfill governmental regulations on the storage of heat in aquifers, which state that the cold and the warm well should be in balance in the long term (Van Steekelenburg et al., 2011). This means that the same amount of heat that is extracted should be injected into the aquifer over multiple years. Rose greenhouses in the Netherlands with supplementary lighting have in general a surplus of heat. The cooling towers are intended to waste surplus heat in summer and to produce cold water to store in the aquifer in winter. These cooling towers have relatively low operating costs.

Electricity is primarily used for supplementary lighting (112.5 $\mathrm{W m^{-2}}$ SON-T). The other consumers of electricity in the greenhouse are the heat pump and cooling towers. In the current case, electricity can be produced with the CHP or can be bought from the public electricity grid. Grower's in the Netherlands can also sell electricity to the grid at a dynamic market price. Electricity consumption from other equipment like pumps and controllers was not taken into account.

Optimal control formulation

In order to optimize the utilization of equipment for the presented configuration, an optimal control problem was formulated. The optimal control formulation of the semi-closed greenhouse configuration is an extension of the formulation of the second configuration (CHP, boiler and two heat buffers) in (Van Beveren et al., 2019), with a heat pump, aquifer heat storage, a cold buffer, and cooling towers.

All heat fluxes are defined as positive heat gains in the direction of the arrows in Fig. 5.2.

Extraction of heat e.g. from greenhouse or buffer was defined as a positive cold flux. All heat and electricity fluxes are expressed in W per square meter greenhouse floor area.

The system contains four different buffers. A buffer heat flux is either positive (unloading of the buffer) or negative (loading of the buffer). For the standard case, heat loss during transport and storage is ignored. Eqs. (5.1) to (5.4) describe the energy content (H) of the high temperature buffer ($H_{HT,buf}$), aquifer (H_{aq}), low temperature heat buffer (H_{LT}), and cold buffer (H_C), respectively.

$$\frac{dH_{HT,buf}}{dt} = -Q_{HT,buf} \tag{5.1}$$

$$\frac{dH_{aq}}{dt} = -Q_{LT,aq} \tag{5.2}$$

$$\frac{dH_{LT}}{dt} = -Q_{LT,buf} \tag{5.3}$$

$$\frac{dH_C}{dt} = -Q_{C,buf} \tag{5.4}$$

The effect of heat loss from the LT and HT buffer was studied before in Van Beveren et al. (2019) and proved to have little effect on the optimization result. Heat loss from the aquifer is about 0.08 % per day (Van Steekelenburg et al., 2011). The effect of incorporating the loss factor for the aquifer was analyzed using the same approach as in Van Beveren et al. (2019).

Since the two Klimrek buffers could be used as low-temperature heat storage or as a storage of cold water, these buffers together are treated in the optimal control formulation as one low-temperature (LT) storage and one cold water storage (C) with varying capacities throughout the year (as depicted in Fig. 5.3). The capacities of the low-temperature buffer and cold buffer were adapted, based on the day of the year, similar to the grower's operation in 2012. The maximal heat storage capacity for a single Klimrek buffer was $1.85\,\mathrm{MJm^{-2}}$ for low temperature water and $0.82\,\mathrm{MJm^{-2}}$ for cold water (Table 5.1). It can be seen that both Klimrek buffers contain LT heat in the first and last period of the year (day 1 to day 75 and day 334 to day 365). From day 146 to day 260, both Klimrek buffers stored cold water. In the remaining periods, one buffer served as low-temperature water storage and the other buffer served as cold water storage.

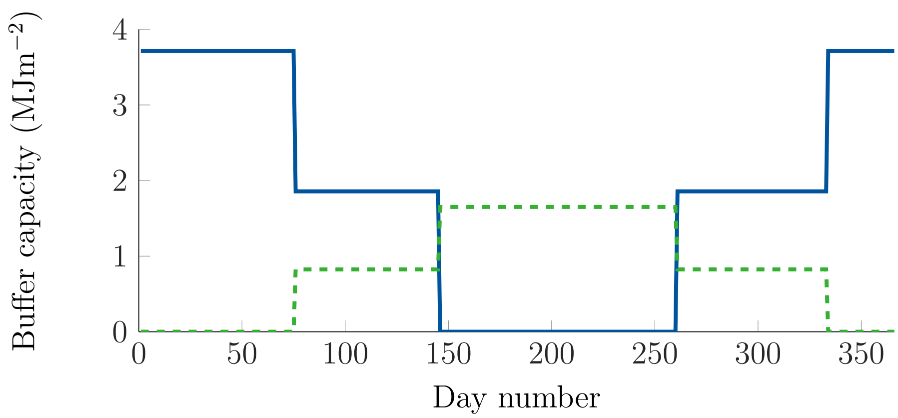


Figure 5.3: Total capacity of the low-temperature heat buffer (—) and cold buffer according to the practical use by the grower in 2012 (- - -). In total, two Klimrek buffers were present in the greenhouse that serve either as a low-temperature buffer (LT) or cold buffer (C).

All buffers have limitations on the minimum and maximum amount of energy that can be stored in the buffer, Eqs. (5.5) to (5.8). The capacities of the buffers and aquifer are given in Table 5.1.

$$0 \leq H_{HT} \leq H_{HT}^{max} \tag{5.5}$$
$$0 \leq H_{aq} \leq H_{aq}^{max} \tag{5.6}$$
$$0 \leq H_{LT} \leq H_{LT}^{max}(t) \tag{5.7}$$
$$0 \leq H_{C} \leq H_{C}^{max}(t) \tag{5.8}$$

To enable a fair comparison between the grower's operation and the optimization, the heat withdrawn or stored in the buffers and aquifer over the day must be considered. Therefore, in the optimization, the initial fill status was taken from the data obtained from the grower. This leads to the following initial state constraints:

$$H_{HT,buf}(t_0) = H_{HT,grower}(t_0), \tag{5.9}$$
$$H_{aq}(t_0) = H_{aq,grower}(t_0), \tag{5.10}$$
$$H_{LT,buf}(t_0) = H_{LT,grower}(t_0), \tag{5.11}$$
$$H_{C,buf}(t_0) = H_{C,grower}(t_0). \tag{5.12}$$

The measured data of the buffers showed sometimes unrealistic values e.g. too large heat extraction in a short period for reasons not understood. Introducing a lower and upper bound with a small deviation of 1 % ($f_{dev} = 0.01$) on the final state constraints of the buffers and aquifer solved this problem. This leads to the following final state constraints:

$$(1 - f_{dev})H_{HT,grower} \leq H_{HT,buf}(t_f) \leq (1 + f_{dev})H_{HT,grower}(t_f), \tag{5.13}$$
$$(1 - f_{dev})H_{aq,grower}(t_f) \leq H_{aq}(t_f) \leq (1 + f_{dev}H_{aq,grower}(t_f), \tag{5.14}$$
$$(1 - f_{dev})H_{LT,grower}(t_f) \leq H_{LT,buf}(t_f) \leq (1 + f_{dev})H_{LT,grower}(t_f), \tag{5.15}$$
$$(1 - f_{dev})H_{C,grower}(t_f) \leq H_{C,buf}(t_f) \leq (1 + f_{dev})H_{C,grower}(t_f). \tag{5.16}$$

When the low-temperature buffer is not used in summer, the heat flux to the buffer should be equal to 0. $b_{LT,buf}$ is an apriori defined boolean (no control variable) that is zero when there is no low-temperature buffer (Fig. 5.3). In the problem formulation this is implemented via the following constraint:

$$0 \leq Q_{LT,buf} \leq b_{LT,buf} Q_{LT,buf}. \tag{5.17}$$

Three different states of heating and cooling can occur in the greenhouse at the same time: 1) heating only, 2) cooling only, and 3) combined heating and cooling. The latter occurs mainly in the spring and autumn season when too high humidity levels in the greenhouse are prevented by cooling out vapor from the air with the heat-exchangers. At the same time, the indoor temperature is increased by heating so that the air can contain more water vapor and the temperature stays within the desired bounds. To cope with these three situations, a boolean b_C was calculated (apriori) from the pre-defined cooling demand and was not a control variable. When the greenhouse had a cooling demand, b_C was equal to one and otherwise, b_C was zero. When a cooling demand exists, heat could only be delivered via the high-temperature heating ($Q_{HT,grh}$). When no cooling demand exists, heat can be delivered via low ($Q_{LT,grh}$) or high-temperature heating (Eq. (5.18)).

$$Q_{HT,grh} + (1 - b_C) Q_{LT,grh} = Q_{tot,grh} \tag{5.18}$$

The high-temperature heat could either come from the boiler ($Q_{HT,boil}$), high-temperature buffer ($Q_{HT,buf}$), or the high-temperature CHP outlet ($Q_{HT,chp}$) (Eq. 5.19). As an extra option, the low-temperature heat produced by the CHP ($Q_{LT,chp}$) could be mixed with the high-temperature heat. The part of the LT heat from the CHP that is added to the high-temperature heat is $Q_{LT,chp,2}$. It was assumed that the resulting warm water is of sufficient temperature for heating the greenhouse. The mixing is inevitable in the summer period when both Klimrek buffers store cold water.

The division of low temperature heat from CHP is determined via Eq. (5.20). Eq. (5.21) is an additional constraint that limits the control variable $Q_{LT,chp,2}$.

$$Q_{HT,grh} = Q_{HT,boil} + Q_{HT,buf} + Q_{HT,chp} + Q_{LT,chp,2} \tag{5.19}$$

$$Q_{LT,chp,1} = Q_{LT,chp} - Q_{LT,chp2} \tag{5.20}$$

$$Q_{LT,chp,2} \leq Q_{LT,chp} \tag{5.21}$$

For reasons of efficiency and avoiding faster deterioration of parts, the boiler and

CHP are preferably not run below a specific minimum operating power. To cope with this operation range of the boiler, a zero-or-range constraint was introduced (Hansen and Huge, 1989). In the case of the boiler it reads:

$$Q_{HT,boil} - Q_{HT,boil}^{max} b_{boil} \leq 0, \tag{5.22}$$
$$Q_{HT,boil} - r_{boil}^{min} Q_{HT,boil}^{max} b_{boil} \geq 0, \tag{5.23}$$
$$Q_{HT,boil} \geq 0, \tag{5.24}$$
$$b_{boil} \in \{0,1\} \tag{5.25}$$

where Eq. (5.22) and Eq. (5.23) give the following constraint for $b_{boil} = 0$: $Q_{HT,boil} = 0$. For $b_{boil} = 1$, the constraint is $r_{boil}^{min} Q_{HT,boil}^{max} \leq Q_{HT,boil} \leq Q_{HT,boil}^{max}$. The value of r_{boil}^{min} was 0.8. Eq. (5.24) is a trivial constraint on the heat flux from the boiler, which can only be positive.

A similar zero-or-range constraint for the CHP is given by Eqs. (5.26) to (5.29). This introduces the next boolean control variable (b_{chp}). The lower bound of the operating range of the CHP (r_{chp}^{min}) was determined from the data of the grower and turned out to be 0.85 in practice.

$$Q_{chp} - Q_{chp}^{max} b_{chp} \leq 0, \tag{5.26}$$
$$Q_{chp} - r_{chp}^{min} Q_{chp}^{max} b_{chp} \geq 0, \tag{5.27}$$
$$Q_{chp} \geq 0, \tag{5.28}$$
$$b_{chp} \in \{0,1\} \tag{5.29}$$

The low-temperature heat fluxes when $Q_{LT,grh}$ is in heating mode were calculated as:

$$Q_{LT,buf} + Q_{LT,hp,out} + Q_{LT,chp} - Q_{LT,chp,2} = (1 - b_C) Q_{LT,grh}. \tag{5.30}$$

The low-temperature heat fluxes when the greenhouse has a cooling demand were calculated as:

$$-Q_{LT,aq} + Q_{C,buf} - Q_{LT,ct} - Q_{LT,hp,in} = b_C Q_{LT,grh}. \tag{5.31}$$

The electricity production of the CHP (E_{chp}) served the greenhouse (E_{grh}), powers the heat pump (E_{hp}) and the cooling towers (E_{ct}), or is sold to the grid ($E_{grid} < 0$, Eq. (5.32)). The cost of electricity generated by the CHP is already accounted for in the gas price.

$$E_{chp} + E_{grid} - E_{hp} - E_{ct} = E_{grh} \tag{5.32}$$

The electricity production by the CHP was calculated as:

$$E_{chp} = \frac{\eta_{E,chp}}{\eta_{Q,chp}} Q_{chp}. \tag{5.33}$$

The ratio between the electrical efficiency of the CHP $\eta_{E,chp}$ and the thermal efficiency $\eta_{Q,chp}$ was obtained from the power data of the CHP from a full year with a five minute time step. A ratio of 0.81 was found (Table 5.1).

The heat pump is either on or off. This is represented by the boolean control variable $b_{hp} \in \{0, 1\}$ in the following equation:

$$Q_{LT,hp,out} = b_{hp} Q_{hp}^{max}. \tag{5.34}$$

The maximum thermal power of the heat pump Q_{hp}^{max} was 62.5 $\mathrm{W m^{-2}}$. The electric power uptake of the heat pump (E_{hp}) is

$$E_{hp} = \frac{Q_{LT,hp,out}}{COP_{hp}} \tag{5.35}$$

where $Q_{LT,hp,out}$ is the heat flux leaving the heat pump. The COP_{hp} (5.5) is the thermal coefficient of performance of the heat pump. The cold flux produced by the heat pump is then calculated as:

$$Q_{LT,hp,in} = Q_{LT,hp,out} - E_{hp} \tag{5.36}$$

Also, cooling towers have no variable control. They are either on or off. This is represented by the boolean control variable $b_{ct} \in \{0, 1\}$. Minimum value $Q_{LT,ct}^{min}$ was introduced to allow cooling tower use on days when the grower did not use them. On other days the capacity was limited to the actual value observed. This was done to avoid the need for modeling the capacity of the cooling tower as a function of the external conditions; the actual operation by the grower served as a proxy. The heat flux to the cooling towers $Q_{LT,ct}$ depends on the maximum realized heat flux on that specific day.

$$Q_{LT,ct} = b_{ct} \max \left(Q_{LT,ct}^{min}, Q_{LT,ct}^{max,grower} \right) \tag{5.37}$$

Following the previous description, the optimization problem has twelve control variables:

$$u = \begin{bmatrix} u_1 \\ u_2 \\ \cdot \\ \cdot \\ \cdot \\ u_{12} \end{bmatrix} = \begin{bmatrix} Q_{LT,buf} \\ Q_{HT,buf} \\ Q_{LT,grh} \\ Q_{HT,boil} \\ Q_{HT,chp} \\ Q_{C,buf} \\ Q_{LT,aq} \\ b_{boil} \\ b_{chp} \\ b_{ct} \\ b_{hp} \\ Q_{LT,chp,2} \end{bmatrix} \tag{5.38}$$

where

$$b_{boil}, b_{chp}, b_{ct}, b_{hp} \in \{0, 1\}, \tag{5.39}$$

and the other variables are continuous and need to satisfy the constraints as described above.

The goal function to minimize the total gas costs, electricity costs for buying or selling electricity (revenues are negative costs) for the given time evolution of the gas price (Eq. (5.41)) and electricity price (Eq. (5.42)) is:

$$\min_u J = \min_u \int_{t_0}^{t_f} \left(p_G \left(G_{boil}(u) + G_{chp}(u) \right) + p_E E_{grid}(u) \right) \, \mathrm{d}t, \tag{5.40}$$

$$p_G(t), t_0 \leq t \leq t_f, \tag{5.41}$$

$$p_E(t), t_0 \leq t \leq t_f, \tag{5.42}$$

where p_G is the (dynamic) gas price (€m^{-3}) and p_E is the (dynamic) electricity price (€J^{-1}). The price for buying and selling electricity were equal, as for the grower. The unit of the gas consumption (G) is $\mathrm{m}^3\mathrm{m}^{-2}\mathrm{s}^{-1}$ and the unit of electricity bought or sold to the grid (E_{grid}) is $\mathrm{W}\mathrm{m}^{-2}$.

The gas consumption of the boiler (G_{boil}) is proportional to the amount of heat produced by the boiler:

$$G_{boil} = \frac{Q_{HT,boil}}{\eta_{boil} \cdot S}. \tag{5.43}$$

where η_{boil} is the boiler efficiency and S the combustion heat of natural gas. The gas consumption of the CHP (G_{chp}) is proportional to the amount of heat produced by the CHP:

$$G_{chp} = \frac{Q_{chp}}{\eta_{Q,chp} S}, \tag{5.44}$$

where the efficiency of the CHP for heat ($\eta_{Q,chp}$) was 0.46. This number was obtained from the total efficiency of the CHP (η_{chp}), which was determined from data from the grower's gas meter and power data.

The capacities of the buffers and aquifer, and power of the equipment are listed in Table 5.1. The costs of the grower were determined with measured data from the electricity and gas meters present in the greenhouse. The (dynamic) prices of electricity and gas were equal in the grower's situation and the optimized situation. The average gas price for 2012 was 0.24 €m^{-3} (SD = 0.017 €m^{-3}, Min = 0.21 €m^{-3}, Max = 0.31 €m^{-3}). The average electricity price for 2012 was 0.05 €kWh^{-1} (SD = 0.112 €kWh^{-1}, Min = −0.45 €kWh^{-1}, Max = 0.54 €kWh^{-1}).

Table 5.1: System defining parameters used for case study.

Symbol	Description	Value	Unit
η_{boil}	Boiler efficiency	0.94	-
$\eta_{E,chp}$	Electrical efficiency of the CHP	0.37	-
$\eta_{Q,chp}$	Thermal efficiency of the CHP	0.46	-
A	Greenhouse area	40 709	m^2 [grh]
COP_{hp}	Coefficient of performance of the heat pump	5.5	$-$
H_{aq}^{max}	Maximum capacity aquifer	540	MJm^{-2} [grh]
$H_{C,buf}^{max}$	Maximum capacity buffer C[a]	1.65×10^6	Jm^{-2} [grh]
$H_{HT,buf}^{max}$	Maximum capacity buffer HT	3.14×10^6	Jm^{-2} [grh]
$H_{LT,buf}^{max}$	Maximum capacity buffer LT[a]	3.71×10^6	Jm^{-2} [grh]
$Q_{HT,buf}^{max}$	Maximum heat flux to buffer HT	150	Wm^{-2} [grh]
$Q_{LT,buf}^{max}$	Maximum heat flux to buffer LT	150	Wm^{-2} [grh]
$Q_{LT,ct}^{min}$	Minimum cooling capacity of the cooling towers	50	Wm^{-2}
$-$	Installed boiler capacity in the greenhouse	2.00	MW
$-$	Installed thermal CHP capacity in the greenhouse	2.52	MW
$-$	Installed heat pump capacity in the greenhouse	2.50	MW
$Q_{HT,boil}^{max}$	Maximum boiler thermal flux	49	Wm^{-2}[grh]
Q_{hp}^{max}	Maximum heat pump thermal flux	62.5	Wm^{-2}[grh]
Q_{chp}^{max}	Maximum CHP thermal flux	62	Wm^{-2}[grh]
$Q_{LT,ct}^{min}$	Minimum thermal flux cooling towers	50	Wm^{-2}
r_{boil}^{min}	Minimum of the range for operating the boiler	0.8	$-$
r_{chp}^{min}	Minimum of the range for operating the CHP	0.85	$-$
S	Combustion heat of natural gas (upper calorific value)	35.17×10^6	Jm^{-3} [gas]
t_f	Final time	86 400	s

[a] Maximum capacity depends on day of the year according to Fig. 5.3.

Optimizations were performed per day ($t_f = 84\,600\,\mathrm{s}$) to stay as close as possible to grower's practice and to be able to compare the optimization results and control of the equipment with the control of the grower and the performance obtained. The consecutive days were optimized independently from each other. The initial buffer and aquifer filling for every day were taken from the grower. The buffer and aquifer filling at the end of the day were, as described before, allowed to deviate slightly around the grower's realization.

All optimizations in this paper were performed using Tomlab optimization software (Edvall and Goran, 2009) in Matlab (version 7, The MathWorks Inc., Natick, USA) on a PC with core i5 CPU 660 3.33 GHz, 4 GB RAM and Windows 7 x64 installed. The optimization problem was solved with TOMLAB/CPLEX for solving large-scale mixed-integer linear and quadratic programming problems. "Tomlab is a general-purpose development, modeling, and optimal control environment in

Matlab for research, teaching, practical solution of optimization problems" (Holmstrom et al., 2010).

Experiments

First, in experiment 1, optimization for the 365 individual days in 2012 was performed for the given heating and cooling demand of the grower. Optimal results were compared with the grower's result. The heating and cooling demand of the grower was obtained by extending the procedure Van Beveren et al. (2019), Appendix 5.B, with measured data from the cold storage, cooling towers, heat pump, and aquifer. Second, in experiment 2, optimizations were performed with the minimal energy input (heating and cooling) obtained from Van Beveren et al. (2015b). The electricity demand remained unchanged compared to Experiment 1. The minimal energy input was obtained with the practical screen positions and supplementary lighting from the grower. It is interesting to compare the standard situation based on pre-defined demands copied from the grower to a situation where these demands themselves are optimized, within the climate constraints set around the values of the grower. This will demonstrate the potential cost saving when stage 1 (minimizing energy input) is coupled to stage 2 (minimizing energy costs).

5.3 Results

First, the optimization results for two individual days, one day in summer and one day in winter, are presented to demonstrate the optimization in detail. The greenhouse air temperature, relative humidity, and CO_2 concentration for these days are shown in Fig. 5.4. Second, the results of daily optimization of the whole year 2012 are presented and compared with the realization of the grower using the realized heating, cooling, and electricity demand as constraints. The electricity demand was the realized electricity consumption of the lamps. The heat delivery to the neighboring greenhouse was accounted for in the heat demand. Last, the daily optimization results are presented using the minimal heating and cooling demand for the year 2012 as constraints, these were obtained by optimizing the energy input to the greenhouse (Van Beveren et al., 2015a).

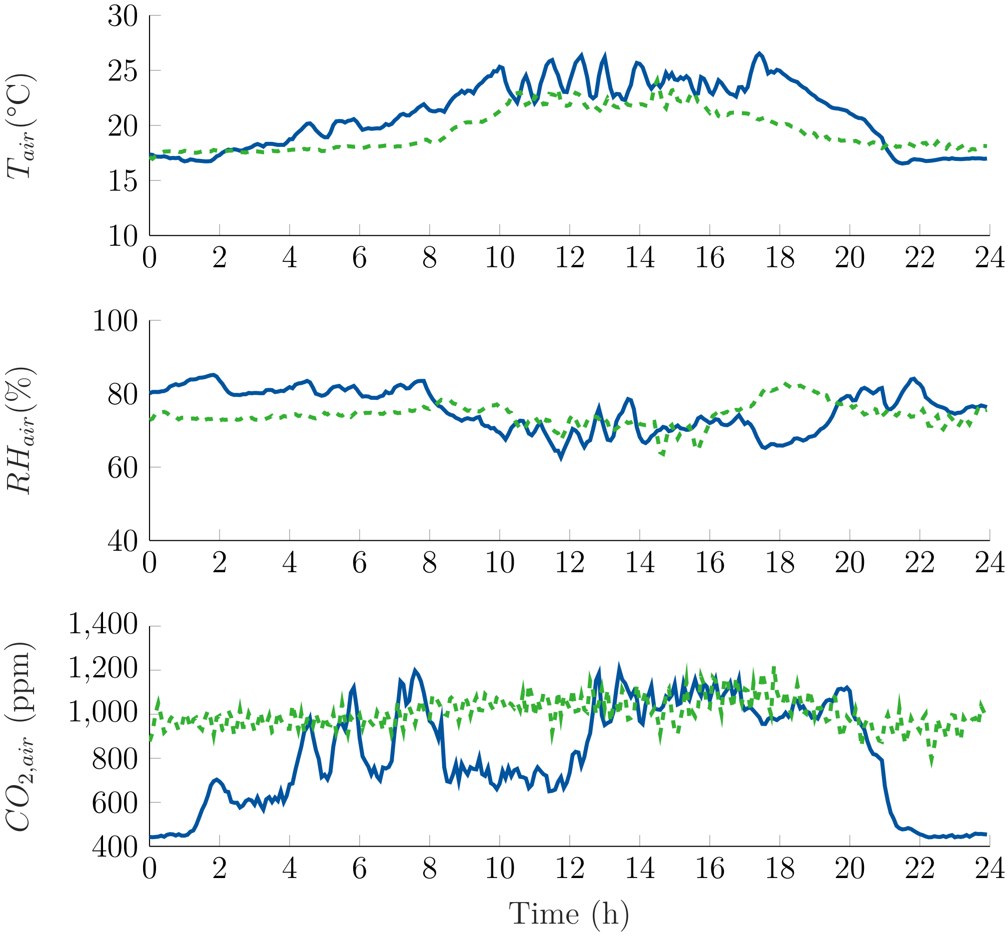


Figure 5.4: Greenhouse climate for June 16, 2012 (——) and March 6, 2012 (- - -): a) greenhouse air temperature (°C), b) Relative humidity (%), c) CO_2 concentration (ppm).

5.3.1 Summer day

The practical heating, cooling, and electricity demand of a warm summer day in 2012 (day number 168, June 16, 2012) is shown in Fig. 5.5. The corresponding prices for electricity and gas are shown in Fig. 5.6. The utilization of the boiler, CHP, heat pump, and cooling towers is shown in Fig. 5.7 for the optimal situation and in Fig. 5.8 for the grower's situation. On June 16, 2012, the outdoor temperature was lower than the greenhouse air temperature for the whole day. The grower used active cooling to cool the greenhouse (12:00 to 21:00 hour) and supplementary lighting (2:00 to 8:30 hour). Supplementary lighting heats the greenhouse air as well. The maximum outdoor radiation was about 1000 $\mathrm{Wm^{-2}}$. Therefore, the shading screen was closed between 11:00 and 16:00 hour. The pipe rail heating system was used during the dark period, and at some moments during the day. Despite the active cooling, the ventilation windows were slightly opened, this is likely to remove water vapor from the greenhouse. Nevertheless, the grower succeeded in maintaining a CO_2 concentration around 1000 ppm during the light period (Fig. 5.4).

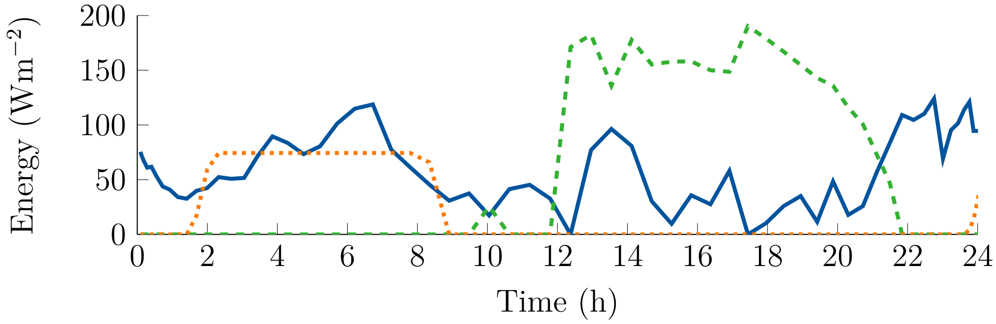


Figure 5.5: Desired heating (——), cooling (- - -), and electricity (for supplementary lighting) profile (⋯⋯) for June 16, 2012 (day number 168).

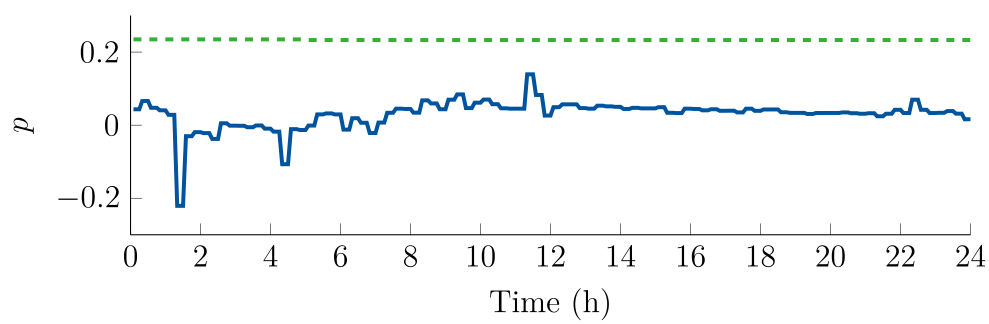


Figure 5.6: Prices for electricity (€$\mathrm{kWh^{-1}}$, ——) and gas (€$\mathrm{m^{-3}}$, - - -) for June 16, 2012 (day number 168).

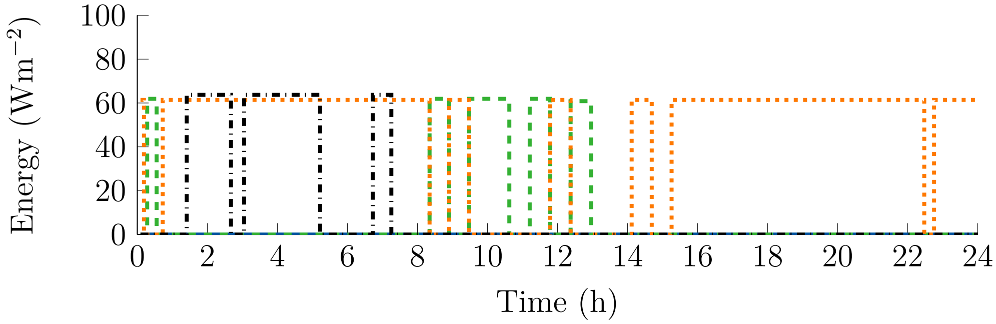


Figure 5.7: Optimal result for June 16, 2012 (day number 168). Boiler (—), CHP (- - -), heat pump (······), and cooling towers (-·-·-).

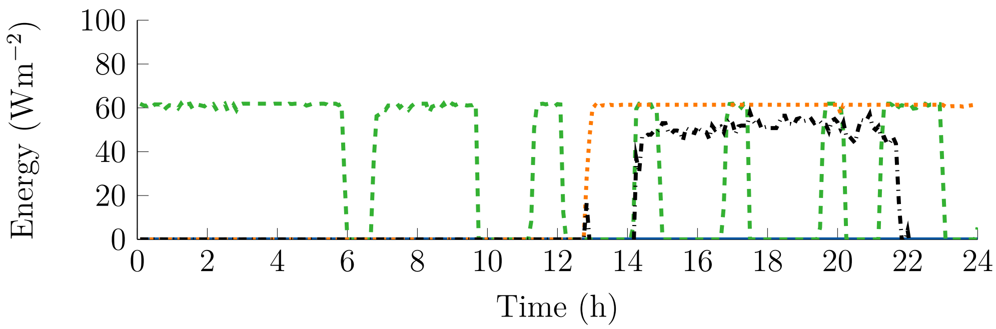


Figure 5.8: Grower result for June 16, 2012 (day number 168). Boiler (—), CHP (- - -), heat pump (······), and cooling towers (-·-·-).

The total energy costs were -0.005 €m^{-2} in the optimal case and 0.044 €m^{-2} in the grower's operation. There was a negative electricity price for some hours in the early morning of day 168 (Fig. 5.6). The effect of this negative price is that it is cheaper to buy electricity from the grid than to generate electricity using the CHP, meaning that the power company rewards electricity consumption. At later hours, the price is positive, but low, thus making it beneficial to use the heat pump. Therefore, the heat pump is used for a longer period in the optimal case compared to the grower's operation. Heat production was not only needed for heating the greenhouse but could also be the result of electricity production with the CHP. In the optimal case, $3.3\,\mathrm{MJm^{-2}}$ of electricity was bought from the grid, while this was $1.5\,\mathrm{MJm^{-2}}$ in the grower's operation. The cooling towers were used by the grower between 14:00 and 22:00 hour, while in the optimal situation they were used in the night to waste heat ahead. This is possible because the cold water could be stored in either the cold buffer or aquifer. The boiler remained switched off in both situations.

5.3.2 Winter day

The practical heating, cooling, and electricity demand of a cold winter day in 2012 (day number 66, March 6, 2012) is shown in Fig. 5.9. The outdoor light level was much lower for the day in March (8.0 MJm^{-2}) compared to the day in June (20.1 MJm^{-2}). Therefore, supplementary lighting was (partially) active for 24 hours (not shown). The lamps were switched on completely between 0:00 and 8:00 hour. The lamps also contribute to heating, therefore the desired heating profile is lower compared to the afternoon period. The maximum outdoor radiation was about 500 Wm^{-2} in the afternoon. Because of the lower outdoor temperature, cooling of the greenhouse was not applied. The greenhouse air temperature was slightly lower compared to June 16 (Fig. 5.4). The corresponding prices for electricity and gas are shown in Fig. 5.10. The utilization of the boiler, CHP, heat pump, and cooling towers is shown in Fig. 5.11 for the optimal situation and in Fig. 5.12 for the grower's situation. Although there was no cooling demand from the greenhouse, the cooling towers were active in the grower's situation between 0:00 and 10:30 hour and between 22:30 and 24:00 hour on this winter day in order to produce cold water that is stored in the aquifer for cooling purposes in summer. The pipe rail heating system was applied the whole day (not shown). The heat-exchangers were used for heating during the dark period and at the end of the afternoon (not shown).

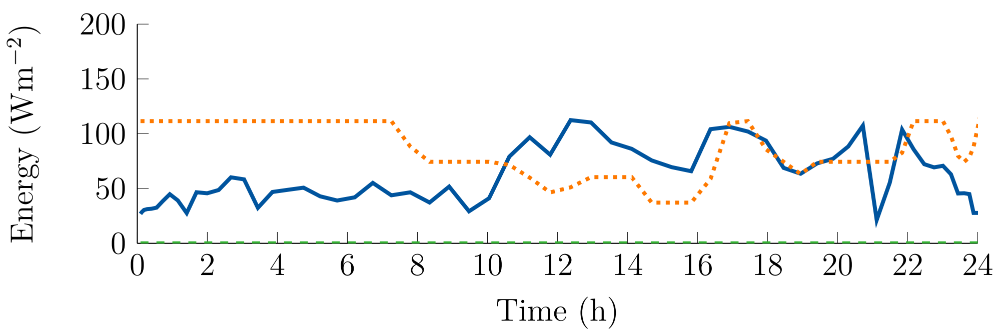


Figure 5.9: Desired practical heating (▬▬), cooling (- - -), and electricity profile (······) for March 6, 2012 (day number 66).

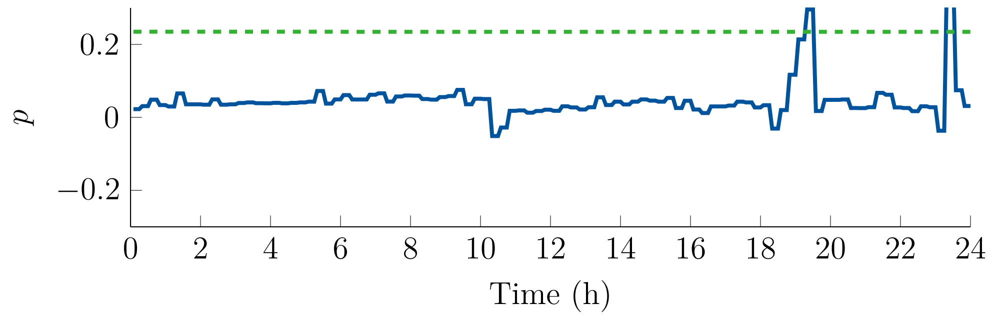


Figure 5.10: electricity (€kWh^{-1},) and gas (€m^{-3},) for March 6, 2012 (day number 66).

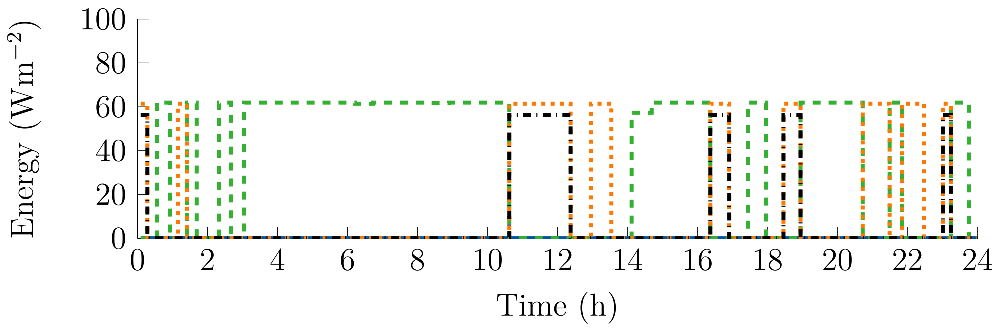


Figure 5.11: Optimal result for March 6, 2012 (day number 66). Boiler (), CHP (), heat pump (), and cooling towers ().

The total energy costs were 0.102 €m^{-2} in the optimal case and 0.112 €m^{-2} in the grower's operation. Around 10:00 hour the electricity price was negative for a short period, but otherwise, it was rather constant on day number 66, except from two high peaks (around 19:00 and 23:00 hours). The effect of the higher price is that the optimization uses the CHP on the moments that the electricity price was high. Consequently, 0.08 MJm^{-2} electricity was delivered to the grid in the optimal case, as opposed to no delivery of electricity by the grower. The heat pump was active between 10:30 and 21:00 hour in the grower's operation, while the optimization distributed the use of the heat pump over the whole day in order to minimize the total energy costs. The cooling towers were activated more frequently for shorter periods in the optimal case. The cooling towers consume electricity, therefore, the cooling towers were active when the electricity price was low.

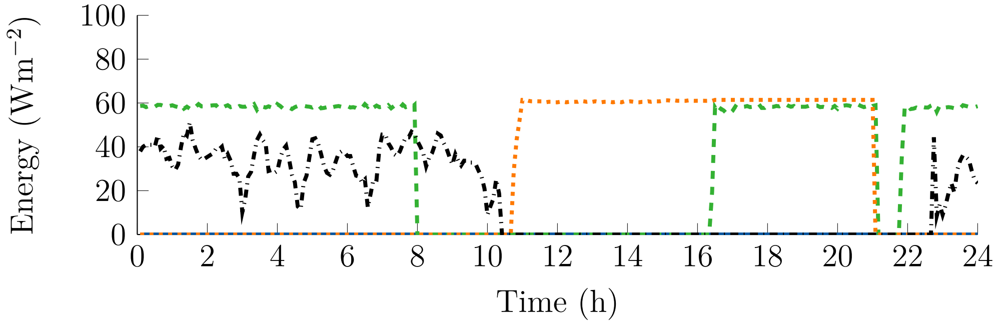


Figure 5.12: Grower result for March 6, 2012 (day number 66). Boiler (—), CHP (- - -), heat pump (⋯), and cooling towers (-·-·-).

5.3.3 Experiment 1: Full year with realized climate

The mean gas and electricity price for 2012 were 0.24 (SD=0.017) €m^{-3} and 0.05 (SD=0.11) €kWh^{-1}, respectively (Section 5.2.3). The total heat demand was 2.4 $GJm^{-2}y^{-1}$, the total cooling demand was 0.7 $GJm^{-2}y^{-1}$, and the total electricity demand of the greenhouse for supplementary lighting was 2.0 $GJm^{-2}y^{-1}$. The total amount of CO_2 dosing was 95.4 kgm^{-2}.

The optimal values of the goal function (Eq. (5.40)) for the daily optimization for all days in 2012 with the heat and cold demand profile of the grower is shown in Fig. 5.13. The difference between optimal operation and the grower's operation is shown in Fig. 5.14.

For all days, the optimal result has lower costs than the grower. The 2012 year costs for the optimal result were 26.79 €m^{-2}, whereas the costs of the grower were 37.71 €m^{-2}. So, the total energy costs in the optimized scenario were 29 % less than the energy cost realized by the grower.

Fig. 5.13 shows that despite the cooling, the highest energy cost occurs in the winter period, which is not surprising. The outside temperature is lower and the day length shorter, which results in a much higher demand for heating and electricity for lighting than in the summer period. Despite this, the difference between the optimization and the grower is smaller in winter. Due to the high demands, there is apparently less freedom for the optimization to shift heat load and electricity trade within the optimization period of one day. A substantial part of the gains of the optimization is therefore obtained in summer (Fig. 5.14).

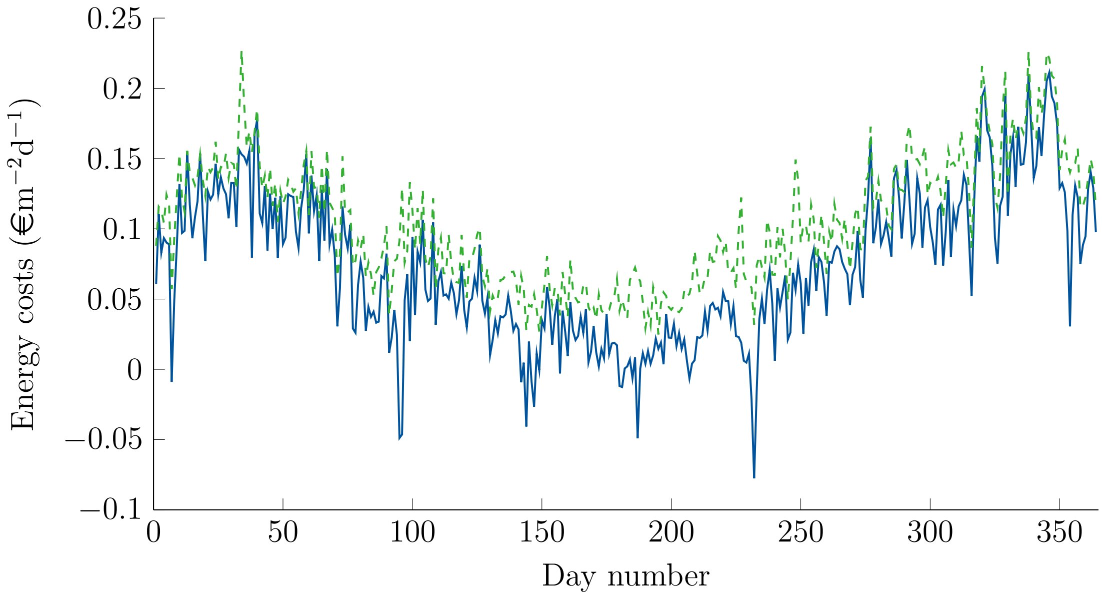


Figure 5.13: Optimal goal function value (—) and grower's result (- - -) for each day in 2012.

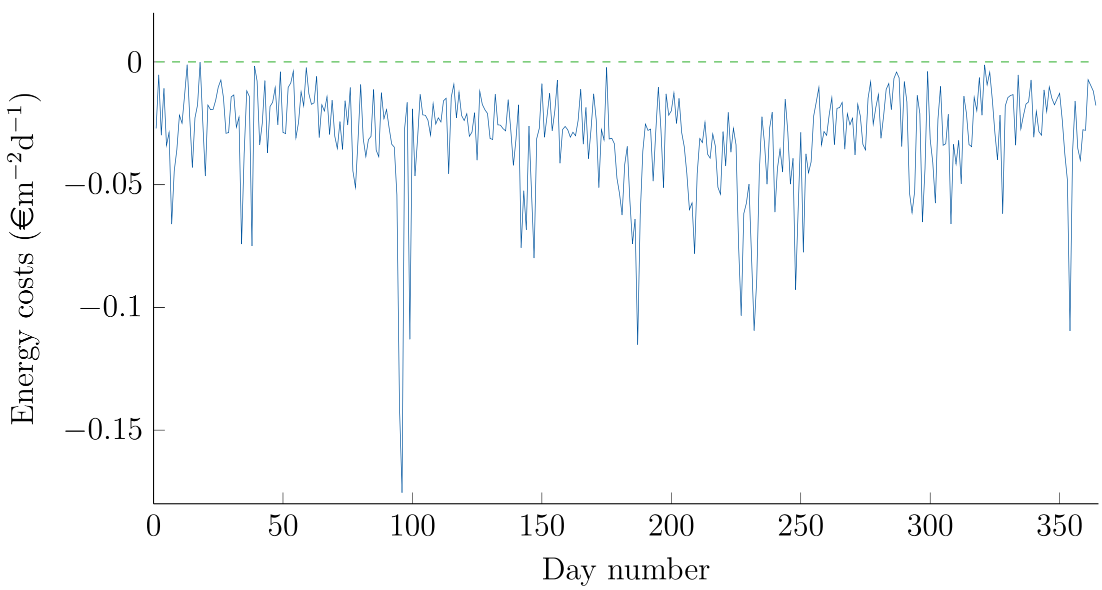


Figure 5.14: Difference between the optimal goal function value and the grower's result per day in 2012.

The utilization of the different equipment for optimal operation, sorted for the whole year 2012, is shown in Fig. 5.15a, and for the grower in Fig. 5.15b. It can be seen that in the grower's operation the CHP was used for 6348 h and operated most of the time at 100 % (62.5 Wm^{-2}) and some time between 85 % (53.1 Wm^{-2}) and 100 % of the maximum capacity. The boiler was operated for only 695 h in 2012. This is because the boiler was only used as a back-up in case of malfunction of the CHP for heat production, or as a back-up for CO_2 production in case of malfunction of the OCAP industrial CO_2 network.

The heat pump was used for 5356 h in the optimal case compared to 3122 h in the grower's operation, while the CHP was used for 3042 h in the optimal case compared to 6348 h in the grower's operation. Thus, the heat pump and the CHP exchanged the number of operating hours roughly. Supplementary lighting was active for 6318 hour in 2012. The CHP was turned on most of the time when the lamps were on in the grower's operation. The cooling towers were operated for 2371 h in the optimal case compared to 2158 h in the grower's operation. The plateau visible in the cooling tower operating curve in the optimal case is due to fixing the cooling tower capacity to a pre-defined value on days without grower data (see Table 5.1). The total amount of wasted heat was 0.55 GJm^{-2} in the optimal case and 0.45 GJm^{-2} in the grower's operation.

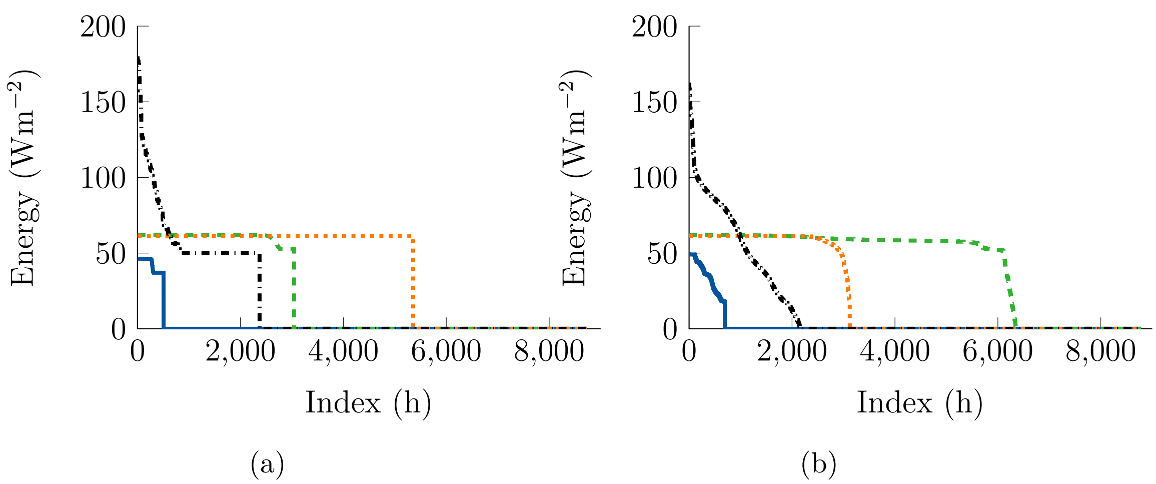


Figure 5.15: Sorted curves for the optimal (a) and grower's situation (b) for the year 2012. Boiler (——), CHP (- - -), heat pump (·······), and cooling towers (-·-·-).

The energy content of the aquifer throughout the year 2012 for the grower's situation is shown in Fig. 5.16. From day number 1 till day number 140 the energy content decreases because heat is extracted and used for heating the greenhouse. From day number 140 till day number 250, the energy content of the aquifer increases because the greenhouse demands cooling and the extracted heat from the greenhouse is stored in the aquifer. After day number 250 the energy content decreases again. Although the amount of energy in the aquifer at the start of each day was equal to the grower, the cumulative net amount of heat extracted from the aquifer in the optimal situation was $100\,\mathrm{MJm^{-2}}$ higher than in the grower's situation. This is possible in the optimization because the final state constraint (per day) on the aquifer energy content (H_{aq}^{max}) was a percentage of the realized energy content by the grower. Therefore, the allowed deviation from the realized amount of energy in the aquifer at the end of the optimization period varied accordingly throughout the year.

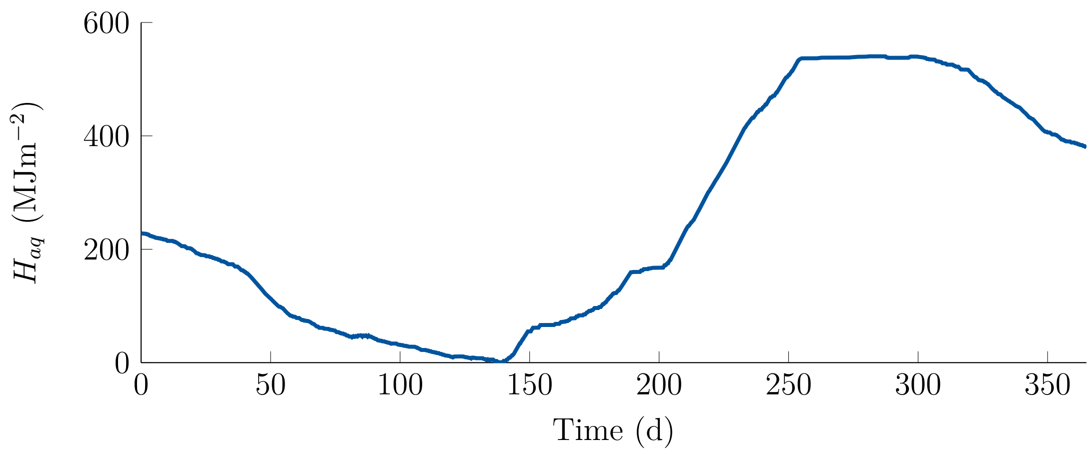


Figure 5.16: Energy content of the aquifer per day for the grower's situation in 2012.

5.3.4 Experiment 2: Full year with minimal energy

Instead of the realized heating and cooling demand of the grower (Section 5.3.3), the optimized energy demand pattern, as obtained from Van Beveren et al. (2015b), was used. The electricity demand remained unchanged, as well as the begin and end constraints on the buffers and aquifer. The total heating demand was 47 % lower and the total cooling demand was 15 % lower compared to the grower (Van Beveren et al., 2015b). With the optimized heating and cooling demand, the total energy costs were 29.9 % less than in the grower's situation for the whole year 2012. The difference between 29 % (cost-saving with realized climate in Experiment 1, Section 5.3.3) and 29.9 % is rather limited. Note that the constraints on the buffers and aquifer do not necessarily match the utilization of the equipment. The optimal heating and cooling demand were not applied in practice and constraints did not necessarily match with the optimized demand. Thus, it was not possible to modify the constraints (buffer and aquifer energy content) in such a way that a fair comparison is possible.

5.4 Discussion

The optimization procedure in this paper is an open-loop optimization. In the current form, the optimization is done for historical days. The practical use of the optimization results is twofold: 1) analysis of the current performance of the system and 2) to demonstrate how the performance can be improved. Implementation of the optimization procedure as a forecasting tool could be done via a receding horizon optimal control approach (Tap et al., 1996; Van Straten et al., 2002; Oldewurtel et al., 2012). Such implementation requires reliable forecasts of the weather and prices of electricity and gas.

Obtaining the demands and operational constraints from the grower's data is difficult and is subject to uncertainty and measurement errors. Modern greenhouses have many different sensors and measuring systems in place. Those systems collect data with different sensors, at different time intervals, and with different accuracy (Bontsema et al., 2011). Several sources of uncertainties and possible errors arise from uncertain measured data. Another factor that introduces uncertainty is the fact that some 'measurements' are not real measurements but calculated data. For the calculations, it is necessary that all data is consistent. It turned out that this was not always the case. For example, the energy content of the buffers and aquifer at the start and end of the daily optimization were calculated from the buffer fill percentage registered by the process control computer and the known buffer capacity. It turned out that these measurements showed sometimes unrealistic values, and with these inconsistencies, it can happen that no optimal solution exists. Introducing a small upper and lower bound on the daily final state of buffers and aquifer solved this problem.

The heat and cold demand patterns of the grower were calculated based on heat and cold fluxes using common energy and mass balance based models of the greenhouse climate (Van Beveren et al., 2015b,a). For application in practice, it is desired to limit the number of model parameters. Also, some parameters are difficult to measure or to determine from historical data. Therefore, the models of the equipment were kept relatively simple in the problem formulation of the optimization. It turned out that the performance of the model was sufficient for optimization.

The optimization period in this study was one day. The aquifer is used in practice to store warm and cold water for longer periods (seasonal storage). The daily initial and final state constraints on the energy in the aquifer were taken equal to the realized energy content in the aquifer by the grower. There are likely other trajectories of the energy content of the aquifer that will lead to lower energy costs when longer optimization periods are used. One solution to the problem of choosing the energy content of the aquifer is to use receding horizon optimal control approach with a pre-defined reference curve for the aquifer energy content with upper and lower bounds over a longer period (Van Ooteghem, 2007b). This at least would show the direction of optimality.

CO_2 for the enrichment of greenhouse air was not taken into account in this paper. The reason is that in this greenhouse an industrial CO_2 source was used. To make the proposed optimization method applicable to greenhouses that use CO_2 from the boiler and/or CHP, the required CO_2 dosing could be incorporated in the optimal control formulation. To do so, the efficiency of the boiler and CHP with respect to CO_2 production needs to be known. As flue gas from the CHP cannot be used directly in the greenhouse, the efficiency and running costs of the flue gas cleaner must be considered as well.

The difference between the cost saving of the optimization with realized climate (Section 5.3.3) and the optimization with minimal energy (Section 5.3.4) was surprisingly small at first sight. It was expected that the proposed two-stage approach would result in more savings, and it would be interesting to know which effort brings most of the benefit: minimizing energy input, or optimizing the operation of the equipment. However, because the aim was to compare the optimized costs with those of the grower, we restricted ourselves to stay close to the constraints as observed. It was demonstrated before (Van Beveren et al., 2019) that relaxing the bounds of the final state constraints will lower the total energy costs, however, to allow comparison with the grower's situation, in this study the constraints were kept equal in both experiments. Furthermore, the energy content of the buffers and aquifer that corresponds to the minimized energy input are not known since this situation was not realized in practice. It is expected that the optimization procedure is also valuable for other energy management problems in different applications e.g. animal housing, commercial buildings, storage facilities with multiple sources of heating, cooling and electricity combined with storage of heat and cold water.

The optimizations were performed for historical days where the energy demand, the realization of the grower, and prices of electricity and gas are fully known in advance. As to the weather, this is not a limitation, as weather forecasts for one single day are fairly reliable, and the optimization is fast enough to obtain the daily operation schedule. However, forecasting the electricity price is more complicated. In addition, the operational schedule calculated for the day may easily be adjusted by recalculation as soon as true prices start to deviate considerably from the pre-set prices. Moreover, the grower can learn from the optimal strategies and try to apply the lessons learned in future decisions. In any case, predictions of weather and prices of electricity and gas are of paramount importance. Finally, it is necessary to translate the optimal strategy, either automatically or manually, to settings in the greenhouse (climate) control system.

5.5 Conclusion

A successful optimization framework was presented for a real commercial greenhouse, taking practical constraints on the utilization of the different equipment into account. Daily energy cost optimization was demonstrated for a 4 ha semi-closed greenhouse with a complex energy equipment configuration existing of a boiler, CHP, multiple short-term buffers, heat pump with aquifer heat storage, and cooling towers.

Optimization of the utilization of advanced energy systems in greenhouses is feasible, and is a major innovation as compared to the current more heuristic approach. Application of open-loop optimization for a realistic greenhouse configuration showed a potential cost saving of 29 % for the year 2012 using the heating, cooling, and electricity demand of the grower. All available equipment was utilized in the optimal situation. The heat pump was operated about 2300 h more than in the grower's situation and the CHP was operated about 3300 h less than in the grower's situation. The expected additional gains of enhancing the beneficial optimal equipment control in this paper by simultaneous optimization of the energy demand could not be demonstrated due to the forced constraints imposed in order to stay close to the climate believed by the grower to be necessary for the health of the crop. The results indicate that combining dynamic optimization with prior knowledge of dynamic gas and electricity prices is beneficial. It underlines that trading of electricity and short-term forecasting of gas and electricity prices in combination with dynamic optimization has a high potential for cost savings in horticultural practice.

5.6 Acknowledgment

The authors thank HortiMaX B.V., Lek Habo Groep B.V., Wageningen U&R Greenhouse Horticulture, and M. Boonekamp for useful discussions and for sharing their data. We thank Agro Energy for supplying the electricity and gas prices for the studied greenhouse. Furthermore, we thank the Dutch Technology Foundation STW of the Netherlands Organization for Scientific Research (NWO) which is partly funded by the Ministry of Economic Affairs for their support.

Appendices

5.A Nomenclature

Table 5.2: Nomenclature

Symbol	Description	Unit
A	Greenhouse floor area	m^2
b	Boolean control variable	−
E	Electricity use[a]	Wm^{-2}
G	Gas use[a]	$m^3m{-}2$
H	Heat content[a]	MJm^{-2}
I	Outdoor radiation	$MJm^{-2}d^{-1}$
J	Goal function[a]	€m^{-2}
p	Price	€
Q	Heat flux[a]	Wm^{-2}
r	Range of operation	−
RH	Relative humidity	%
S	Heat of combustion of natural gas[b]	MJm^{-3}
t	Time	s
T	Temperature	°C
u	Control variable	
v	Speed	ms^{-1}
η	Efficiency	−
Subscript		
aq	Aquifer	
$boil$	Boiler	
buf	Buffer	
C	Cold	
ct	Cooling towers	
chp	Combined heat an power installation	
des	Desired	
E	Electricity	
f	Final	
G	Gas	
$glob$	Global	
grh	Greenhouse	
$grid$	Public electricity grid	
HT	High Temperature	
hp	Heat pump	
in	In	
LT	Low Temperature	
out	Out	
$wind$	Wind	
Superscript		
min	Minimum	
max	Maximum	
sum	Sum	

[a] per unit greenhouse floor area
[b] upper calorific value

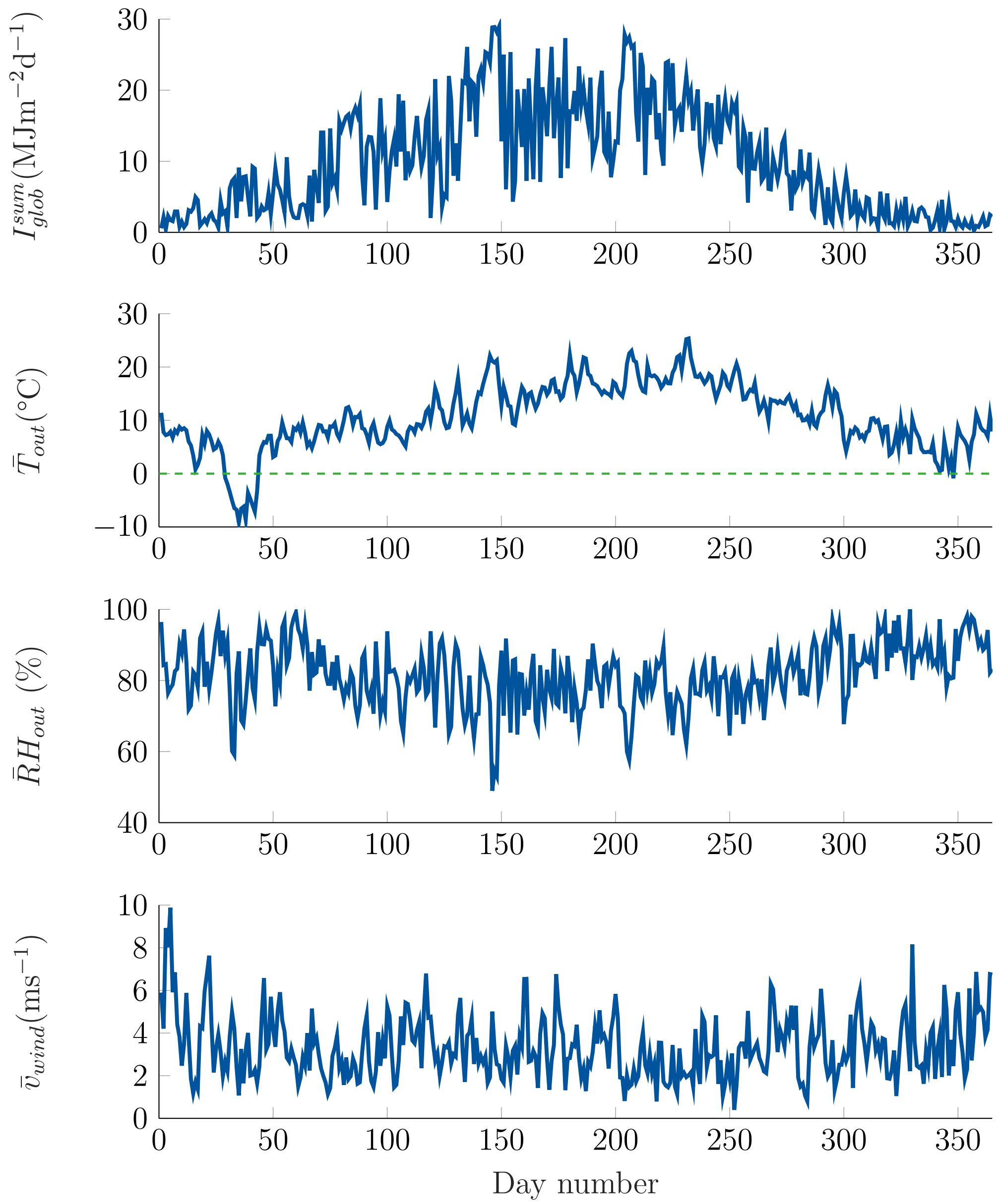


Figure 5.17: Outdoor climate for Bleiswijk, the Netherlands in 2012: a) Radiation sum (MJm^{-2}d^{-1}), b) Average temperature (°C), c) Average relative humidity (%), d) Average wind speed (ms^{-1}).

6
Conclusion and discussion

P.J.M. van Beveren

6.1 Introduction

Costs of gas and electricity, social acceptance of greenhouse crop production, and agreements between the horticultural sector and the government in The Netherlands increased the quest for energy saving in modern greenhouse horticulture. This has led to investments of growers in a wide variety of equipment for controlling the greenhouse climate. To modify the indoor environment, growers can use air conditioning units for heating and cooling, pipe rail heating systems, a CO_2 supply system, different types of screens, ventilation windows, and supplementary lighting. CO_2 and electricity are commonly generated by a combined heat and power installation (CHP). Equipment for production, storage, and conversion of thermal energy include (a combination of) CHP's, boilers, heat pumps, short-term buffers, aquifer heat storage, cooling towers, and geothermal sources. Given the broad range of available climate conditioning equipment and energy sources, their optimal deployment in view of energy conservation has become a complex matter. A guideline in solving the operational management of the grower could be to focus on an operation that minimizes energy and costs. This is possible by minimizing the energy input to the greenhouse and by minimizing the costs for the required energy.

The main objective of this thesis was to develop an optimization framework for minimizing the total energy consumption and energy costs of greenhouse horticulture in the Netherlands. Sub-objectives were to

1. develop an optimization framework that minimizes the total energy demand of greenhouses (chapters 2 and 3).
2. develop an optimization framework that minimizes the energy costs of greenhouses (chapters 4 and 5).
3. quantify the costs saving of the framework for a commercial test case (chapters 4 and 5).
4. quantify the energy saving of the framework for a commercial test case (chapters 2 and 3).

In theory, the problem of optimal operation under known external conditions can be solved by dynamic optimization based on models of all components of the system, including the crop Tap (2000); Van Ooteghem (2007b); Vanthoor (2011). However, this approach has some significant drawbacks with regard to the application in practice e.g. the need for complex crop models and computational complexity. Therefore, a two-stage approach was proposed in this thesis. In the first stage, the grower defines desired trajectories for the greenhouse climate, i.e. the climate recipe. Then, the optimal demands for heating, cooling, and CO_2 were calculated using models of greenhouse climate physics. The optimal energy distribution of the energy demand over the various types of equipment was calculated using models of the technical infrastructure.

In this thesis, the proposed model-based two-stage approach was successfully demonstrated for one 4 ha rose nursery in Bleiswijk, the Netherlands. The potential energy and cost savings of dynamic optimization were shown for this test greenhouse. The energy optimization in the first stage resulted in a theoretical 47 % reduction in heating, 15 % reduction in cooling, and 10 % reduction in CO_2 injection for the year 2012 (Chapter 3). The costs optimization in the second stage resulted in a potential cost savings of 29 %, given the prices for gas and electricity and the known weather (Chapter 5). The results showed that optimization of the greenhouse energy system is feasible and beneficial. The two-stage method is in close connection with the grower's daily practice.

This chapter elaborates on the research results and main assumptions in this thesis regarding the two-stage approach, model performance, technical challenges, and future perspectives.

6.2 Comments on the two-stage approach

The two-stage approach separates control of the greenhouse climate from the management of energy resources. In stage 1, bounds are set to define the desired greenhouse climate instead of defining production goals. The optimization in stage 1 results in minimal energy input to the greenhouse. By setting bounds for the climate, the grower controls the different processes in the greenhouse that are difficult to measure, predict and to model, but known, observed, and believed by the grower. Furthermore, advanced crop production models are not needed. This is advantageous because many aspects that are important for crop management like infection risk for diseases, pest control, etc are not included in current crop models and are (yet) difficult to monitor. Another advantage of omitting crop production models in the optimization is that the optimization period can be shorter than one whole production cycle.

The two-stage approach is close to the practical implementation of control systems present at greenhouses. The first stage is flexible in the sense that different actuators for greenhouse climate control can be incorporated in the greenhouse climate model and in the optimization routine. The most important greenhouse characteristics are incorporated in the parameters of the greenhouse climate model. The optimal control formulation in stage 1 does not need to maintain a minimum pipe temperature, in contrast to current practice. The methodology, however, allows for implementing a minimum pipe temperature, as demonstrated in Chapter 3. Growers could have specific reasons to maintain a minimum pipe temperature in the greenhouse such as stimulating crop transpiration (air movement) and to prevent condensation on leaves and fruits (Teitel et al., 1999). Including the minimum pipe temperature in the optimization reduced the potential energy saving.

The second stage minimizes the costs for realizing the heat and electricity demand. Potentially, costs can be saved in this stage because of the dynamic prices for gas and electricity and the presence of heat buffers through which supply and demand of energy can be partially decoupled. The flexibility of this stage is that different equipment for storage and production of warm and cold water and electricity can be incorporated into the model and optimization routine. The structure of the total procedure remains unchanged when components are added or removed. A library with the most common equipment would help to configure the optimization procedure depending on the greenhouse and equipment configuration.

The energy-saving resulting from stage 1 seems optimistic, however, previous studies on optimizing the greenhouse climate and energy consumption reported savings between 8 % (Tap, 2000) to 52 % (Van Ooteghem, 2007a). The energy savings in stage 1 depend largely on the choice of the bounds and the availability and correctness of the weather forecast. In the optimizations in Chapters 2 and 3, full prior knowledge of the weather was assumed, so the 'weather forecast' was perfect. The possibilities for costs savings within the energy demand constraints obtained from stage 2 must come from three elements: (1) the better exploitation of the allowable bounds around the demand trajectories (2) profiting from the most efficient operating point of energy equipment (3) profiting from forecasts or prior knowledge about gas and electricity prices. It is not easy to quantify the relative contribution of each to the final optimal result.

As to the utilization of the energy demand bounds, it is clear that allowance of other energy trajectories than those realized by the grower would increase the potential for energy saving, and, consequently, costs savings. However, this is constraint by the necessity to stick - in stage 1 - to the bounds set by the grower. The basis for the bounds was the realization of the grower. It was assumed that the realized climate was the desired climate, however, this is not necessarily the case for the whole year. For example, it could be that the desired greenhouse temperature was higher than the realised temperature during the cold period in February. Furthermore, the desired climate of the grower is not necessarily the greenhouse climate resulting in the highest production or highest financial result. To utilize the potential of the temperature bounds most, temperature integration (Korner et al., 2003) over a longer period could be implemented. For different crops, the implementation and allowance of deviation from the bounds will be different.

The possibilities of cost savings by energy management based on forecasts of electricity and gas prices entirely depend upon the quality of short-term energy and price forecasts. Short-term energy forecasts can either come from stage 1 or any other system that translates a weather forecast to the desired greenhouse climate. The quality of the commercially available short-term, 24 hours, weather forecasts is reasonably good. There are even possibilities to improve the local weather forecast using local weather data, which is usually available from the outdoor climate measurements, and Kalman filtering (Doeswijk and Keesman, 2005). Therefore, it is expected that the effect of uncertainty in the weather will have a marginal effect on the energy and cost-saving when closing the loop in a Receding Horizon Optimal Control implementation.

Short-term prediction of electricity prices is more difficult and is not as commonly available. The electricity market in the Netherlands is subject to increasingly large fluctuations in supply and demand, which leads to strongly fluctuating prices that are difficult to predict. The effect of strongly fluctuating and uncertainty in prices could be investigated by a kind of gaming scenarios or Monte-Carlo simulation. It is clear that the cost-saving largely depends on the quality and availability of the price forecast, and further investigation on the source of the energy savings could lead to valuable insights for growers.

6.3 Comments on the model performance

The climate model in this thesis (Chapter 2 and 3) aimed to serve the optimization. One requirement for the application of optimization methods was that the models should be simple and compact (Lentz, 1998). Therefore, the greenhouse climate model was kept as simple and compact as possible, and still performs well. An explanatory dynamic greenhouse climate model with three balances was developed based on the literature. López-Cruz et al. (2018) presented an overview of the development and analysis of dynamical mathematical models of greenhouse climate. Most other greenhouse climate models for optimal and predictive control have 3-5 states. Models with more states, parameters, and processes, as for example the model in (Van Ooteghem, 2007a), lead to more complexity. Complex models are more difficult to validate and apply in practice since more parameters need to be estimated. The precision of a more complex model could be higher and explain all processes in more detail. However, if a model is simple and accurate at the same time this would be preferable to use in the optimization. Most model parameters needed in the presented greenhouse climate model are known from the properties of the greenhouse or can be estimated with commonly measured data in commercial greenhouses. Estimation of the parameters could be performed based on historical data (Guzmán-Cruz et al., 2009) and or online as shown in (Boaventura Cunha et al., 1997; Speetjens et al., 2009).

Validation of greenhouse climate models over a longer period is rarely presented in the literature. Especially for regions with large seasonal differences in outdoor conditions, it is necessary to validate the model for a period that includes those differences. In this thesis, the climate model was validated for one full year. In most of the literature, the performance measures were in the same range as the performance measures found in Chapters 1 and 2 (i.e. (El Ghoumari et al., 2005; Baptista et al., 2010; Du et al., 2012; Righini et al., 2020)). None of them performed an analysis of the measured and simulated data for one whole year with very different weather circumstances in a commercial scale greenhouse, as was done in this thesis.

The models for the equipment in Chapters 4 and 5 were kept relatively simple for optimization purposes, similar to the greenhouse climate model. It is possible to extend the models and include dynamics in the utilization of the equipment. However, there is a trade-off between a perfect description of the system and the optimization result. Extending the models with a more detailed description of the heat pump could lead to a better model performance regarding the heat pump. It also means that the model needs more parameters that are possibly unknown and difficult to estimate. Current parameters like the capacity and size of equipment are available in practice. Those numbers are needed as constraints for the optimization. Costs for pumps were not taken into account in the model and heat loss from the system was neglected. However, technically it is possible to incorporate them into the model. The trade-off between cost and benefits of system completeness (perfect model description) versus complexity has to be made here as well.

6.4 Technical challenges

In practice, many different configurations and combinations of equipment for heat and cold production and storage occur. The work in this thesis aimed to be a starting point for optimizing and understanding the optimal scheduling of these systems. Optimization requires a model description for each part of the system that describes the behavior sufficiently. On the other hand, the optimization benefits from simple models in order to minimize calculation time and convergence to optimal solutions. The capacity and size of equipment are often easily available. Those numbers are needed as constraints for the optimization.

Completeness and correctness of the measurement data are important for the successful application of the optimization procedures. The optimization needs measurement data and control signals for lamps and screens (if applicable) as input. Furthermore, measurement data is necessary to compare the optimization result with the grower's realization. Modern greenhouses have many different sensors and measuring systems in place. Those systems collect data with various sensors, at different time intervals, and with different accuracy. Several sources of uncertainties and possible errors occur from the measurement data. It turned out that measurement data from the equipment (pump data, temperature sensors, etc.) sometimes showed unrealistic values, and with these inconsistencies, no optimal solution may exist.

Another factor that introduces uncertainty is the fact that some 'measurements' are not real measurements but calculated data. Measured input data must be mutually consistent for the optimization. It turned out that this was not always the case. For example, the energy content of the buffers and aquifer at the start and end of the daily optimization were calculated from the buffer fill percentage registered by the process control computer and the known buffer capacity. It turned out that the calculated and measured data were not always consistent. Introducing a small upper and lower bound on the daily terminal state of buffers and aquifer solved this problem. Filtering techniques and data processing could solve some of the problems with uncertainty in measurement data as well. However, this will also depend on the measurements themselves; e.g. type, frequency, number of sensors, the configuration of equipment, etc. Proper pre-processing and checking of the measurement data could also prevent the optimization from not finding feasible solutions. For historical days, a solution should always exist, namely the realization of the grower.

The calculation time of the optimization is an important aspect for implementation in practice. The optimizations in this thesis were all performed per day. The calculation time was within the order of minutes. This is within the time interval of the data. Despite the short calculation time, there are possibilities to decrease calculation time by e.g. using a faster computer and optimizing the code. Therefore, no problems are expected with calculation time in practice.

6.5 Future perspectives

In this thesis, all optimizations were performed afterward and can be used as a tool to analyze the performance and find possibilities for improvement. This is the first step, but is not yet ready for day-to-day application in practice. This first step is important for successful implementation and to help the grower build trust in the outcome of these kinds of systems (Van Straten et al., 2000). For both stages and the combination of the two stages, three steps can be distinguished for implementation of the optimization routines in practice:

1. Implementation as a forecasting tool one day ahead.
2. Implementation as a forecasting tool for longer time periods.
3. Implementation as a forecasting tool with online control.

Forecasting one day ahead

In order to implement the optimization procedure as a forecasting tool (1), a receding horizon optimal control approach would be suitable Tap (2000); Van Straten et al. (2002); Van Ooteghem et al. (2005); Oldewurtel et al. (2012). For stage one, the upper and lower bounds on the climate variables (temperature, relative humidity, and CO_2 concentration) for the next day have to be supplied to the optimization procedure. Those bounds could be set manually by the grower, based on e.g. the weather forecast and state of the crop. Similarly, a prediction of the external inputs (supplementary lighting and screen positions) should be provided for the optimization. Again, the grower should supply these data to the optimization. The choice of the bounds is a critical factor for the energy demand of the solution (Chapter 3). For example, allowing a higher temperature in the greenhouse reduces the ventilation and CO_2 demand. The results of the optimization are optimal temperature, humidity, and CO_2 trajectories for the coming day. It is also possible to run the optimization multiple times per day.

The second stage needs a reliable weather forecast and price forecasts for electricity and gas for the coming day. To obtain optimal utilization of the equipment the initial and final buffer filling for all buffers should be supplied. The initial buffer filling is then the current energy content of the different buffers. The energy content at the end of the optimization period should be supplied by the grower. This can also be a minimal filling per buffer. The grower should consider the future heat demand and prices for electricity and gas when specifying these constraints. The future heat demand could be derived from the optimization in the first stage of the energy input. If the final buffer constraints are not supplied, the optimization is likely to empty the buffers, such that the amount of heat to be generated is minimized. When the electricity price is high and the heat demand on the next day is low, it is profitable to run the CHP. The surplus heat is then stored in the heat buffer. This would not have been possible when the heat buffer was already full.

Forecasting longer time period

All optimizations in this thesis were performed for individual days. Optimization of energy input and utilization of equipment can also be done for multiple days (2). Optimization of multiple consecutive days is expected to decrease energy use and costs since the buffers can be used more effectively. In case of a longer optimization period, the buffers have more freedom and time to anticipate to the desired heat and electricity profile. This is supported by the results of the sensitivity analysis on the final buffer filling (Chapter 3).

Another potential energy saving is in minimizing the energy input to the greenhouse for multiple days. The bounds on the climate variables in Chapters 1 and 2 were hard boundaries. It was demonstrated that relaxing the bounds for temperature reduced the energy input substantially (Chapter 1). Relaxing the bounds for RH and CO_2 reduced energy input to the greenhouse as well (Chapter 2). Optimization of energy input over a longer period of several days, combined with relaxing the temperature bounds and incorporating the concept of temperature integration could potentially decrease energy use further. Temperature integration allows for more variation of the greenhouse temperature, as long as the average temperature over a certain period is realized (Sigrimis et al., 2000; Körner and Challa, 2003). Warm of cold periods are allowed, as long as they are compensated within the specified period.

Forecasting with online control

The optimizations in this thesis are all open-loop optimizations. In order to apply the results of the optimization directly in the greenhouse (3), the optimization system should be connected to real-time data from sensors and actuators in the greenhouse. The optimal climate trajectories cannot be put in the greenhouse process control computer directly and have to be translated into settings in order to be realized in the greenhouse. This can be done manually by the grower, or automatically with an additional tool to determine the greenhouse climate based on the grower's actual settings. As to the weather, this is not a limitation, as weather forecasts for one single day are fairly reliable, and the optimization is fast enough to obtain the daily operation schedule. However, forecasting the electricity price is more complicated. It depends on the energy trading strategy and contracts of the grower if the future electricity and gas price are known. In addition, the operational schedule calculated for the day may easily be adjusted by recalculation as soon as true prices start to deviate considerably from the pre-set prices.

Summary

Costs of gas and electricity, societal acceptance of greenhouse crop production, and agreements between the horticultural sector and the government in The Netherlands increased the quest for energy saving in modern greenhouse horticulture. This has led to investments of growers in a wide variety of equipment for controlling the greenhouse climate. To modify the indoor environment, growers can use air conditioning units for heating and cooling, pipe rail heating systems, a CO_2 supply system, different types of screens, ventilation windows, and supplementary lighting. CO_2 and electricity are commonly generated by a combined heat and power installation (CHP). Equipment for production, storage, and conversion of thermal energy include (a combination of) CHP's, boilers, heat pumps, short term buffers, aquifer heat storage, cooling towers, and geothermal sources. Given the broad range of available climate conditioning equipment and energy sources, their optimal deployment in view of energy conservation has become a complex matter.

The main objective of this thesis was to develop an optimization framework for minimizing the total energy consumption and energy costs of greenhouse horticulture in the Netherlands. Sub-objectives were to

1. develop an optimization framework that minimizes the total energy demand of greenhouses (chapter 2 and 3).
2. develop an optimization framework that minimizes the energy costs of greenhouses (chapter 4 and 5).
3. quantify the costs saving of the framework for a commercial test case (chapter 4 and 5).
4. quantify the energy saving of the framework for a commercial test case (chapter 2 and 3).

A two-stage approach was proposed in this thesis in order to minimize the energy consumption and costs of modern greenhouses. In the first stage, the grower defines desired trajectories for the greenhouse climate, i.e. the climate recipe. Then, optimal control techniques using models of the greenhouse climate physics, are used to calculate the demand for heating, cooling, and CO_2 . In the second

stage, this energy demand serves as a reference, an optimal energy distribution of this demand over the various types of equipment was calculated using models of the technical infrastructure. An optimal control approach of minimizing the energy input of a commercial greenhouse (stage 1) was demonstrated in chapters 2 and 3. Subsequently, minimizing the energy costs of the same greenhouse was demonstrated in chapters 4 and 5. The studied greenhouse was a 4 ha rose nursery in Bleiswijk, the Netherlands.

In chapter 2, optimal control trajectories that minimize the total external energy input while maintaining greenhouse air temperature and humidity between grower-defined bounds were calculated with a dynamic optimization tool. By giving the grower the lead in defining the bounds, the method stays as close as possible to the grower's daily practice and experience, and no crop production models and market prices are needed. The underlying dynamic model of temperature and humidity, based on known physical principles and parameters, compared very well with unique, year-round measurements from the studied greenhouse. A relatively simple crop transpiration model was validated separately, with very good results.

It was shown that over twelve selected days, distributed over the entire year, the energy-saving potential as compared to the actual grower's practice is substantial. This potential was related to the definition of lower and upper bounds, less natural ventilation at colder days, and more natural ventilation and less heating at warmer days. The prominent role of the bounds was demonstrated. Relaxing the temperature and humidity bounds decreases the energy input to the greenhouse. While this is obvious, the quantification of the effect as demonstrated here is of great interest to growers.

The optimization framework developed in chapter 2 was extended in chapter 3 with the CO_2 balance. Heating, cooling, the amount of natural ventilation, and the injection of industrial CO_2 were the control variables. This optimization resulted in a theoretical 47 % reduction in heating, 15 % reduction in cooling, and 10 % reduction in CO_2 injection for the year 2012. The optimal control formulation does not need to maintain a minimum pipe temperature, in contrast to current practice. The methodology, however, allows for implementing a minimum pipe temperature, as demonstrated in Chapter 3. Including the minimum pipe temperature in the optimization reduced the potential energy saving.

Optimization results depend on the bounds. Consequently, the sensitivity of the optimization result to the bounds for temperature, humidity, CO_2 concentration, and maximum amount of CO_2 per day was investigated. Relaxing the temperature and humidity bounds decreases the energy input to the greenhouse. While this is obvious, the quantification of the effect as demonstrated here is of great interest to growers. The effect on optimal energy input of different bounds for temperature, humidity, CO_2 concentration, and maximum amount of CO_2 per day was analyzed. The more freedom is allowed to the climate variables, the higher the potential energy saving. However, in practice, the grower is in charge of defining the bounds. Thus, the potential energy saving critically depends on the choice of these bounds. This outcome has value to the grower with respect to decision making because the energy saving can be quantified, which is currently not possible in practice.

The second stage deals with realizing the heat and electricity demand of the greenhouse with minimal costs. In chapter 4, first, a simplified, but realistic, configuration with a single buffer and boiler was presented. Second, minimizing the energy costs with a heating and electricity demand using a boiler, CHP, and heat buffers was demonstrated for 63 days in 2012. On those days overall cost savings of 20 % were obtained. This shows that a given heat demand does not come with a fixed price to pay. Rather, benefits can be obtained by determining the utilization of the equipment by dynamic optimization. It also appears that prior knowledge of gas and electricity prices in combination with dynamic optimization has a high potential for cost savings in horticultural practice. A sensitivity analysis was performed to study which (input) factors influence the optimization the most. The results of the sensitivity analysis showed that the total energy cost for the studied greenhouse was more sensitive to the electricity demand than to the heating demand.

In chapter 5, the energy costs with the complete energy installation, as present in the studied greenhouse, were minimized for the whole year 2012. The installed equipment contained a boiler, a CHP (combined heat and power installation), different buffers, a heat pump, and aquifer heat storage. Furthermore, cooling towers were present. The results showed that optimization of the energy system is feasible and beneficial. Potential energy cost savings of 29 % were obtained for the optimized situation, given the prices for gas and electricity, and the known weather. It was shown that it is beneficial to combine dynamic optimization with prior knowledge of gas and electricity prices for complex configurations. It underlines that trading and short-term forecasting of gas and electricity prices in combination with dynamic optimization have a high potential for cost savings in horticultural practice.

In this thesis, the proposed model-based two-stage approach was demonstrated for one test greenhouse. The potential energy and cost savings of dynamic optimization were successfully shown for this test greenhouse. The potential energy and cost savings of dynamic optimization were shown for this test greenhouse. The energy optimization in the first stage resulted in a theoretical 47 % reduction in heating, 15 % reduction in cooling, and 10 % reduction in CO_2 injection for the year 2012 (Chapter 3). The costs optimization in the second stage resulted in a potential cost savings of 29 %, given the prices for gas and electricity and the known weather (Chapter 5). The results showed that optimization of the greenhouse energy system is feasible and beneficial. The two-stage method is in close connection with the grower's daily practice. It is to be expected that with online application in practice the energy and cost savings will be lower, but still substantial. The application of the two-stage approach in practice seems promising. A number of challenges still need to be solved for this, such as tuning the models online, availability of consistent data, including weather forecasts, and price information.

Samenvatting

Kosten van gas en elektriciteit, maatschappelijke acceptatie van glastuinbouw en afspraken tussen de tuinbouwsector en de overheid in Nederland vergrootten de zoektocht naar energiebesparing in de moderne glastuinbouw. Dit heeft in de afgelopen decennia geleid tot investeringen van telers in een breed scala aan apparatuur om het kasklimaat te beheersen. Om het kasklimaat aan te passen, kunnen telers gebruik maken van verschillende methoden voor verwarming en koeling, CO_2 dosering, verschillende soorten schermen, ventilatieramen en belichting. CO_2 en elektriciteit worden veelal opgewekt door een warmtekrachtkoppelingsinstallatie (WKK). Apparatuur voor productie, opslag en conversie van warmte omvat (een combinatie van) WKK's, boilers, warmtepompen, buffers, aquifer-warmteopslag, koeltorens en geothermische bronnen. Gezien het brede scala aan beschikbare apparatuur en energiebronnen is het optimaal inzetten daarvan met het oog op energiebesparing een complexe zaak geworden.

Het hoofddoel van dit proefschrift was het ontwikkelen van een optimalisatiekader voor het minimaliseren van het totale energieverbruik en de energiekosten van de glastuinbouw in Nederland. Subdoelen waren:

1. het ontwikkelen van een een optimalisatieraamwerk dat de totale energievraag van kassen minimaliseert (hoofdstuk 2 en 3).
2. het ontwikkelen van een optimalisatieraamwerk dat de energiekosten van kassen minimaliseert (hoofdstuk 4 en 5).
3. het kwantificeren van de kostenbesparing van het raamwerk voor een commerciële kas (hoofdstuk 4 en 5).
4. het kwantificeren van de energiebesparing van het raamwerk voor een commerciële kas (hoofdstuk 2 en 3).

In dit proefschrift wordt een tweetrapsbenadering gepresenteerd om het energieverbruik en de kosten van moderne kassen te minimaliseren. In de eerste fase definieert de teler gewenste trajecten voor het kasklimaat, oftewel het klimaatrecept. Vervolgens worden optimale regeltechnieken in combinatie met modellen van de kasklimaatfysica gebruikt om de benodigde verwarming, koeling en CO_2

te berekenen. In de tweede fase dient deze energievraag als referentie. Met behulp van modellen van de technische infrastructuur is een optimale energieverdeling van deze vraag over de verschillende soorten apparatuur berekend. Het minimaliseren van de energie-input van een commerciële kas met optimale besturingstechnieken (fase 1) werd gedemonstreerd in hoofdstuk 2 en 3. Vervolgens werd het minimaliseren van de energiekosten van dezelfde kas gedemonstreerd in hoofdstuk 4 en 5. De bestudeerde kas was een 4 ha rozenkwekerij in Bleiswijk, Nederland.

In hoofdstuk 2 werden optimale regeltrajecten berekend die de totale externe energie-input minimaliseren, terwijl de temperatuur en vochtigheid van de kaslucht binnen door de teler gedefinieerde grenzen worden gehouden met een dynamische optimalisatietool. Door de teler de grenzen te laten bepalen blijft de methode zo dicht mogelijk bij de dagelijkse praktijk en ervaring van de teler en zijn er geen teeltmodellen en marktprijzen nodig. Het onderliggende dynamische model van temperatuur en luchtvochtigheid, gebaseerd op bekende fysische principes en parameters, kwam goed overeen met unieke, jaarrond metingen uit de bestudeerde kas. Een relatief eenvoudig gewastranspiratiemodel werd apart gevalideerd, met zeer goede resultaten.

Gebleken is dat op twaalf geselecteerde dagen, verdeeld over het hele jaar, het energiebesparingspotentieel ten opzichte van de praktijk van de teler groot is. Dit potentieel hangt samen met de definitie van onder- en bovengrenzen, minder natuurlijke ventilatie op koudere dagen en meer natuurlijke ventilatie en minder verwarming op warmere dagen. De prominente rol van de grenzen werd gedemonstreerd. Door de temperatuur- en vochtigheidsgrenzen te versoepelen, neemt de energietoevoer naar de kas af. Hoewel dit voor de hand ligt, is de kwantificering van het effect zoals hier aangetoond van groot belang voor telers.

Het in hoofdstuk 2 ontwikkelde optimalisatiekader is in hoofdstuk 3 uitgebreid met de CO_2 balans. Verwarming, koeling, de hoeveelheid natuurlijke ventilatie en de injectie van industriële CO_2 waren de stuurvariabelen. Deze optimalisatie resulteerde in een theoretische reductie van 47 % in verwarming, 15 % reductie in koeling en 10 % reductie in CO_2 -injectie voor het jaar 2012. De optimale besturing hoeft, in tegenstelling tot de huidige praktijk, geen minimum buistemperatuur aan te houden. De methodiek maakt het echter wel mogelijk om een minimum buistemperatuur te implementeren, zoals aangetoond in hoofdstuk 3. Het meenemen van de minimum buistemperatuur in de optimalisatie verminderde de potentiële energiebesparing.

Optimalisatieresultaten zijn afhankelijk van de grenzen. Daarom werd de gevoeligheid van het optimalisatieresultaat voor de grenzen voor temperatuur, vochtigheid, CO_2 concentratie en maximale hoeveelheid CO_2 per dag onderzocht. Door de temperatuur- en vochtigheidsgrenzen te versoepelen, neemt de energietoevoer naar de kas af. Hoewel dit voor de hand ligt, is de kwantificering van het effect zoals hier aangetoond van groot belang voor telers. Het effect op de optimale energie-input van verschillende grenzen voor temperatuur, vochtigheid, CO_2 concentratie en maximale hoeveelheid CO_2 per dag werd geanalyseerd. Hoe meer vrijheid de klimaatvariabelen hebben, hoe hoger de potentiële energiebesparing. In de praktijk bepaalt de teler echter de grenzen. De potentiële energiebesparing hangt in grote mate af van de keuze van deze grenzen. Deze uitkomst heeft waarde voor de teler bij de besluitvorming omdat de energiebesparing kwantificeerbaar is, wat nu in de praktijk niet mogelijk is.

De tweede fase gaat over het realiseren van de warmte- en elektriciteitsvraag van de kas met minimale kosten. In hoofdstuk 4 werd eerst een vereenvoudigde, maar realistische configuratie met een enkele buffer en ketel gepresenteerd. Daarna is voor 63 dagen in 2012 het minimaliseren van de energiekosten met een warmte- en elektriciteitsvraag met een ketel, WKK en warmtebuffers gedemonstreerd. Op die dagen werd een totale kostenbesparing van 20 % behaald. Dit toont aan dat een bepaalde warmtevraag niet gepaard gaat met een vaste prijs. In plaats daarvan kunnen voordelen worden behaald door de inzet van de apparatuur te bepalen door dynamische optimalisatie. Ook blijkt dat voorkennis van gas- en elektriciteitsprijzen in combinatie met dynamische optimalisatie een groot potentieel heeft voor kostenbesparingen in de tuinbouwpraktijk. Er is een gevoeligheidsanalyse uitgevoerd om te onderzoeken welke factoren de optimalisatie het meest beïnvloeden. Uit de resultaten van de gevoeligheidsanalyse bleek dat de totale energiekost voor de bestudeerde kas gevoeliger was voor de elektriciteitsvraag dan voor de warmtevraag.

In hoofdstuk 5 zijn de energiekosten met de complete energie-installatie, zoals aanwezig in de bestudeerde kas, geminimaliseerd voor het hele jaar 2012. De geïnstalleerde apparatuur bevatte een ketel, een WKK, verschillende buffers, een pomp, en een aquifer. Verder waren er koeltorens aanwezig. De resultaten toonden aan dat optimalisatie van het energiesysteem mogelijk is en financiele voordelen biedt. Potentiële energiekostenbesparingen van 29 % werden verkregen voor de geoptimaliseerde situatie, gegeven de prijzen voor gas en elektriciteit, en het (vooraf) bekende weer. Er is aangetoond dat het voordelig is om dynamische optimalisatie te combineren met voorkennis van gas- en elektriciteitsprijzen voor complexe configuraties. Dit onderstreept dat handel en kortetermijnprognoses van gas- en elektriciteitsprijzen in combinatie met dynamische optimalisatie een groot potentieel hebben voor kostenbesparingen in de tuinbouwpraktijk.

In dit proefschrift werd de voorgestelde modelgebaseerde tweetrapsbenadering gedemonstreerd voor één kas. De potentiële energie- en kostenbesparingen van dynamische optimalisatie werden met succes aangetoond voor deze kas. Voor deze kas werden de potentiële energie- en kostenbesparingen van dynamische optimalisatie getoond. De energie-optimalisatie in de eerste fase resulteerde in een theoretische 47 % reductie in verwarming, 15 % reductie in koeling en 10 % reductie in CO-injectie voor het jaar 2012 (hoofdstuk 3). De kostenoptimalisatie in de tweede fase resulteerde in een potentiële kostenbesparing van 29 %, gegeven de prijzen voor gas en elektriciteit en het bekende weer (hoofdstuk 5). De resultaten toonden aan dat optimalisatie van het energiesysteem in de kas mogelijk is. De tweetrapsmethode sluit nauw aan bij de dagelijkse praktijk van de teler. Het is te verwachten dat bij online toepassing in de praktijk de energie- en kostenbesparing lager, maar nog steeds substantieel zal zijn. De toepassing van de tweetrapsbenadering in de praktijk lijkt veelbelovend. Hiervoor moeten nog een aantal uitdagingen worden opgelost, zoals het online parameteriseren van de modellen, beschikbaarheid van consistente data en prijsinformatie.

Acknowledgments

Finally, my thesis is ready. I would like to express my thanks to all of you who helped and supported me during the years I worked on my thesis. The first years I was stationed at the Wageningen UR Greenhouse Horticulture group, later at the Farm Technology Group in the PhD room. The last years, with my colleagues of B-Mex.

My special thanks go to my supervising team and initiaters of the project, my promotors Eldert van Henten and Gerrit van Straten and my co-promotor and daily supervisor Jan Bontsema. This project can be seen as a continuation of the long history of modeling and optimization of greenhouse climate in Wageningen. Dear Eldert, your assistance during writing and publishing of the four papers and your view on the structure of papers and the thesis helped me a lot. Thanks for guiding me and improving my scientific skills. Thanks for your creative ideas and problem solving approach. Dear Gerrit, thanks for your thoughts and ideas during the project. Your feedback was often very constructive and practical. Dear Jan, I'm very thankful that you were my supervisor. Even after your retirement you where willing to supervise me en help me finish the project. I appreciate your ability to apply theoretical knowledge in practice and broad interest in many different topics. I experienced it to be a honour to be supervised by the three of you and the unique combination of knowledge and experience.

I am grateful to the STW for supporting this project financially. I would like to thank the companies who contributed to the project and took place in the user committee. Special thanks to Ad de Koning from Ridder Growing Solutions, Marcel Boonekamp (former grower at Boonekamp Roses), Jan Fransen from Lek/Habo B.V., and Silke Hemming from Wageningen UR Greenhouse Horticulture. The discussions we had were always very pleasant and assured the focus of the project. The practical viewpoints and considerations from the growers and business point of view were very welcome and useful. Silke, thanks for hosting me in your team during the first period. This gave me the opportunity to experience both the university and the applied research institutes of Wageningen UR.

Thanks to all colleagues of the Farm Technology Group. I liked the pleasant atmosphere and discussions during breaks. I also enjoyed our PhD diners and other activities. Bert, thanks for your assistance and contribution to the fourth paper.

I would like to thank the students whom I had the privilege to supervise during this project, Yicheng Hao who worked on the modelling of heat buffers, and Jesper Voois who worked on the exploration of the dataset of the equipment.

This PhD-thesis reflects results of research conducted in a time period of about ten years. During these years many people contributed to the work and the discussions on the subject. I would like to express my gratitude to all who supported me. Thanks to my colleagues at B-Mex. Fokke, thanks for the courage and trust to hire me as your first employee at B-Mex in 2015. Many thanks for the opportunity to finish my PhD project and develop myself further within the company. I'm looking forwards to continue the work with our team in order to make the climate and crop models available to growers and farmers in practice.

Finally I would like to thank PE&RC for all support and training. I enjoyed the PE&RC staff attitude, activities, workshops and their approach to PhD- candidates. Meeting other PhD candidates from other groups really broadened my view and interests within the Wageningen domain.

Special thanks to my family and friends. Thanks to my parents for all the opportunities they gave me and for supporting me throughout. Maaike, I'm so happy that we met in 2016 and proud of our two sons Daniël and Nathan. Thank you for all your love and support.

Dodewaard, March 2022

References

ASHRAE, 2011. HVAC applications, in: ASHRAE Handbook of HVAC applications. American Society of Heating, Refrigerating and Air Conditioning Engineers, Atlanta. chapter 24.

Bailey, B.J., 2002. Optimal control of carbon dioxide enrichment in tomato greenhouses. Acta Hort (ISHS) Tropical and Subtropical Greenhouses 578, 63–69. doi:10.17660/ActaHortic.2002.578.6.

Bakker, J.C., Bot, G.P.A., Challa, H., Van de Braak, N.J., 1995. Greenhouse climate control: An integrated approach. Wageningen Academic Publishers, Wageningen. doi:10.1109/ARMS.1991.154441.

Bakker, J.C., De Zwart, H.F., Campen, J.B., 2006. Greenhouse cooling and heat recovery using fine wire heat exchangers in a closed pot plant greenhouse: Design of an energy producing greenhouse, in: Acta Hort. (ISHS) 719, pp. 63–270. doi:10.17660/ActaHortic.2006.719.29.

Baptista, F.J., Bailey, B.J., Meneses, J.F., Navas, L.M., 2010. Greenhouses climate modelling. Tests, adaptation and validation of a dynamic climate model. Spanish Journal of Agricultural Research 8, 285–298.

Berenguel, M., Yebra, L.J., Rodriguez, F., 2003. Adaptive control strategies for greenhouse temperature control, in: European Control Conference, Cambridge, UK. pp. 2747–2752. doi:10.23919/ECC.2003.7086457.

Blanco, I., Vox, G., Mugnozza, G.S., 2014. Technical evaluation for a solar absorption cooling system to be applied for greenhouse climate control, in: International Conference of Agricultural Engineering, pp. 6–10.

Boaventura Cunha, J., Couto, C., Ruano, A.E., 1997. Real-time parameter estimation of dynamic temperature models for greenhouse environmental control. Control Engineering Practice 5, 1473–1481. doi:10.1016/S0967-0661(97)00145-7.

Bontsema, J., Hemming, J., Stanghellini, C., De Visser, P., Van Henten, E.J., Budding, J., Rieswijk, T., Nieboer, S., 2007. Online estimation of the transpiration in greenhouse horticulture, in: Proceedings Agricontrol 2007, pp. 29–34.

Bontsema, J., Van Henten, E.J., Gieling, T.H., Swinkels, G.L.A.M., 2011. The effect of sensor errors on production and energy consumption in greenhouse horticulture. Computers and Electronics in Agriculture 79, 63–66. doi:10.1016/j.compag.2011.08.008.

Bozchalui, M.C., Cañizares, C.A., 2014. Optimal Energy Management of Greenhouses in Smart Grids. IEEE Transactions on Smart Grid 6, 827–835. doi:10.1109/TSG.2014.2372812.

Brand, I.R.A., Planje, W.G., Ruigrok, I.J., 2008. Alternatieven voor seizoenopslag in de glastuinbouw. Technical Report. TNO. Apeldoorn.

Buchholz, M., Jochum, P., Zaragoza, G., 2005. Concept for water, heat and food supply from a closed greenhouse -the watergy project. Acta Horticulturae 691, 509–516. doi:10.17660/ActaHortic.2005.691.60.

Camacho, E.F., Bordons, C., 2012. Model predictive control in the process industry. Springer Science & Business Media.

Cámara-Zapata, J.M., Sánchez-Molina, J.A., Rodríguez, F., López, J.C., 2019. Evaluation of a dehumidifier in a mild weather greenhouse. Applied Thermal Engineering 146, 92–103. doi:10.1016/j.applthermaleng.2018.09.107.

Campen, J.B., Bot, G.P.A., De Zwart, H.F., 2003. Dehumidification of Greenhouses at Northern Latitudes. Biosystems Engineering 86, 487–493. doi:10.1016/j.biosystemseng.2003.08.008.

Campen, J.B., Kempkes, F.L.K., 2011. Climatic Evaluation of Semi-Closed Greenhouses. Acta Hort. (ISHS) 893, 495–502. doi:10.17660/ActaHortic.2011.893.49.

Chalabi, Z.S., Bailey, B.J., Wilkinson, D.J., 1996. A real-time optimal control algorithm for greenhouse heating. Computers and Electronics in Agriculture 15, 1–13. doi:10.1016/0168-1699(95)00053-4.

Chandan, V., Do, A.T., Jin, B., Jabbari, F., Brouwer, J., Akrotirianakis, I., 2012. Modeling and Optimization of a Combined Cooling, Heating and Power Plant

System, in: American Control Conference (ACC), Montreal, QC. pp. 3069–3074. doi:10.1109/ACC.2012.6315606.

Cho, H., Smith, A.D., Mago, P., 2014. Combined cooling, heating and power: A review of performance improvement and optimization. Applied Energy 136, 168–185. doi:10.1016/j.apenergy.2014.08.107.

Courtois, N., Petit, V., Thiéry, D., 2008. Reversible Climatisation of Greenhouses in France Using Aquifer Thermal Energy Storage : Pre-Feasibility Study. Acta Hort. (ISHS) 801, 819–826.

Day, W., 1998. The value of crop and greenhouse models in greenhouse environmental control, in: Crop Models in Protected Cultivation, pp. 295–303. doi:10.17660/ActaHortic.1998.456.35.

De Gelder, A., Dieleman, J.A., Bot, G.P.A., Marcelis, L.F.M., 2012. An overview of climate and crop yield in closed greenhouses. Journal of Horticultural Science and Biotechnology 87, 193–202. doi:10.1080/14620316.2012.11512852.

De Jong, T., 1990. Natural ventilation of large multi-span greenhouses. Ph.D. thesis. Wageningen University. Wageningen, The Netherlands.

De Zwart, H.F., 1996. Analyzing energy-saving options in greenhouse cultivation using a simulation model. Ph.D. thesis. Landbouwuniversiteit Wageningen.

De Zwart, H.F., 2008. Overall Energy Analysis of (Semi) Closed Greenhouses. Acta Hort. (ISHS) 801, 811–818.

De Zwart, H.F., 2011. The Sunergy Greenhouse - One Year of Measurements in a Next Generation Greenhouse, in: Proc. IS on High Technology for Greenhouse Systems - Greensys2009, pp. 351–358.

De Zwart, H.F., 2014. Energy Conserving Dehumidification of Greenhouses. Acta Horticulturae 1037, 203–210. doi:10.17660/ActaHortic.2014.1037.21.

De Zwart, H.F., Janssen, H.J.J., 2010. Transfer capacity of the OPAC106 heat exchanger. Technical Report. Wageningen UR Greenhouse Horticulture. Wageningen.

De Zwart, H.F., Kempkes, F.L.K., 2007. Characterizing of cooling equipment for closed greenhouses. Acta Hort. (ISHS) , 409–416.

Dieleman, J., Hemming, S., 2011. Energy saving: from engineering to crop management. Acta Hort. (ISHS) 893, 65–74. doi:10.17660/ActaHortic.2011.893.2.

Doeswijk, T.G., Keesman, K.J., 2005. Adaptive weather forecasting using local meteorological information. Biosystems Engineering 91, 421–431. doi:10.1016/j.biosystemseng.2005.05.013.

Du, J., Bansal, P., Huang, B., 2012. Simulation model of a greenhouse with a heat-pipe heating system. Applied Energy 93, 268–276. doi:10.1016/j.apenergy.2011.12.069.

Edvall, M.M., Goran, A., 2009. Tomlab quick start guide. Technical Report. Tomlab Optimization Inc.. San Diego, CA, USA.

El Ghoumari, M.Y., Tantau, H.J., Serrano, J., 2005. Non-linear constrained MPC: Real-time implementation of greenhouse air temperature control. Computers and Electronics in Agriculture 49, 345–356. doi:10.1016/j.compag.2005.08.005.

Fransen, J., 2015. Personal communication.

Fuentes-Cortés, L.F., Ponce-Ortega, J.M., Nápoles-Rivera, F., Serna-González, M., El-Halwagi, M.M., 2015. Optimal design of integrated CHP systems for housing complexes. Energy Conversion and Management 99, 252–263. doi:10.1016/j.enconman.2015.04.036.

Gieling, T.H., Campen, J.B., Dieleman, J.A., Garcia, N., Janssen, H.J.J., Kempkes, F.L.K., 2011. Monitoring of Climate Variables in Semi-Closed Greenhouses. Acta Hort. (ISHS) 893, 1073–1080. doi:10.17660/ActaHortic.2011.893.122.

Grisey, A., Grasselly, D., Rosso, L., Amaral, F.D., Melamedoff, S., 2011. Using Heat Exchangers to Cool and Heat a Closed Tomato Greenhouse : Application in the South of France. Acta Horticulturae 893, 405–412.

Gutman, P.O., Lindberg, P.O., Ioslovich, I., Seginer, I., 1993. A Non-Linear Optimal Greenhouse Control Problem Solved by Linear Programming. Journal of Agricultural Engineering Research 55, 335–351. doi:10.1006/jaer.1993.1054.

Guzmán-Cruz, R., Castañeda-Miranda, R., García-Escalante, J.J., López-Cruz, I.L., Lara-Herrera, A., de la Rosa, J.I., 2009. Calibration of a greenhouse climate model using evolutionary algorithms. Biosystems Engineering 104, 135–142. doi:10.1016/j.biosystemseng.2009.06.006.

Haeseldonckx, D., Peeters, L., Helsen, L., D'haeseleer, W., 2007. The impact of thermal storage on the operational behaviour of residential CHP facilities and the overall CO2 emissions. Renewable and Sustainable Energy Reviews 11, 1227–1243. doi:10.1016/j.rser.2005.09.004.

Hansen, P., Huge, J., 1989. Implicit Treatment of 'Zero or Range' Constraints in a Model for Minimum Cost Foundry Alloys. Management Science 35, 367–371. doi:10.1287/mnsc.35.3.367.

Hemming, S., Balendonck, J., Dieleman, J.A., De Gelder, A., Kempkes, F.L., Swinkels, G.L., De Visser, P.H., De Zwart, H.F., 2017. Innovations in greenhouse systems - Energy conservation by system design, sensors and decision support systems. Acta Horticulturae 1170, 1–15. doi:10.17660/ActaHortic.2017.1170.1.

Holmström, K., 2001. Practical Optimization with the TOMLAB Environment in Matlab, in: Proceedings of the 42nd SIMS Conference, Telemark University College, Porsgrunn, pp. 89–108.

Holmstrom, K., Anders, O.G., Edvall, M.M., 2010. User's guide for TOMLAB 7.1. Technical Report. Tomlab Optimization Inc.

Husmann, H.J., Tantau, H.J., 2001. Integrated optimization of energy supply systems in horticulture using genetic algorithms. Computers and Electronics in Agriculture 31, 47–59. doi:10.1016/S0168-1699(00)00173-3.

Incrocci, L., Stanghellini, C., Kempkes, F.L.K., 2008. Carbon dioxide fertilization in Mediterranean greenhouses: when and how is it economical?, in: International Symposium on Strategies Towards Sustainability of Protected Cultivation in Mild Winter Climate, pp. 135–142.

Ioslovich, I., Gutman, P.O., Linker, R., 2009. Hamilton-Jacobi-Bellman formalism for optimal climate control of greenhouse crop. Automatica 45, 1227–1231. doi:10.1016/j.automatica.2008.12.024.

Kamp, P.G.H., Timmerman, G.J., 1996. Computerized environmental control in greenhouses. Ed. IPC Plant, Ede.

Katsoulas, N., Kittas C., Baille, A., Katsoulas, N., Kittas, C., Baille, A., 2001. Estimating transpiration rate and canopy resistance of a rose crop in a fan-ventilated greenhouse. International Symposium on Growing Media and Hydroponics 548 548, 303–309. doi:10.17660/ActaHortic.2001.548.34.

Kempkes, F.L.K., Janse, J., Hemming, S., 2014. Greenhouse Concept with High Insulating Double Glass with Coatings and New Climate Control Strategies; from Design to Results from Tomato Experiments. Acta Hort. (ISHS) 1037, 83–92. doi:10.17660/ActaHortic.2014.1037.6.

Kim, S.H., Lieth, J.H., 2001. Modeling diurnal variation of whole-plant photosynthesis of greenhouse roses. Acta Hort. (ISHS) 547, 111–119. doi:10.17660/ActaHortic.2001.547.14.

Kim, S.H., Lieth, J.H., 2003. A coupled model of photosynthesis, stomatal conductance and transpiration for a rose leaf (Rosa hybrida L.). Annals of botany 91, 771–81. doi:10.1093/aob/mcg080.

Kintner-Meyer, M., Emery, A., 1995. Optimal control of an HVAC system using cold storage and building thermal capacitance. Energy and Buildings 23, 19–31. doi:10.1016/0378-7788(95)00917-M.

Körner, O., Challa, H., 2003. Design for an improved temperature integration concept in greenhouse cultivation. Computers and Electronics in Agriculture 39, 39–59. doi:10.1016/S0168-1699(03)00006-1.

Korner, O., Challa, H., Körner, O., 2003. Design for an improved temperature integration concept in greenhouse cultivation. Computers and Electronics in Agriculture 39, 39–59. URL: http://www.sciencedirect.com/science/article/pii/S0168169903000061.

Körner, O., Holst, N., 2005. Model based humidity control of botrytis in greenhouse cultivation. Acta Horticulturae 691, 141–148. doi:10.17660/ActaHortic.2005.691.15.

LEI Wageningen UR, 2015. www.agrimatie.nl. URL: www.agrimatie.nl.

Lentz, W., 1998. Model applications in horticulture: a review. Scientia Horticulturae 74, 151–174.

Linker, R., Seginer, I., Gutman, P.O., 1998. Optimal CO2 control in a greenhouse modeled with neural networks. Computers and Electronics in Agriculture 19, 289–310. doi:10.1016/S0168-1699(98)00008-8.

Lopez-Cruz, I.L., Fitz-Rodríguez, E., Salazar Moreno, R., Kacira, M., 2018. Development and analysis of dynamical mathematical models of greenhouse climate : A review. European Journal of Horticultural Science , 269–280doi:10.17660/eJHS.2018/83.5.1.

López-Cruz, I.L., Fitz-Rodríguez, E., Salazar-Moreno, R., Rojano-Aguilar, A., Kacira, M., 2018. Development and analysis of dynamical mathematical models of greenhouse climate: A review. European Journal of Horticultural Science 83, 269–279. doi:10.17660/eJHS.2018/83.5.1.

Ma, Y., Borrelli, F., Hencey, B., Packard, A., Bortoff, S., 2009. Model Predictive Control of thermal energy storage in building cooling systems. Proceedings of the 48h IEEE Conference on Decision and Control (CDC) held jointly with 2009 28th Chinese Control Conference , 392–397doi:10.1109/CDC.2009.5400677.

Medrano, E., Lorenzo, P., Sánchez-Guerrero, M.C., Montero, J.I., 2005. Evaluation and modelling of greenhouse cucumber-crop transpiration under high and low radiation conditions. Scientia Horticulturae 105, 163–175. doi:10.1016/j.scienta.2005.01.024.

Mitra, S., Sun, L., Grossmann, I.E., 2013. Optimal scheduling of industrial combined heat and power plants under time-sensitive electricity prices. Energy 54, 194–211. doi:10.1016/j.energy.2013.02.030.

Molenaar, J., Bokhove, O., Ramaekers, L., Van De Leur, J., Gvozdenovic, N., Bakri, T., Archer, C., Reeves, C., 2007. Optimizing a closed greenhouse, in: Proceedings of the 58st European Study Group Mathematics with Industry, pp. 55–68.

Montero, J.I., Van Henten, E.J., Son, J.E., Castilla, N., 2009. Greenhouse engineering: New technologies and approaches. Acta Hort. (ISHS) 893, 51–63.

Nederhoff, E.M., Vegter, J.G., 1994. Photosynthesis of stands of tomato cucumber and sweet pepper under different CO2 concentrations. Annals of botany 73, 353–361.

Oldewurtel, F., Parisio, A., Jones, C.N., Gyalistras, D., Gwerder, M., Stauch, V., Lehmann, B., Morari, M., 2012. Use of model predictive control and weather forecasts for energy efficient building climate control. Energy and Buildings 45, 15–27. doi:10.1016/j.enbuild.2011.09.022.

Ooka, R., Ikeda, S., 2015. A review on optimization techniques for active thermal energy storage control. Energy and Buildings doi:10.1016/j.enbuild.2015.07.031.

Opdam, J.J.G., Schoonderbeek, G.G., Heller, E.M.B., De Gelder, A., 2005. Closed Greenhouse: a Starting Point for Sustainable Entrepreneurship in Horticulture. Acta Hort. (ISHS) 691, 517–524. doi:10.17660/ActaHortic.2005.691.61.

Pagliarini, G., Rainieri, S., 2010. Modeling of a thermal energy storage system coupled with combined heat and power generation for the heating requirements of a University Campus. Applied Thermal Engineering 30, 1255–1261. doi:10.1016/j.applthermaleng.2010.02.008.

Papadakis, G., Frangoudakis, A., Kyritsis, S., 1992. Mixed, forced and free convection heat transfer at the greenhouse cover. Journal of Agricultural Engineering Research 51, 191–205. doi:10.1016/0021-8634(92)80037-S.

Pavlov, G.K., Olesen, B.W., 2012. Thermal energy storage-A review of concepts and systems for heating and cooling applications in buildings: Part 1-Seasonal storage in the ground. HVAC and R Research 18, 515–538. doi:10.1080/10789669.2012.667039.

Pohlheim, H., Heißner, A., 1999. Optimal control of greenhouse climate using real-world weather data and evolutionary algorithms, in: Proceedings of the Genetic and Evolutionary Computation Conference, Citeseer. pp. 1672–1677.

Qian, T., Dieleman, J.A., Elings, A., 2011. Comparison of Climate and Production in Closed, Semi-Closed and Open Greenhouses. Acta Hort. (ISHS) 893, 807–814. doi:10.17660/ActaHortic.2011.893.88.

Qian, T., Dieleman, J.A., Elings, A., Marcelis, L.F., 2012. Leaf photosynthetic and morphological responses to elevated CO2concentration and altered fruit number in the semi-closed greenhouse. Scientia Horticulturae 145, 1–9. URL: http://dx.doi.org/10.1016/j.scienta.2012.07.015, doi:10.1016/j.scienta.2012.07.015.

Ren, H., Gao, W., Ruan, Y., 2008. Optimal sizing for residential CHP system. Applied Thermal Engineering 28, 514–523. doi:10.1016/j.applthermaleng.2007.05.001.

Righini, I., Vanthoor, B., Verheul, M.J., Naseer, M., Maessen, H., Persson, T., Stanghellini, C., 2020. A greenhouse climate-yield model focussing on additional light, heat harvesting and its validation. Biosystems Engineering 194, 1–15. doi:10.1016/j.biosystemseng.2020.03.009.

Rodríguez, F., Berenguel, M., Guzmán, J.L., Ramírez-Arias, A., 2015a. Advice and suggestions for greenhouse technicians and producers, in: Modeling and Control of Greenhouse Crop Growth. Springer International Publishing. chapter 5, pp. 215–219. doi:10.1007/978-3-319-11134-6.

Rodríguez, F., Berenguel, M., Guzmán, J.L., Ramírez-Arias, A., 2015b. Climate and irrigation control, in: Modeling and Control of Greenhouse Crop Growth. chapter 3, pp. 99–196. doi:10.1007/978-3-319-11134-6.

Rodriguez, F., Guzmán, J.L., Berenguel, M., Arahal, M.R., 2008. Adaptive hierarchical control of greenhouse crop production. Int. J. Adapt. Control and Signal Processing 22, 180–197. doi:10.1002/acs.

Ros, M., Read, A., Uilenreef, J., Limbeek, J., 2014. Start of a CO2 hub in Rotterdam: Connecting CCS and CCU. Energy Procedia 63, 2691–2701. doi:10.1016/j.egypro.2014.11.291.

Rutquist, P.E., Edvall, M.M., 2010. PROPT - Matlab Optimal Control Software.

Sapounas, A., Katsoulas, N., Slager, B., Bezemer, R., Lelieveld, C., 2020. Design , Control , and Performance Aspects of Semi-Closed Greenhouses. Agronomy 10, 1–22. doi:doi:10.3390/agronomy10111739.

Schütz, T., Streblow, R., Müller, D., 2015. A comparison of thermal energy storage models for building energy system optimization. Energy and Buildings 93, 23–31. doi:10.1016/j.enbuild.2015.02.031.

Seginer, I., 1989. Optimal greenhouse production under economic constraints. Agricultural Systems 29, 67–80. doi:10.1016/0308-521X(89)90071-1.

Seginer, I., Hwang, Y., Boulard, T., Jones, J.W., 1996. Mimicking an expert greenhouse grower with a neural-net policy. Transactions of the ASAE 39, 299–306.

Seginer, I., Ioslovich, I., 1998. Seasonal Optimization of the Greenhouse Environment For a Simple Two-stage Crop Growth Model. Journal of Agricultural Engineering Research 70, 145–155. doi:10.1006/jaer.1997.0261.

Seginer, I., Van Beveren, P., Van Straten, G., 2018. Day-to-night heat storage in greenhouses: 3 Co-generation of heat and electricity (CHP). Biosystems Engineering 172. doi:10.1016/j.biosystemseng.2018.05.006.

Sigrimis, N., Anastasiou, A., Rerras, N., 2000. Energy saving in greenhouses using temperature integration: a simulation survey. Computers and Electronics in Agriculture 26, 321–341. URL: http://dx.doi.org/10.1016/S0168-1699(00)00083-1, doi:10.1016/S0168-1699(00)00083-1.

Speetjens, S.L., Stigter, J.D., Van Straten, G., 2009. Towards an adaptive model for greenhouse control. Computers and Electronics in Agriculture 67, 1–8.

Stanghellini, C., 1987. Transpiration of greenhouse crops. Ph.D. thesis. Landbouwuniversiteit Wageningen. Wageningen, The Netherlands.

Stanghellini, C., 2010. Personal communication.

Stanghellini, C., Bontsema, J., De Koning, A., Baeza, E.J., 2011. An algorithm for optimal fertilization with pure carbon dioxide in greenhouses. Acta Hort. (ISHS) , 119–124doi:10.17660/ActaHortic.2012.952.13.

Stanghellini, C., De Jong, T., 1995. A model of humidity and its applications in a greenhouse. Agricultural and forest meteorology 76, 129–148. doi:10.1016/0168-1923(95)02220-R.

Stanghellini, C., Van 't Ooster, A., Heuvelink, E., 2019. Greenhouse horticulture: technology for optimal crop production. Wageningen Academic Publishers, Wageningen.

Tap, R.F., 2000. Economics-based optimal control of greenhouse tomato crop production. Ph.D. thesis. Wageningen University. Wageningen.

Tap, R.F., Van Willigenburg, L.G., Van Straten, G., 1996. Receding horizon optimal control of greenhouse climate based on the lazy man weather prediction, in: Proc. Of 13th IFAC World Congress, San Francisco, pp. 387–392.

Teitel, M., Baeza, E.J., Montero, J.I., 2012. Greenhouse Design: Concepts and Trends. Acta Hort. (ISHS) , 605–620doi:10.17660/ActaHortic.2012.952.77.

Teitel, M., Segal, I., Shklyar, A., Barak, M., 1999. A Comparison between Pipe and Air Heating Methods for Greenhouses. Journal of Agricultural Engineering Research 72, 259–273. doi:10.1006/jaer.1998.0370.

Vadiee, A., Martin, V., 2012. Energy management in horticultural applications through the closed greenhouse concept, state of the art. Renewable and Sustainable Energy Reviews 16, 5087–5100. doi:10.1016/j.rser.2012.04.022.

Vadiee, A., Martin, V., 2013. Energy analysis and thermoeconomic assessment of the closed greenhouse – The largest commercial solar building. Applied Energy 102, 1256–1266. doi:10.1016/j.apenergy.2012.06.051.

Vadiee, A., Martin, V., 2014. Energy management strategies for commercial greenhouses. Applied Energy 114, 880–888. doi:10.1016/j.apenergy.2013.08.089.

Van Beveren, P.J.M., Bontsema, J., Van Straten, G., Van Henten, E.J., 2013. Minimal Heating and Cooling in a Modern Rose Greenhouse, in: Arto, V. (Ed.), 4th IFAC Conference on Modelling and Control in Agriculture, Espoo, Finland. pp. 282–287. doi:10.3182/20130828-2-SF-3019.00026.

Van Beveren, P.J.M., Bontsema, J., Van Straten, G., Van Henten, E.J., 2015a. Minimal heating and cooling in a modern rose greenhouse. Applied Energy 137, 97–109. doi:10.1016/j.apenergy.2014.09.083.

Van Beveren, P.J.M., Bontsema, J., Van Straten, G., Van Henten, E.J., 2015b. Optimal control of greenhouse climate using minimal energy and grower defined bounds. Applied Energy 159, 509–519. doi:10.1016/j.apenergy.2015.09.012.

Van Beveren, P.J.M., Bontsema, J., Van Straten, G., Van Henten, E.J., 2019. Optimal utilization of a boiler, combined heat and power installation, and heat buffers in horticultural greenhouses. Computers and Electronics in Agriculture 162, 1035–1048. doi:10.1016/j.compag.2019.05.040.

Van Den Bulck, N., Coomans, M., Wittemans, L., Hanssens, J., Steppe, K., 2013. Monitoring and energetic performance analysis of an innovative ventilation concept in a Belgian greenhouse. Energy and Buildings 57, 51–57. doi:10.1016/j.enbuild.2012.11.021.

Van der Valk, R., Van der Poll, W., 2007. Actieplan voor een klimaatneutrale glastuinbouw (Action plan for climate-neutral greenhouse horticulture). Technical Report. Stichting Natuur en Milieu and LTO Glaskracht (in Dutch).

Van der Velden, N.J.A., Smit, P.X., 2013. Groei elektriciteitsconsumptie glastuinbouw: hoe verder? Technical Report. LEI Wageningen UR. Wageningen.

Van der Velden, N.J.A., Smit, P.X., 2014. Energiemonitor van de Nederlandse glastuinbouw 2013. Technical Report. LEI Wageningen UR. Wageningen.

Van der Velden, N.J.A., Smit, P.X., 2018. Energiemonitor van de Nederlandse glastuinbouw 2017. Technical Report. Wageningen Economic Research. Wageningen.

Van der Velden, N.J.A., Smit, P.X., 2019. CO2-behoefte glastuinbouw 2030. Technical Report. Wageningen Economic Research. Wageningen.

Van Henten, E.J., 1994. Greenhouse climate management: an optimal control approach. Ph.D. thesis. Wageningen University. Wageningen. doi:10.1016/S0308-521X(94)90280-1.

Van Henten, E.J., Bontsema, J., 2008. Open-Loop Optimal Temperature Control in Greenhouses, in: Proc. IS on Greensys2007, pp. 629–636.

Van Henten, E.J., Bontsema, J., 2009. Time-scale decomposition of an optimal control problem in greenhouse climate management. Control Engineering Practice 17, 88–96. doi:10.1016/j.conengprac.2008.05.008.

Van Henten, E.J., Bontsema, J., Van Straten, G., 1997. Improving the efficiency of greenhouse climate control: An optimal control approach. Netherlands Journal of Agricultural Science 45, 109–125.

Van Ooteghem, R., 2007a. Optimal Control Design for a Solar Greenhouse. Ph.D. thesis. Wageningen University. doi:10.3182/20101206-3-JP-3009.00054.

Van Ooteghem, R.J.C., 2007b. Optimal control design for a solar greenhouse. Ph.D. thesis. Wageningen University. Wageningen.

Van Ooteghem, R.J.C., Van Willigenburg, L.G., Van Straten, G., 2005. Receding Horizon Optimal Control of a Solar Greenhouse, in: Acta Hort. (ISHS), pp. 797–806. doi:10.17660/ActaHortic.2005.691.98.

Van Steekelenburg, A., Hoogervorst, W., Van Antwerpen, A., 2011. Inventarisatie Thermische wateropslagsystemen Inleiding. Technical Report. HAS Kennis-Transfer. 's-Hertogenbosch.

Van Straten, G., 1999. Acceptance of optimal operation and control methods for greenhouse cultivation. Annual Reviews in Control 23, 83–90. doi:10.1016/S1367-5788(99)90065-2.

Van Straten, G., Challa, H., Buwalda, F., 2000. Towards user accepted optimal control of greenhouse climate. Computers and Electronics in Agriculture 26, 221–238. doi:10.1016/S0168-1699(00)00077-6.

Van Straten, G., Van Henten, E.J., Van Willigenburg, L.G., Van Ooteghem, R.J.C., 2010. Optimal control of greenhouse cultivation. CRC Press. doi:10.1201/b10321.

Van Straten, G., Van Willigenburg, L.G., Tap, R.F., 2002. The significance of crop co-states for receding horizon optimal control of greenhouse climate. Control Engineering Practice 10, 625–632. doi:10.1016/S0967-0661(02)00023-0.

Van 't Ooster, A., Van Henten, E.J., Janssen, E.G.O.N., Bot, G.P.A., Dekker, E., 2007. Development of concepts for a zero-fossil-energy greenhouse. Acta Hort. (ISHS) 1990, 725–732. doi:10.17660/ActaHortic.2008.801.84.

Van Willigenburg, L.G., Van Henten, E.J., Van Meurs, W., 2000. Three time-scale digital optimal receding horizon control of the climate in a greenhouse with a heat storage tank, in: Proceedings Int. Conf. Modelling and control in agriculture, horticulture and post-harvested processing (Agricontrol), pp. 184–189.

Vanhoudt, D., Desmedt, J., Van Bael, J., Robeyn, N., Hoes, H., 2011. An aquifer thermal storage system in a Belgian hospital: Long-term experimental evaluation of energy and cost savings. Energy and Buildings 43, 3657–3665. doi:10.1016/j.enbuild.2011.09.040.

Vanthoor, B.H.E., 2011. A model-based greenhouse design method. Ph.D. thesis. Wageningen University. Wageningen.

Vanthoor, B.H.E., Stanghellini, C., van Henten, E.J., de Visser, P.H.B., 2011. A methodology for model-based greenhouse design: Part 1, a greenhouse climate model for a broad range of designs and climates. Biosystems Engineering 110, 363–377. doi:10.1016/j.biosystemseng.2011.06.001.

Vermeulen, P., 2014. Combined Heat and Power (CHP) as a possible method for reduction of the CO2 Footprint of Greenhouse Horticulture. Journal of Energy Challenges and Mechanics 1, 37–40.

Vermeulen, P., Van der Lans, C., 2011. Combined Heat and Power (CHP) as a Possible Method for Reduction of the CO2 Footprint of Organic Greenhouse Horticulture, in: Proc. Rist IC on Organic Greenhouse Hort., pp. 61–68. doi:10.17660/ActaHortic.2011.915.7.

Von Zabeltitz, C., 2010. Integrated Greenhouse Systems for Mild Climates. Springer, Berlin, Heidelberg. doi:10.1007/978-3-642-14582-7.

Wallach, D., Makowski, D., Jones, J.W., Brun, F., 2014. Model Evaluation, in: Working with dynamic crop models. Academic Press. chapter 9, pp. 345–406. doi:10.1016/B978-0-12-397008-4.00009-5.

Yu, Z.J., Huang, G., Haghighat, F., Li, H., Zhang, G., 2015. Control strategies for integration of thermal energy storage into buildings: State-of-the-art review. Energy and Buildings 106, 203–215. doi:10.1016/j.enbuild.2015.05.038.

Zaheer-uddin, M., Zheng, G.R., 2000. Optimal control of time-scheduled heating, ventilating and air conditioning processes in buildings. Energy Conversion & Management 41, 49–60. doi:10.1016/S0196-8904(99)00094-1.

Curriculum Vitae

Pieter Jacobus Matthias (Peter) van Beveren was born on October 26, 1988 in Vlissingen, the Netherlands. After receiving his VWO diploma in 2006, he started the BSc program in Agrotechnology at Wageningen University. In 2010, he completed this program and received the CLAAS Innovation award for his thesis on labor registration in tomato cultivation. He continued his MSc in Agricultural and Bioresource Engineering at Wageningen University, which he completed in 2011. His thesis was about modelling micro algae cultivation in tubular sytems. This research was published in the journal of Applied Energy. His internship was at AMAZONEN-Werke in Hasbergen, Germany. In October 2011, he started his PhD research on optimal management of energy resources in greenhouse horticulture. Peter joined the company B-Mex B.V. in October 2015. This company is focused on sustainable exploitation of greenhouse climate and crop models and making them available for growers. Since 2017, Peter is a partner in the company.

List of Publications

Refereed articles in a scientific journal

Slegers, P.M., Van Beveren, P.J.M., Wijffels, R.H., Van Straten, G., & Van Boxtel, A.J.B. (2013). Scenario analysis of large scale algae production in tubular photobioreactors. Applied Energy, 105, 395–406. doi.org/10.1016/j.apenergy.2012.12.068

Van Beveren, P.J.M., Bontsema, J., Van Straten, G., & Van Henten, E.J. (2015). Minimal heating and cooling in a modern rose greenhouse. Applied Energy, 137, 97–109. doi.org/10.1016/j.apenergy.2014.09.083

Van Beveren, P.J.M., Bontsema, J., Van Straten, G., & Van Henten, E.J. (2015). Optimal control of greenhouse climate using minimal energy and grower defined bounds. Applied Energy, 159, 509–519. doi.org/10.1016/j.apenergy.2015.09.012

Van Mourik, S., Van Beveren, P.J.M., Lopez-Cruz, I.L., & Van Henten, E.J. (2019). Improving climate monitoring in greenhouse cultivation via model based filtering. Biosystems Engineering, 181, 40–51. doi.org/10.1016/j.biosystemseng.2019.03.001

Seginer, I., Van Straten, G., & Van Beveren, P.J.M. (2017). Day-to-night heat storage in greenhouses: 1 Optimisation for periodic weather. Biosystems Engineering, 161, 174–187. doi.org/10.1016/j.biosystemseng.2017.06.024

Seginer, I., Van Straten, G., & Van Beveren, P.J.M. (2017). Day-to-night heat storage in greenhouses: 2 Sub-optimal solution for realistic weather. Biosystems Engineering, 161, 188–199. doi.org/10.1016/j.biosystemseng.2017.06.023

Seginer, I., Van Beveren, P.J.M., & Van Straten, G. (2018). Day-to-night heat storage in greenhouses: 3 Co-generation of heat and electricity (CHP). Biosystems Engineering, 172. doi.org/10.1016/j.biosystemseng.2018.05.006

Van Beveren, P.J.M., Bontsema, J., Van Straten, G., & Van Henten, E.J. (2019). Optimal utilization of a boiler, combined heat and power installation, and heat

buffers in horticultural greenhouses. Computers and Electronics in Agriculture, 162, 1035–1048. doi.org/10.1016/j.compag.2019.05.040

Seginer, I., Van Straten, G., & Van Beveren, P.J.M. (2020). Day-to-night heat storage in greenhouses: 4. Changing the environmental bounds. Biosystems Engineering, 192, 90–107. doi.org/10.1016/j.biosystemseng.2020.01.005

Van Beveren, P.J.M., Bontsema, J., Van 't Ooster, A., Van Straten, G., & Van Henten, E. J. (2020). Optimal utilization of energy equipment in a semi-closed greenhouse. Computers and Electronics in Agriculture, 179, 105800. doi.org/10.1016/j.compag.2020.105800

Conference papers

Van Beveren, P.J.M., Bontsema, J., Van Straten, G., & Van Henten, E.J. (2013). Minimal Heating and Cooling in a Modern Rose Greenhouse. 4th IFAC Conference on Modelling and Control in Agriculture, Agricontrol 2013 (pp. 282–287). Espoo, Finland. doi.org/10.3182/20130828-2-SF-3019.00026

Seginer, I., Van Straten, G., & Van Beveren, P.J.M. (2016). Optimal Day-to-Night Greenhouse Heat Storage: Square-Wave Weather. In 5th IFAC Conference on Sensing, Control and Automation Technologies for Agriculture, Agricontrol 2016 (Vol. 49, pp. 375–380). Seattle, WA, USA. doi.org/10.1016/j.ifacol.2016.10.069

López-Cruz, I.L., Van Beveren, P.J.M., Van Mourik, S., & Van Henten, E.J. (2017). Performance of extended and unscented Kalman filters for state and parameter estimation of a greenhouse climate model. In International Symposium on New Technologies and Management for Greenhouses - GreenSys 2015 (Vol. 1170, pp. 175–181). Evora, Portugal. doi.org/10.17660/ActaHortic.2017.1170.20

Seginer, I., Van Straten, G., & Van Beveren, P.J.M. (2020). Modelling evapotranspiration in off-line simulations of greenhouse climate control. In International Symposium on Advanced Technologies and Management for Innovative Greenhouses: GreenSys 2019 (Vol. 1296, pp. 341–348). Angers, France. doi.org/10.17660/ActaHortic.2020.1296.44

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

Review of literature (5 ECTS)

- Scheduling and control of energy production, consumption and storage systems

Post-graduate courses (6 ECTS)

- C++ Course; TU Eindhoven (2011)
- Model predictive control; European Embedded Control Institute (2013)

Invited review of (unpublished) journal manuscript (2 ECTS)

- Computers and Electronics in Agriculture (COMPAG) (2013)
- Journal of Energy Efficiency (2014)

Deficiency, refresh, brush-up courses (6 ECTS)

- Systems and control theory (2012)

Competence strengthening / skills courses (4.6 ECTS)

- Competence assessment; WGS (2012)
- Presentation skills; Language Services of Wageningen UR (2012)
- Techniques for writing and presenting a scientific paper; WGS (2012)
- Scientific publishing; WGS (2012)
- Scientific writing; Language Services of Wageningen UR (2013)

PE&RC Annual meetings, seminars and the PE&RC weekend (3 ECTS)

- PE&RC Weekend first years (2012)
- PE&RC Day (2012, 2013, 2014)
- PE&RC Weekend mid-term (2014)
- PE&RC Weekend last years (2015)

Discussion groups / local seminars / other scientific meetings (6 ECTS)

- MSN Member and coordinator of the discussion group (2012-2015)

International symposia, workshops and conferences (10.6 ECTS)

- 4th IFAC Conference on Modelling and Control in Agriculture, Horticulture and Post Harvest Industry (2013)

- Smart Energy Systems Meeting; poster and oral presentation; NWO/STW (2013)
- Benelux Meeting on Systems and Control (2013, 2014, 2015)
- An Innovative truth: congres over duurzame ICT & energie; poster presentations (2013, 2015)

Lecturing / supervision of practical's / tutorials (6 ECTS)

- Greenhouse Technology (2012, 2013, 2014)

Supervision of MSc student (3 ECTS)

- Modelling of heat buffers

Colophon

This research was funded by the Dutch Technology Foundation STW, which is part of the Netherlands Organisation for Scientific Research (NWO), and which is partly funded by the Ministry of Economic Affairs.

Cover design: Peter van Beveren
Printed by: Proefschriftmaken.nl