Dynamic optimisation of thermal energy systems

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DYNAMIC OPTIMISATION OF THERMAL ENERGY SYSTEMS

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DYNAMIC OPTIMISATION OF THERMAL ENERGY SYSTEMS

PROEFSCHRIFT

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Preface

The research described in this thesis was performed during the period from July 1985 to December 1988 within the framework of a project financed by Novem, the Netherlands agency for energy and the environment, and further supported by Bredero Energy Systems, TNO and STW.
The research activities were mainly concentrated in the System and Control Technology Group of Eindhoven University of Technology.
Contributors to the project were (in arbitrary order):

- Students of the Faculties of Technical Physics and Mechanical Engineering.
- Representatives of TNO and Bredero Energy Systems, who contributed with practical advice and fruitful discussions.
- Colleagues of the System and Control Technology Group.

Abstract

In this thesis the principle of dynamic optimisation is applied to a class of thermal energy systems.
In dynamic optimisation the aim is to choose the values of the adjustable input variables of a process as a function of time, so as to ensure the best performance over a given period.
The class of thermal energy processes considered may have the following components: heat pump, heat exchanger, short- and/or long-term sensible heat storage, collectors, user-demand circuit. The common process activity is the transfer of heat from a heat source (waste heat, solar and/or ambient heat, geothermal heat) to a heat-demanding component (e.g. industrial process heat, space heating, domestic hot water). The most important characteristics of such processes are:
- The nonlinear behaviour as a function of adjustable variables such as flow rates.
- The disturbance patterns acting upon the process (given by the heat supply and demand patterns, such as may be caused by weather variations).
- The possibility of different operational modes.

The aim of the research has been twofold:
- The application of a suitable method of dynamic optimisation to a realistic, representative process.
- Obtaining optimal control strategies and translating them into simple, near-optimal strategies, and using dynamic optimisation as a tool for a more economical design of the processes considered.

The dynamic behaviour of the components is described by mathematical models. The dynamic optimal control is achieved by a new, dedicated optimisation method, which was developed in this research and will be treated in this thesis.

By means of a number of representative optimisation results obtained for different conditions it is indicated how dynamic optimisation leads to a better designed and better controlled process.
The sensitivity of the optimal control to variations in the disturbance patterns is studied, together with adaptation techniques which can be used to approach optimal control in practical situations.

The result is a basically new design procedure for thermal energy systems, in which the control aspects are taken into account systematically, the final upshot being a system with better chosen dimensions and a better control.

Samenvatting

In dit onderzoek wordt het principe van dynamische optimalisering toegepast op een klasse van warmtetechnische processen.
Dynamische optimalisering houdt in: het kiezen van de beinvloedbare ingangsvariabelen van een proces als functie van de tijd, aan de hand van een bepaald criterium.
De bestudeerde klasse warmtetechnische processen bestaat uit de volgende componenten: warmtepomp, warmtewisselaar, warmte-opslag voor korte en/of lange termijn, collectoren, gebruikscircuit. Centraal staat de overdracht van warmte van een bepaalde warmtebron (bijv. afvalwarmte, bodemwarmte, zonnewarmte en/of warmte uit de buitenlucht) naar een warmtegebruiker (voor bijv. industriële proceswarmte of ruimteverwarming). De belangrijkste karakteristieken van deze processen zijn:

- Het niet-lineaire gedrag als functie van de ingangsvariabelen.
- De verstoringspatronen die op de processen inwerken (gevormd door de warmtevraag- en aanbodpatronen, en vaak beinvloed door het weer).
- De mogelijkheid van verschillende bedrijfsvormen.

Het doel van het onderzoek was tweeledig:

- Het toepassen van een methode voor dynamische optimalisering op de bovenbeschreven klasse van processen.
- Vanuit het oogpunt van die processen: het vinden van optimale besturingsstrategieën, het vertalen daarvan naar simpele, bijna-optimale strategieën, en het gebruik van dynamische optimalisering als hulpmiddel bij het ontwerp van deze processen.

Het dynamisch gedrag van de bestudeerde processen wordt beschreven door wiskundige modellen. De dynamisch optimale besturing wordt bepaald met een nieuwe, in dit onderzoek ontwikkelde, optimaliseringsmethode, die in dit proefschrift beschreven wordt.

Aan de hand van een aantal representatieve resultaten verkregen onder uiteenlopende condities wordt aangegeven hoe dynamische optimalisering leidt tot een beter ontworpen en beter bestuurd proces. De gevoeligheid van de optimale besturing voor veranderingen in de verstoringspatronen wordt bestudeerd, en aangegeven wordt hoe door middel van adaptatie het proces bijgestuurd kan worden teneinde in praktijksituaties een zo goed mogelijke besturing te realiseren.

Het onderzoek resulteert in een nieuwe ontwerpprocedure voor warmtetechnische processen, waarin op een systematische manier de besturingsaspecten van het proces meegenomen worden zodat het uiteindelijke resultaat een beter gedimensioneerd en beter bestuurd proces is.

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List of Symbols

a	number of active constraints	[-]
A	active constraint matrix [1:a,1:m]	[-]
Ac	collector area	[m^2]
Aco	condenser heat exchanging area	[m^2]
Aev	evaporator heat exchanging area	[m^2]
Ag	coefficient in linear relationship seasonal storage	[^oC]
b	see p. 26	[-]
b0	coefficient in linear relationship	[^oC]
b1	coefficient in linear relationship	[-]
B	see p. 26	[-]
Bg	constant in linear relationship seasonal storage	[-]
C	constraint matrix [1:r,1:m]	[-]
Cb	heat transfer coefficient building(s)	[W/K]
COP	heat pump coefficient of performance	[-]
d	number of significant decimals in F	[-]
eF	absolute accuracy in F	[*]
Etadau	fraction of heat demand delivered by aux. heater	[-]
Etacol	collector efficiency (IQcol/IQe)	[-]
f	scalar function	[*]
$\underline{f}$	system function [1:s]	[*]
F	criterion function	[*]
Fc	collector flow	[kg/s]
Fcd	bypass flow heat pump	[kg/s]
Fch	flow for preheating condenser	[kg/s]
Fd	flow in heating system	[kg/s]
Fg(i)	flow in concentric ring seasonal storage	[kg/s]
Fgtot	total flow in seasonal storage	[kg/s]
Fh	condenser flow	[kg/s]
Fl	evaporator flow	[kg/s]
Fmax	maximum flow	[kg/s]
Fmin	minimum flow	[kg/s]
fr	switch-on fraction of system	[-]
$\underline{g}$	gradient $\partial F/\partial \underline{u}$ [1:m]	[*]
$\underline{gp}$	projected gradient [1:m]	[*]
$\underline{h}$	upper boundary [1:r]	[*]
$\underline{hp}$	upper boundary design variables [1:rp]	[*]
H	Hamiltonian	[*]
Hc	characteristic function collector	[-]
Hd	characteristic function heating system	[-]
HP	heat pump unity sizing factor	[-]

i	index	[-]
IQ...	energy, time-integral of power ...	[J]
IQg0	heat content long-term storage at t=tb	[J]
IQg1	heat content long-term storage at t=te	[J]
IQggr	energy loss long-term storage in radial direction	[J]
IQggz	energy loss long-term storage in vertical direction	[J]
IQvt0	heat content short-term storage at t=tb	[J]
IQvt1	heat content short-term storage at t=te	[J]
j	index	[-]
k	number of iterations	[-]
$\underline{l}$	lower boundary [1:r]	[*]
$\underline{l}$p	lower boundary design variable [1:rp]	[*]
L	momentary contribution to criterion	[*]
m	number of control variables	[-]
mv(i)	mass of register i in storage vessel	[kg]
M	positive definite symmetric matrix [1:m,1:m]	[-]
Mbyp	bypass mass short-term storage on demand side	[kg]
Mv	mass of storage medium in storage vessel	[kg]
n	time step index	[-]
$\underline{n}$i	normal vector of i-th constraint ($1 \leq i \leq r$)	[*]
N	maximum number of time-steps	[-]
Na	number of adaptation time-steps	[-]
Nc	rotation speed of heat pump compressor	[1/min]
Ngrid	number of grid points in long-term storage model	[-]
Npipe	number of pipes in seasonal storage	[-]
Nreg	number of registers in short-term storage	[-]
$\underline{p}$	parameter vector	[*]
$\underline{p}$	search direction [1:m]	[*]
$\underline{p}$	costate	[*]
P	projection matrix [1:m,1:m]	[-]
P	penalty function	[*]
PI	performance index	[*]
Q_i^j	$= \frac{\partial x(j)}{\partial u(i)}$	[*]
Qaux	auxiliary heat	[W]
Qcol	power delivered by collector	[W]
Qd	heat demand	[W]
Qe	= Fc*γw*(Teq-Tic)	[W]
Qgshp	power consumption of heat pump	[W]
Qgsau	power consumption of auxiliary heating	[W]
Qhp	power delivered by heat pump	[W]
Qig	power injected in long-term storage	[W]
Qog	power extracted from long-term storage	[W]
Qpump	power consumption circulation pumps	[W]
Qs	solar irradiation	[W/m^2]
Qtot	total power consumption	[W]
r	number of constraints	[-]
rp	number of design variables	[-]
s	number of state variables	[-]

t	time	[s]
tb	start of optimisation interval	[s]
te	end of optimisation interval (te = tb+N.Δt)	[s]
Ta	ambient temperature	[^oC]
Tb	required indoor temperature	[^oC]
Tco	condenser temperature	[^oC]
Td	demand temperature	[^oC]
Teq	equivalent ambient temperature	[^oC]
Tev	evaporator temperature	[^oC]
Tg(i)	temperature of grid point i in seasonal storage	[^oC]
Tic	collector inlet temperature	[^oC]
Tig	seasonal storage inlet temperature	[^oC]
Tih	condenser inlet temperature	[^oC]
Til	evaporator inlet temperature	[^oC]
Toc	collector outlet temperature	[^oC]
Tod	output temperature heating system	[^oC]
Tog	seasonal storage outlet temperature	[^oC]
Toh	condenser outlet temperature	[^oC]
Tol	evaporator outlet temperature	[^oC]
Tvt(i)	short term storage temperature	[^oC]
$\underline{u}$	control vector [1:m]	[*]
UAd	heat transfer coefficient heating system	[W/K]
Uc	collector heat loss coefficient	[$W/m^2/K$]
V	continuous return function	[*]
V'	discrete return function	[*]
Vc	swept volume of piston compressor	[m^3]
Vg	seasonal storage volume	[m^3]
Vv	short-term storage volume	[m^3]
W(n)	weighting function	[*]
$\underline{x}$	state vector [1:s]	[*]
$\underline{x}$d(n)	desired state trajectory	[*]
$\underline{z}$	disturbance vector	[*]

Creek symbols

α	step	[-]
β	see p. 26	[-]
γw	specific heat of water	[J/kg/K]
$\Delta\alpha$	step size	[-]
Δt	time-step	[s]
ΔThb	indoor temperature rise because of internal heat sources	[^oC]
ε	small real number	[-]
ϵ	step size for numerical differentiation	[*]
$\underline{\lambda}$	vector with Lagrange-multipliers [1:m]	[*]
ν(t)	arbitrary function of time	[*]
σ	standard deviation	[*]
ϕ	end cost function	[*]
ω(t)	arbitrary function of time	[*]

1 Introduction

1.1 Scope of this thesis

One of the main objectives of systems and control engineering is to achieve a better design and operation of a process under study. The term "better" is fairly arbitrary and can be associated with "safer, cheaper, cleaner, faster" and the like. For non-stationary processes this objective can be achieved by dynamic optimisation, by which I understand the optimisation of the design and/or operation of a dynamical process with regard to a certain criterion over a given period of time. The field of research associated with the optimal operation of a process is called "optimal control". Major developments of this area were made in the fifties and sixties of this century, but thanks to the growing possibilities of computer hardware and software, this subject is still rapidly developing.

In this thesis the techniques of dynamic optimisation are applied to thermal energy systems. By thermal energy systems we consider here systems using industrial residual or waste heat, solar or ambient heat, possibly incorporating a heat pump and heat storage components, meant for the supply of industrial process heat, hot tap water and/or space heating. The general idea of these systems is that there is a form of heat supply which is non-stationary, and a form of heat demand, also non-stationary, and that there are temporary discrepancies between supply and demand that may be balanced by heat storage. Some important aspects of these systems are the potential for energy conservation, and related economic and environmental considerations.

Although the individual components may be more or less well-established, some important general questions regarding the best ways of dimensioning and operating these systems are as yet unsolved. A reason for this can be found in the nature of the problem: in many thermal energy systems the performance is influenced by weather variables such as ambient temperature and solar irradiation. These variables show a certain deterministic behaviour (diurnal and seasonal variations), but also a stochastic component, which makes it difficult to develop reliable design rules without over-dimensioning the system, and to establish efficient and robust operational strategies. Dynamic optimisation, as discussed in this thesis, is in my opinion the only theoretically sound approach to overcome these problems.

An important aspect of dynamic optimisation is that it provides the optimal operational strategy if the independent variables (weather or other supply and load variables) are known a priori. In practical situations any assumed pattern will differ from reality. In this thesis the crucial step of the translation of dynamically optimal solutions to practicable strategies is investigated in various ways, an example of this being the use of adaptation techniques.

Based on the concept of dynamic optimisation, a new procedure for designing thermal energy systems is proposed. One predominant characteristic of this procedure is that optimally controlled, instead of conventionally controlled, design alternatives are compared. Another is that the procedure often leads to insights and design concepts that often seem hard-to-believe and to accept at first, but turn out to be obviously true, once insight has adapted to their compelling underlying logic.

1.2 Historical background

In the research on thermal energy systems, the control strategy tends to be a neglected subject, whereas a great deal of attention has been paid to the design, for example: the sizing of the components to obtain the system with the best economic or energetic performance (under conventional control). The few authors who did pay attention to control reported optimal control strategies for relatively simple systems under restrictive conditions.
Several "design tools" have been developed; programme packages providing the optimal dimensions for given system layout, supply and demand patterns. The use of these tools is fairly widespread, eventhough different tools sometimes yield quite different results.
In recent years, a tendency may be discerned towards the development of better operational strategies, the results however are mainly application-dependent, and the synthesis of new strategies is generally an ad-hoc process.

In the System and Control Technology Group of Eindhoven University of Technology, research on the applications of dynamic optimisation started in 1972. Among other things, the technique has been applied to models of world dynamics [RAD88] and slowly varying petrochemical processes [MEI81]. In 1977, research on thermal solar energy systems was initiated. The emphasis was on modelling, simulation and control. In 1981 research was extended to systems incorporating a heat pump, and in 1982 a pilot study on seasonal storage of solar heat in the ground was started. In 1985 a new project was started covering all aspects of the control of thermal energy systems. The project was financed by the Netherlands Agency for Energy and the Environment (NOVEM), and included support from Bredero Energy Systems, STW and TNO, the Netherlands Organisation for Applied Scientific Research. The research described in this thesis was done within the framework of this project.

1.3 Formulation of the aims of this research

From the above it will be clear that the objectives of this thesis may be formulated from two viewpoints:
From the point of view of optimal control the aim is to study:

- Application of the method of dynamic optimisation to an interesting class of realistic, non-stationary, non-linear physical processes.
- Investigation of the modifications in the optimisation method necessary to ensure convergence of the iterative calculation procedure.

From the point of view of thermal energy systems the objectives are:
- To use dynamic optimisation as a design tool for thermal energy systems.
- To determine dynamic optimal control strategies for different configurations, and to use these as a guideline for deriving practicable, near-optimal control strategies.

From both points of view the aim is:
- To study the use of dynamic optimisation as a technique for finding practicable and superior ways of controlling technical systems.

At this point it is important to stress that in this thesis the emphasis is on the investigation of the control and design aspects, and not on the precise modelling of any specific thermal energy system. Thus, mathematical models are used to adequately describe the behaviour of the components, ignoring secondary effects. Nevertheless, the approach taken in this work is believed to be applicable to systems described by more refined mathematical models, but such efforts are beyond the scope of this thesis, which focuses on the conceptual framework and the method of approach, rather than on the numerical results for a specific system.

1.4 Contents of this thesis

Chapter 2 provides an introduction to dynamic optimisation. The basic techniques are discussed, and a computational method and some of its specific features are described. A brief overview is given of the application of adaptive control, as a technique to tune a control strategy on the basis of actual information.
The thermal processes studied are described in Chapter 3. First the selected components are explained, together with their mathematical models and the assumptions made. After that a possible system layout is dealt with. Some characteristics of the systems considered are discussed from the point of view of system and control technology.
The relationship between the optimisation method and the application is focused in Chapter 4. The effects of the characteristics of the system on the optimisation method are dealt with, together with the system-dependent modifications that were developed. In Section 4.6 the new design procedure for thermal energy systems is presented. Sections 4.7 to 4.9 provide a brief state-of-the-art review.
Chapter 5 discusses the results of the optimisation of various systems.
Finally, Chapter 6 gives conclusions and recommendations.

As pointed out before, the final aim is to achieve a better design and control of the systems under study. To get a better insight in the approach taken in this thesis, Fig. 1.1 gives a schematic view of the conceptual framework to be kept in mind before turning to the Chapters 2 to 4. This figure provides a global view of the steps in the proposed design procedure, to be completed in more detail in Section 4.6.

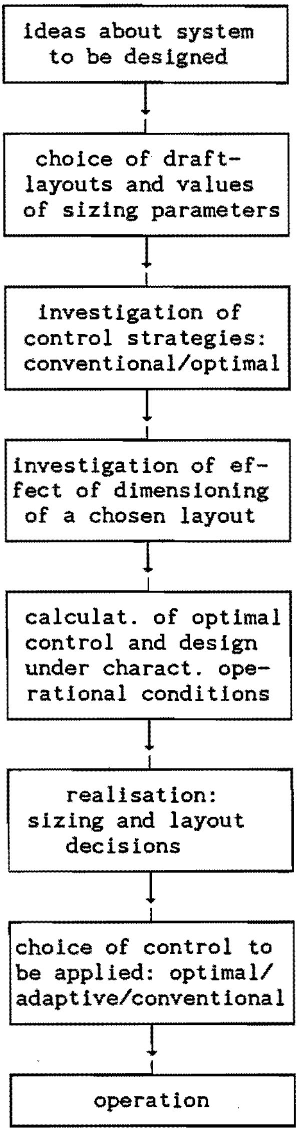


Fig. 1.1: The conceptual framework for the proposed design method.

2 Dynamic Optimisation

2.1 Introduction

This chapter surveys the techniques and the applicability of dynamic optimisation. A numerical solution procedure for dynamic optimal control problems is discussed, and some basic concepts of the application of adaptation techniques are treated.

To introduce the concept of dynamic optimisation, the following general process scheme is considered:

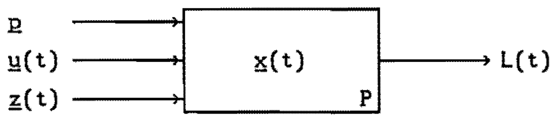


Fig. 2.1: General process scheme.

A process P is described by state variables $\underline{x}(t)$, and influenced by time-independent design variables $\underline{p}$, time-dependent control variables $\underline{u}(t)$, and disturbances $\underline{z}(t)$. The state variables are defined as the minimum set of variables, which contain sufficient information about the past history of the system to permit computation of all future states of the system if the future inputs and the equations describing the system are given [ELG67].
The design variables refer to parameters which determine the characteristics or the sizing of the process.
The disturbances, also referred to as external influences, are the non-controllable inputs of the process, which can have both a deterministic and a stochastic nature.
The process performance is judged by means of a cost function L, depending on the inputs, the state variables and time (only the time-dependence is indicated in Fig. 2.1).
In dynamic optimisation the problem is to choose $\underline{u}(t)$ over a given period [tb,te] so as to optimise a performance index or criterion function PI:

$$\min_{\underline{u}} PI = \min_{\underline{u}} \int_{tb}^{te} L(t')dt' \qquad (2.1)$$

It is important to note the difference between static, momentary and dynamic optimisation. In static optimisation it is assumed that the control variables are constant (independent of time) during the interval [tb,te]. In momentary optimisation the control variables at any instant t = t' are chosen so as to optimise the momentary cost function L(t'), irrespective of the possible future consequences.

In this thesis it is assumed that the control variables may be independent of the state variables $\underline{x}(t)$ and the disturbances. In other words: a situation is considered in which the structure and the parameters of the (feedback and/or feedforward-) controller are unknown, and the process inputs can be adjusted freely (see Fig. 2.2c). The output variables $\underline{y}(t)$ in Fig. 2.2 are assumed to be related to the momentary cost function L(t).

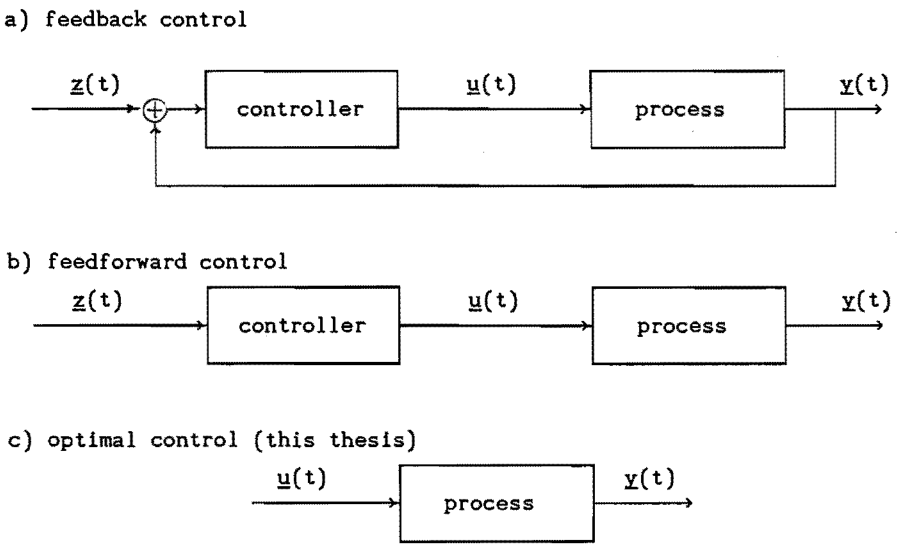


Fig. 2.2: Various control structures.

Thus the situation is somewhat different from the conventional types of control. The arrangements a and b (see Fig. 2.2) result in the traditional optimal control problems, leading to solutions under the restrictions imposed by the type of control (feedforward or feedback) and the structure of the controller.

2.1.1 Dynamic optimisation and process control

In process automation, optimal control of linear (or linearised) stationary processes is a well-established domain with fairly widespread potential applications . But there is a shift towards semi-stationary and non-stationary (for example: batch-wise) processes, where a dynamical approach to optimal operation is necessary. There is also a shift from conventional (PID) control towards other, microprocessor-based control algorithms, and as a result the application of advanced optimised operational strategies, possibly combined with model identification and adaptation, is coming within reach. Therefore it is to be expected that dynamic optimisation will play a role of increasing importance in process automation. This is supported by the experiences in the field of logistics management where, for example, scheduling or inventory control problems are solved. In that field, linear programming techniques, which may be considered as the linear variants of the dynamic optimisation technique to be discussed in Section 2.2.3, are commonly used.

2.1.2 Advantages and disadvantages of dynamic optimisation

The advantages of a dynamic optimisation approach are generally twofold: First, dynamic optimisation leads to a better process operation under varying circumstances, provided these variations can be predicted sufficiently accurately. But even if such predictions are not available in practice, dynamic optimisation turns out to be quite useful in that its results serve as a yardstick against which improvements in operational strategies can be judged, certainly a posteriori, or as a guideline for deriving near-optimal control strategies.
A second advantage of dynamic optimisation is that it may lead to a better process design, on the one hand because, as will be explained later, design (sizing-) parameters can be optimised in the same computational procedure, on the other hand because bottlenecks in the process may be detected.
Our experiences with dynamic optimisation have shown that it is also a very effective way to detect shortcomings in the mathematical models used.

A disadvantage of the dynamic optimisation approach is that the operational strategies obtained may not be directly applicable, because they are based on an assumed pattern of disturbances. If the deviations from these patterns are relatively large, or, in other words, if the predictions are not sufficiently accurate, it may be necessary to

change the operational strategy in order to avoid inefficient operation, or for safety reasons. In other words: it is not guaranteed that the optimal strategy is practicable, or sufficiently robust. Section 2.1.3 treats an optimisation procedure which overcomes this disadvantage.
The lack of a priori knowledge of disturbances may be mastered by applying adaptation techniques to an optimal control strategy. Some ideas on adaptation are outlined at the end of this chapter.

Before turning to the methods of solving dynamic optimisation problems, it is necessary to point out that the dynamic optimisation problem as formulated in Section 2.1.1 is mathematically quite clear, and that for processes with a mathematically "decent" behaviour an optimal solution will exist. But in view of the (dis-)advantages mentioned in this section, the question arises whether it is necessary to know the global optimal solution very accurately, if the aim is just to obtain a better control and design of a process. Of course this question can not be answered without the ability to quantify the aims. But it indicates that dynamic optimisation of a realistic process is not just a pure mathematical problem. Knowledge of the process and the circumstances is essential to arrive at a practicable solution. From that viewpoint it is also evident that dynamic optimisation should be regarded as an interactive process, in which mathematical optimisation and process insight go hand in hand.
This forms the background for the treatment of the optimisation procedure. In Section 2.4.9 some consequences for the optimisation method are dicussed.

2.1.3 The incremental approach

In Section 2.2 some methods of applying dynamic optimal control will be discussed. Before turning over to these theoretical and mathematical tools, another method of dynamic optimisation has to be mentioned, because it is up till now probably the most common used in practice. It is evident that the performance of a dynamical process may also be improved by experiments. A trial-and-error procedure using different control strategies, combined with a great deal of process knowledge and "feeling", may, conceivably, in due time result in a strategy that is better, closer to optimal in a sense, and thus forms a potentially robust way of optimisation. However, this experimental method, sometimes referred to as the "incremental approach", has some clear disadvantages: it is a very time-consuming and expensive way to arrive at the optimum, especially if the number of control variables is large. Moreover, it can only be applied to an existing process. For these reasons it is beyond the scope of this work.

2.1.4 The use of dynamic optimisation as a design tool

Traditionally, dynamic optimisation techniques are mostly used to find the best control inputs of a system with a prescribed configuration and dimensions. Many process design habits and procedures, including those in the field of thermal energy, show that system dimensioning and layout take place in the top of the design decision sequence (Fig. 2.3), whereas system control is considered in a much later phase, well after the major design decisions have been taken. Fig. 2.3 gives a stylised view of a design procedure.

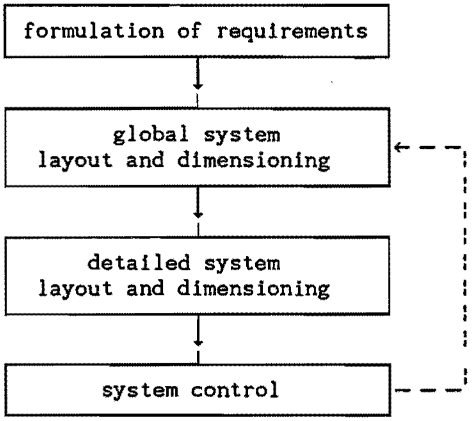


Fig. 2.3: A stylised representation of a design decision procedure.

The reason for this well-established hierarchy is quite clear: the items are ranked according to their influence on the performance of the system. In this section it is shown that with the aid of dynamic optimisation a better design procedure can be developed.

One important observation is that the successive steps in the design procedure mentioned above are not without important interactions: No step can be taken without making some assumptions on the other steps. For instance: for global dimensioning it is necessary to be able to distinguish the possible operational modes of the system and to assume for every mode the range of values of all control variables. These choices will undoubtedly affect the dimensioning in this step of the procedure. Later in the design procedure, the system control may be optimised with regard to some criterion, which will generally lead to other values of the control variables than assumed in the dimensioning step. This suggests that the best overall result can only be obtained if the design procedure is equiped with some iterative loops that include system control (e.g. the dotted line in Fig. 2.3) rather than being a strictly sequential procedure.

In this thesis a new design method is proposed for dynamical systems like the thermal energy systems to be discussed in Chapter 3. One predominant characteristic of this method (see Section 4.6.3) is that optimally controlled, instead of conventionally controlled, design alternatives are compared. This selection, based on optimal control, leads to a better choice of the system design. The optimal control strategy of the best design alternative serves as a starting point for deriving simpler, near-optimal, robust control strategies.
In this chapter the emphasis will be on the first step in the proposed design method: the calculation of the optimal control of a specific design alternative.

The proposed design procedure reflects a tendency towards an integrated method of approach, that can be discerned in several fields of research, like in process engineering and in information systems theory. Examples are: automation systems for buildings, computer-integrated manufacturing, decision support systems, expert systems. A reflection of this "think twice before you start to build"-principle can be found in the field of information systems design, as illustrated by Dietz [DIE87] in Fig. 2.4.

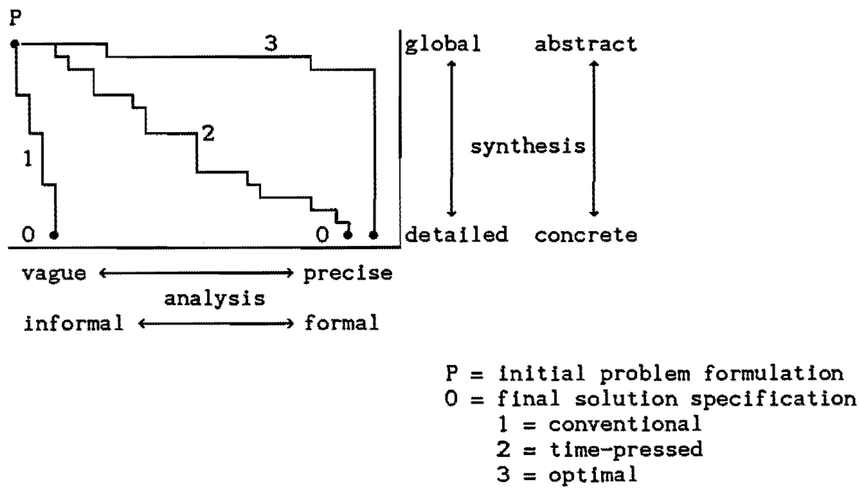


Fig. 2.4: The design problem of information systems (after [DIE87]).

In this figure the horizontal axis indicates the problem analysis, ranging from vague and informal to precise and formal, and the vertical axis reflects the synthesis of the solution, from a global and abstract level to a detailed and concrete level. Three possible ways to arrive at a solution are indicated.
The conventional step-by-step approach (curve 1) is comparable with the incremental approach of Section 2.1.3. An approach which is considered suitable for time-pressed situations is given by curve 2: the analysis step is reduced. According to Dietz, the best way to arrive at the solution is to start with a thorough problem analysis on an abstract level, followed by the synthesis (curve 3).
The latter approach is then comparable to the proposed design method including system control, as mentioned before.

2.2 Theoretical background and conceptual framework.

In this section a brief general description of a dynamic optimisation problem is given. For illustrative purposes the system inputs $\underline{z}(t)$ and $\underline{p}$ are omitted.
The dynamic behaviour of a system is described by the system equations:

$$\dot{\underline{x}} = \underline{f}(\underline{x},\underline{u},t), \qquad t\in[tb,te] \tag{2.2}$$

$$\underline{x} = \underline{x}(t) \qquad \underline{x}: [tb,te] \rightarrow R^s$$

$$\underline{u} = \underline{u}(t) \qquad \underline{u}: [tb,te] \rightarrow R^m$$

$$\underline{f}: R^s * U * [tb,te] \rightarrow R^s, \qquad U \subseteq R^m$$

where $\underline{x}$ is the state vector, $\underline{u}$ is the control vector, t is time, s the number of state variables, m the number of control variables, and U the domain of $\underline{u}$.

The aim is to choose $\underline{u}$ so as to minimise the performance index, or criterion function, also denoted as $F(\underline{u})$:

$$PI = F(\underline{u}) = \int_{tb}^{te} L(\underline{x},\underline{u},t)dt \tag{2.3}$$

For mathematical or physical reasons it may be necessary to impose restrictions upon the control vector and/or the state vector.
The domain of $\underline{u}$, the control vector, is assumed to be defined by the following linear inequality constraints:

$$\underline{l} \leq C\underline{u} \leq \underline{h} \tag{2.4}$$

where:
$C = C[i,j]$, $1 \leq i \leq r$, $1 \leq j \leq m$, : constraint matrix
$\underline{l} = (l_1, \ldots, l_r)^T$: lower boundary
$\underline{h} = (h_1, \ldots, h_r)^T$: upper boundary
$\underline{u} = (u_1, \ldots, u_m)^T$: control vector
r : number of constraints
m : number of control variables.

Several mathematical techniques have been developed to solve dynamic optimisation problems. In the next sections the three fundamental approaches are summarized, emphasizing the problems that arise when applying these methods to realistic process models, i.e.: non-linear, complicated and/or constrained.
These approaches are:
- Variational calculus;
- Pontryagin's maximum principle;
- Dynamic programming.

2.2.1 Variational calculus

The basic idea of this method (also referred to as the Euler-Lagrange method) is to assume that an optimal solution exist, and to investigate the effect of variations around the optimal state trajectory $\underline{x}^{opt}(t)$ and the optimal control $\underline{u}^{opt}(t)$:

$$\begin{aligned} \underline{x}(t) &= \underline{x}^{opt}(t) + \epsilon\, \underline{\upsilon}(t) \\ \underline{u}(t) &= \underline{u}^{opt}(t) + \epsilon\, \underline{\omega}(t) \end{aligned} \tag{2.5}$$

where ϵ is a small real number, $\upsilon(t)$ and $\omega(t)$ are arbitrary functions of time.

It can be derived [SAC77, BRO74] that a necessary condition for an optimum (the first derivative being 0) is fulfilled if the so-called Euler-Lagrange equation (2.6) is satisfied, together with the transversality conditions (2.7):

$$\left[\frac{\partial L}{\partial \underline{x}}\right]^T - \left(\left[\frac{\partial L}{\partial \underline{u}}\right]^T \cdot \left[\frac{\partial \underline{f}}{\partial \underline{u}}\right]^{-1} \cdot \frac{\partial \underline{f}}{\partial \underline{x}}\right) - \frac{d}{dt}\left(\left[\frac{\partial L}{\partial \underline{u}}\right]^T \cdot \left[\frac{\partial \underline{f}}{\partial \underline{u}}\right]^{-1}\right) = \underline{0}^T \qquad (2.6)$$

$$\left[\frac{\partial L}{\partial \underline{u}}\right]^T \cdot \left[\frac{\partial \underline{f}}{\partial \underline{u}}\right]^{-1} \cdot \underline{\nu}(t)\Bigg|_{tb}^{te} = 0 \qquad (2.7)$$

The equations (2.6) and (2.7) are based on the assumption that the criterion function ($F(\underline{u})$) is continuous and has continuous first order derivatives, and that state and control variables are also continuous functions of time.
A sufficient condition for an extremum is obtained by determining the second order derivative of the criterion function with respect to ϵ in $\epsilon=0$. For most practical cases, however, this is not necessary [SAG77].

These necessary and sufficient conditions do not guarantee that the global optimal solution is obtained (see also Section 2.4.9 and). They only provide a so-called local optimum or "weak" optimum.

Analytical solution of equations (2.6) and (2.7) is possible for very simple problems (linear system equations, quadratic criterion function). However, this may result in a so-called Two Point Boundary Value problem (TPBVP), which is generally difficult to solve.
Constraints in state and control variables can be tackled in this approach by introducing an extra term (penalty function) in the criterion function, but this usually introduces non-linearity, in which the expressions become very cumbersome, and analytical solutions can no longer be obtained [SAG77].

The drawbacks of the variational approach can now be summarised:
- Solving the TPBVP is difficult.
- Constraints are difficult to handle.
- The requirements of continuity, as mentioned above, are too strong for a lot of practical cases.

This makes the variational method not suitable for the problems considered in this thesis.

2.2.2 Pontryagin's maximum principle

An improvement of the variational approach, that allows constraints in the control variables without the need for a penalty function in the criterion, is given by the maximum principle of Pontryagin [SAG77], which states that the minimum of the criterion can be obtained by maximising the so-called Hamiltonian of the system:

$$H = \underline{p}^T \underline{f} \qquad (2.8)$$

where $\underline{p}$ is the costate of the system, related to H and $\underline{x}$ via the canonical equations:

$$\dot{\underline{x}} = \frac{\partial H}{\partial \underline{p}} \qquad (2.9)$$

$$\dot{\underline{p}} = \frac{\partial H}{\partial \underline{x}} \qquad (2.10)$$

Along with the (possible) boundary conditions at t=tb and t=te, this constitutes a TPBVP, and this forms the main drawback of this method. The difference between the variational approach and the maximum principle is that the criterion function need not be quadratic to allow analytical solution, that constraints in the control variables are quite easily coped with, and that the controls do not have to be continuous functions of time.

2.2.3 Dynamic programming (Bellman)

Dynamic programming, as introduced by Bellmann [BEL57], may be viewed as providing an algorithm for the solution of multistep decision processes, based on the following two principles:

The embedding principle:
An optimal control problem with a fixed initial state over a period of time [tb,te] may be viewed as a special case of a general problem with a variable initial state over a variable period of time [t,te].

The principle of optimality:
Every control strategy that is optimal over a period [tb,te] is necessarily optimal over any subperiod [t,te] with tb < t < te.

The application of dynamic programming generally does not lead to an analytical solution of the problem. For discrete-time systems the method gives, by repeatedly applying the principle of optimality, a recurrent relationship which may be used to calculate the optimal control [BRO74]. In this way a N-step decision process is replaced by N times a one-step decision process.
For continuous-time systems a similar approach is taken. By defining the so-called continuous return function:

$$V(\underline{x}(t),\underline{u}(t),t) = \min_{\underline{u}} \int_{t}^{te} L(\underline{x},\underline{u},t)dt' \qquad (2.11)$$

the dynamic optimal control is given by the solution of the Hamilton-Jacobi partial differential equation:

$$\frac{\partial V}{\partial t} + \min_{\underline{u}} \{L(\underline{x},\underline{u},t) + \left[\frac{\partial V}{\partial \underline{x}}\right]^T \underline{f}(\underline{x},\underline{u},t)\} = 0 \qquad (2.12)$$

For linear systems with a quadratic criterion this equation is reduced to the well-known Riccati equation, an ordinary differential equation which gives the optimal control in a state feedback form (cf. Fig. 2.2a).

It should be pointed out that dynamic programming does not provide different results in optimisation, but possibly a more efficient way of solution, by avoiding the TPBVP's of the preceding sections.
However, for the non-linear systems considered here the Hamilton-Jacobi equation can only be solved iteratively with very much computational efforts. And for the discrete-time recurrent approach mentioned above the computational requirements are very large, if the number of time-steps and the number of discrete states are large (the so-called "curse of dimensionality").
This indicates that the practical use of this method is limited to the class of simple linear-quadratic systems.

From Sections 2.2.1 to 2.2.3 it can be concluded that already much research has been devoted to the solution of dynamic optimisation problems, but that the principal methods suffer from severe drawbacks when applied to the class of systems to be studied in this thesis. It must be pointed out that the methods mentioned above, with their theoretical and computational restrictions, all come down to analytical ways of treating the necessary conditions for an optimum, based on an analytical model of the system and the performance index.
The next section discusses a numerical method for the solution of dynamic optimal control problems. It is felt that such an approach is more powerful, because it is applicable to a broad variety of problems, for example if the system equations are not available in a closed analytical form. The difference with the methods of Sections 2.2.1 to 2.2.3 is that the numerical method directly searches for points satisfying the necessary conditions, whereas in the other methods the solutions are given indirectly in differential equations (Eq. 2.6, 2.7, 2.9, 2.10 and 2.12) based on the same necessary conditions.

2.3 Numerical solution

The solution methods for dynamic optimisation problems discussed in the previous sections have severe practical disadvantages, especially if the problem has the following properties:
- the system equations are non-linear.
- the criterion function is not a quadratic expression in $\underline{x}$ and/or $\underline{u}$.
- the control variables are bounded.
- the number of control and state variables is large (e.g. >100).

The thermal energy systems discussed in this thesis have these properties in common. Consequently: a numerical solution method is needed.
In the System and Control Technology Group Pontryagin's maximum principle was used for a number of applications since 1972, and the experiences were generally good. In order to test the potentials of alternatives based on Bellman's principles, an iterative method related to dynamic programming was also used with good experiences for various applications. This method was selected to be used as the basis for the optimisation procedure in this work.

This section discusses the most important class of iterative methods of solution, based on the following simple algorithm:

1) find a feasible initial control strategy

2) calculate the value of $F(\underline{u})$, the criterion function for this control strategy

3) if F does not change anymore: finish, else go on with 4)

4) change the control strategy, based on information about F, and return to 2)

Starting with an appropriately chosen initial control strategy, the system equations and the performance index are calculated over the interval [tb,te], and based on information about the state variables and F, the control is changed, until a predefined convergence criterion is fulfilled. In this thesis the system equations are assumed to be discretised in N time-intervals Δt.
The various iterative optimisation methods can be divided, based on the information about system equations and criterion function needed. If the gradient $\partial F/\partial \underline{u}$ is not known, zero-order methods like the simplex method can be used. In situations where the gradient is known, steepest descent methods or other gradient-type methods tend to be preferred, unless an explicitly known Hessian $\partial^2 F/\partial \underline{u}^2$ enables the use

of second-order methods like the Newton method [GIL81]. The zero-order methods tend to be very computer time consuming if the number of control variables is large, whereas the second-order methods require the evaluation of the Hessian which is also elaborate for problems with a large number of variables. Therefore we have chosen for first-order methods.
In the literature the conjugate gradient method is often proposed as the most suitable method for "large-scale" problems (the number of independent variables exceeding 100) with an explicitly known gradient, it providing a significantly better convergence rate with a minor increase in computing time as compared to steepest descent methods. Especially in the neighbourhood of the optimal solution, when the criterion function can usually be approximated by a quadratic function, the convergence rate is better.
To illustrate this, a property of conjugate directions is given:

A set of m non-zero vectors $\underline{p}_1, \ldots, \underline{p}_m$ is called M-conjugate with regard to a symmetric positive definite matrix M, if:

$$\underline{p}_i^T M \underline{p}_j = 0 \quad \text{for } i \neq j, \quad i,j = 1, \ldots, m. \tag{2.13}$$

The optimisation of a quadratic expression in $\underline{u}$ (with a term $\underline{u}^T M \underline{u}$) will take not more than m iterative steps if M-conjugate search directions are used, and if the determination of the optimum along the search direction is exact.

This property makes the conjugate gradient method a good choice, which is supported by many experiences mentioned in the literature [GIL81], even for non-quadratic functions and even if the line search is not exact. Conjugate search directions can be calculated with the following equations of Fletcher and Reeves [GIL81] (where k denotes the number of successive iterations).

$$\underline{p}^{(0)} = -\underline{g}^{(0)} \tag{2.14}$$

$$\underline{p}^{(k)} = -\underline{g}^{(k)} + \frac{\underline{g}^{(k)T}\underline{g}^{(k)}}{\underline{g}^{(k-1)T}\underline{g}^{(k-1)}}\,\underline{p}^{(k-1)} \quad \text{for } k \geq 1,$$

where $\underline{g}^{(k)}$ is the gradient of the criterion function:

$$\underline{g}^{(k)} = \partial F / \partial \underline{u}^{(k)} \tag{2.15}$$

and $\underline{u}^{(k)}$ is the control vector in the k-th iteration.

If the line search is not exact, the search direction has to be reset in the negative gradient direction after a number of iterations, to avoid an accumulation of errors, which leads to bad convergence properties in specific cases [GIL81].

As pointed out earlier in this section, the control variables have to satisfy certain linear constraints (Eq. 2.4 in Section 2.2). In some practical situations the constraints may be non-linear. For these cases, dedicated methods, like Sequential Quadratic Programming, have been proposed in the literature [MAC87].

To cope with the linear constraints in the control variables, a so-called "active set strategy" can be used. The i-th constraint is called:

- active in $\underline{u}$ if $C[i]\underline{u} = l_i$ or $C[i]\underline{u} = h_i$
- passive if $C[i]\underline{u} > l_i$ and $C[i]\underline{u} < h_i$
- violated if $C[i]\underline{u} < l_i$ or $C[i]\underline{u} > h_i$

where C[i] is the i-th row of the constraint matrix. The main principle of the active set strategy is to treat active inequality constraints as equality constraints, and to search for a minimum along these constraints, to avoid the zigzagging effect that is otherwise encountered in specific situations [GIL81].
If the minimum along the active constraints is found, the so-called Lagrange multipliers (to be discussed lateron) can be calculated to check whether or not the minimum along the constraints is a true (local or global) minimum in the domain of $\underline{u}$. If not, the associated active constraint is considered to be potentially passive, and thus treated as an inequality constraint. According to the sign of the Lagrange multiplier it is decided whether or not to abandon the constraint. In the latter case a minimum is found and the optimisation process is terminated. In the former case the search domain is extended with one degree of freedom. The search direction in the new active set is then also adjusted by performing a new projection of the gradient on the constraints that are still active.

It is important to stress that some of the features of optimisation methods, as suggested in the literature, are based on the assumption that the criterion function is a smooth quadratic one. If this assumption is not valid the advantageous effect of these features can turn out to a disadvantageous effect on convergence, according to our experiences.
An illustration of this discrepancy between mathematical theory and computational practice is the way to cope with constraints: the effect of the active set strategy on the speed of convergence is not clear in the presence of local minima, especially if many of these local minima occur along the constraints.

2.4 Computational procedure

This section describes the optimisation method that is applied in this thesis. The method tackles discrete dynamic optimisation problems with a large number of control and state variables (>100), and a criterion function F that is not necessarily smoothly near-quadratic.
The conjugate gradient algorithm of Fletcher-Reeves is employed, with either an active set strategy or a dedicated projection strategy to cope with the linear constraints, to be discussed in Section 2.4.3.
In order to minimise the use of computer CPU-time and memory, various modifications had to be developed for different stages of the computational procedure. These modifications will be given extra attention below.

The development of the modified method started with the formulation of a number of requirements:
- It should be possible to solve nonlinear problems with linear constraints, non-quadratic criteria.
- The procedure should be "transparant": a person working with it being able to monitor and control the optimisation process.
- The procedure should be universal to the extent that it should be possible to solve most cases in the general problem area (see Chapter 4) without major alterations.

Despite the fact that several software packages are commercially available for solving (dynamic) optimisation problems, we had to develop a new package because our experience with these packages showed that one or more of the requirements were not fulfilled satisfactorily. In general the packages operate according to a "black-box" principle, with as input an optimisation problem formulated in a number of mathematical operations and as output (if any), the optimal values of the parameters, without providing insight into, or giving an opportunity to control, the processes in between. Further, most packages were found to be very helpful for solving relatively simple problems (linear system equations, quadratic performance index, small number of control and state variables). These black-box approaches were not suitable for the large-scale optimisation problems to be dealt with here.

The basic algorithm of the optimisation procedure is shown in Fig. 2.5 and discussed below.

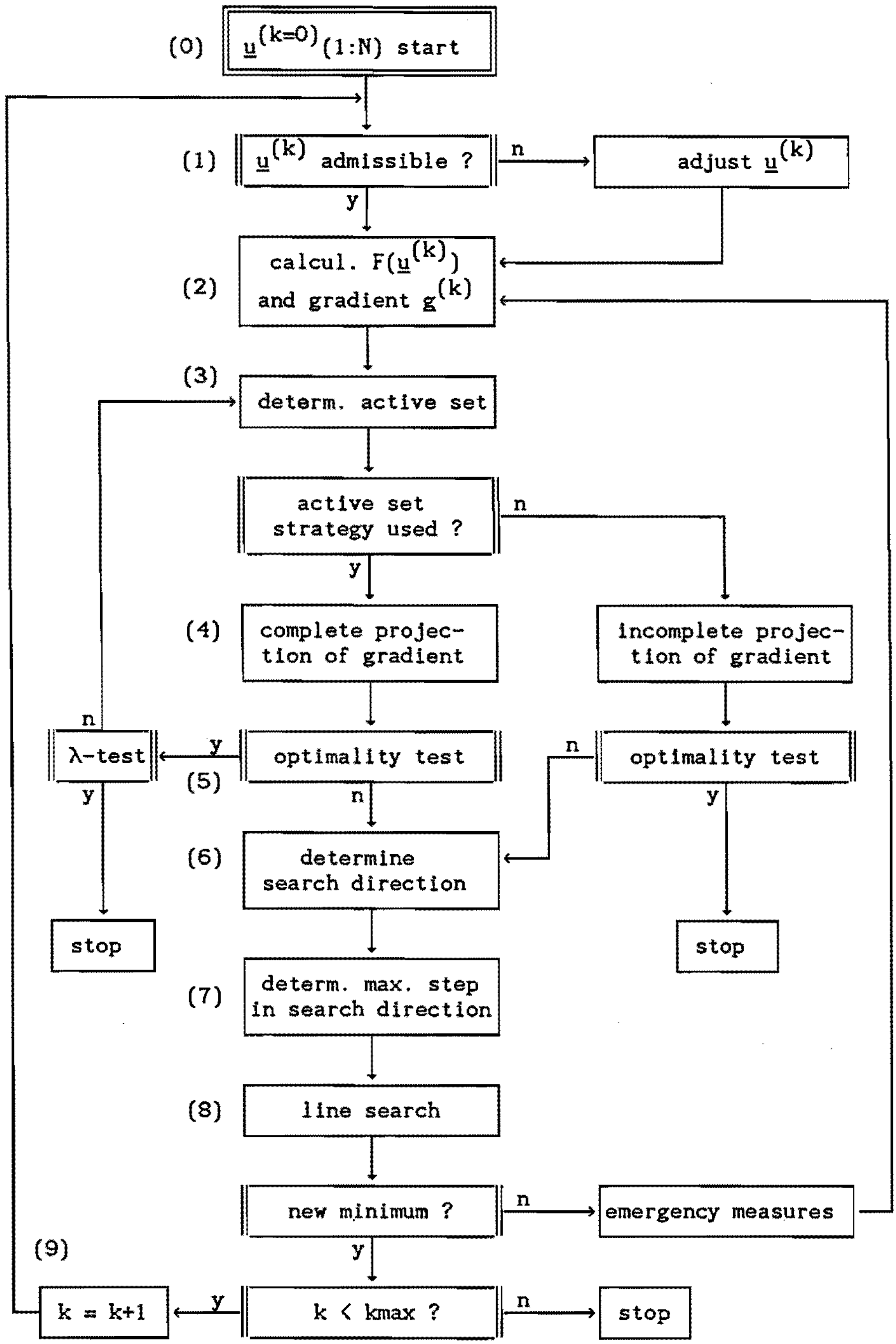


Fig. 2.5: Flowdiagram of the optimisation procedure. The numbers at the left correspond with the steps in the algorithm, as discussed in the text.

(0) Choose an initial control $\underline{u}^{(0)}$.

(1) Check whether $\underline{u}^{(k)}$ is admissible.

(2) Calculate the functional $F(\underline{u}^{(k)})$ and the gradient $g^{(k)}$.

(3) Determine the active constraints in $\underline{u}$.

(4) Project the gradient on the intersection of the tangent planes of the active constraints and calculate the Lagrange multipliers $\underline{\lambda} = (\lambda_1, \ldots ,\lambda_a)$, where a is the number of active constraints. If the active set strategy is not used: use the incomplete projection discussed in Section 2.4.3.

(5) Check whether $\underline{u}^{(k)}$ is optimal in the active set. If $\underline{u}^{(k)}$ is optimal and the active set is changed based on information of the Lagrange multipliers: return to (3).
If $\underline{u}^{(k)}$ is optimal without a change in the active set, or without using the active set strategy: finish.

(6) Determine a new search direction $\underline{p}^{(k)}$.

(7) Determine the maximum step α_{MAX} that can be taken in the search direction so that the constraints in $\underline{u}$ are just not violated.

(8) Perform a line search along $\underline{p}^{(k)}$ and calculate the new $\underline{u}$.

(9) $k = k+1$: Return to (1).

Some of the steps in the algorithm are treated in more detail in the next sections. Some "emergency measures", to be applied if the convergence is bad, are discussed in Section 2.4.9.

2.4.1 Checking the control strategy

If the constraint matrix C differs much from a simple unity matrix, it can be difficult to find an initial control strategy satisfying all constraints. If $\underline{u}^{(0)}$ is not admissible, a special projection procedure is used to search for the nearest point within the domain, and this

point in control space is taken as the new initial control.
The next control strategies $\underline{u}^{(k)}$ are also checked and possibly adjusted in this way.

2.4.2 Calculation of the gradient

The gradient $g^{(k)}$ can be calculated numerically and analytically. For numerical calculation the following central difference formula is used:

$$g(i)_m = \frac{\partial F}{\partial u(i)_m} = \frac{F(u(i)_m+\epsilon) - F(u(i)_m-\epsilon)}{2\epsilon} \qquad (2.16)$$

where $u(i)_m$ denotes the m-th component of the control vector in the i-th time-step, and $g(i)_m$ the associated gradient.
The step size ϵ depends on the scaling of $\underline{u}$ and F and on the absolute accuracy e_F in the calculation of the functional. As will be discussed later, F and $\underline{u}$ are scaled between -1 and 1. This allows us to apply an empirical formula for the calculation of ϵ, given by Gill et al. [GIL81]:

$$\epsilon = 2\sqrt{\frac{e_F}{1 + |F|}} \qquad (2.17)$$

Analytical determination of g requires analytical differentiation of F and the time-discretised system equations. To establish a relationship for this analytical gradient, I define the discrete return function V', which is the discrete-time equivalent of the return function defined in Section 2.2.3 (Eq. 2.11), without the "min"-operator:
$\underline{u}$

$$V'(\underline{x}(i-1),\underline{u}(i:N),i) = \phi(\underline{x}_N,N) + \sum_{j=i}^{N} L(\underline{x}(j-1),\underline{u}(j),j)\Delta t \qquad (2.18)$$

where L(x(j-1),u(j),j) is the contribution to the criterion function per unit of time in step j, with $1 \leq j \leq N$, $\underline{u}(i)$ is the control vector in time step i, $\underline{x}(i-1)$ is the state vector at the start of time step i, and $\phi(\underline{x}(N),N)$ are the so called "end costs" associated with $\underline{x}(N)$, the terminal state of the system.

It can be derived that the gradient can be calculated with the following recurrent relationship:

$$\frac{\partial V'}{\partial \underline{x}(N)} = \frac{\partial \phi}{\partial \underline{x}(N)} \qquad (2.19)$$

$$\frac{\partial V'}{\partial \underline{x}(i)} = \frac{\partial L(i+1)}{\partial \underline{x}(i)}.\Delta t + \left[\frac{\partial \underline{x}(i+1)}{\partial \underline{x}(i)}\right]^T \cdot \frac{\partial V'}{\partial \underline{x}(i+1)} \qquad 1 \leq i \leq N-1 \quad (2.20)$$

$$\frac{\partial V'}{\partial \underline{u}(i)} = \frac{\partial L(i)}{\partial \underline{u}(i)}.\Delta t + \left[\frac{\partial \underline{x}(i)}{\partial \underline{u}(i)}\right]^T \cdot \frac{\partial V'}{\partial \underline{x}(i)} \qquad 1 \leq i \leq N \quad (2.21)$$

and

$$\frac{\partial F}{\partial \underline{u}(i)} = \frac{\partial V'}{\partial \underline{u}(i)} \qquad 1 \leq i \leq N \quad (2.22)$$

These are relationships backwards in time. The derivatives needed are, apart from (2.19):

$$\frac{\partial \underline{x}(i+1)}{\partial \underline{x}(i)}, \quad \frac{\partial L(i+1)}{\partial \underline{x}(i)} \qquad 1 \leq i \leq N-1$$

$$\frac{\partial \underline{x}(i)}{\partial \underline{u}(i)}, \quad \frac{\partial L(i)}{\partial \underline{u}(i)} \qquad 1 \leq i \leq N$$

It is customary to calculate these derivatives together with the system equations, which means: forward in time. Determination of these derivatives in each time step yields the gradients $\partial V/\partial \underline{u}(i)$ (Eq. 2.19 to 2.21), which are combined to calculate the total gradient $\partial F/\partial \underline{u}(1:N)$ (Eq. 2.22).

Analytical calculation of the gradient in this way will generally take less CPU-time than numerical determination. But if the number of state variables is much larger than the number of control variables (which is generally the case in the systems considered here), the matrices $\partial \underline{x}(i+1)/\partial \underline{x}(i)$ are very large and the use of computer memory may be excessive.
The storage of these gradients might be avoided if, after a simulation forward in time, a simulation backward in time is performed in which the gradients are calculated and directly used in the recurrent relationship. This backward-time simulation can cause complications in specific situations, and therefore this approach is not taken here.

The approach developed for the present purpose is to reformulate the recurrent relationship in order to obtain a relation that can be evaluated in forward time. I introduce a set of matrices defined as:

$$Q_i^j = \left[\frac{\partial \underline{x}(j)}{\partial \underline{u}(i)}\right]^T \qquad \text{if } j = i$$

$$Q_i^j = \left[\frac{\partial \underline{x}(i)}{\partial \underline{u}(i)}\right]^T \cdot \left[\frac{\partial \underline{x}(i+1)}{\partial \underline{x}(i)}\right]^T \cdots\cdots \left[\frac{\partial \underline{x}(j)}{\partial \underline{x}(j-1)}\right]^T \qquad \text{if } j > i \qquad (2.23)$$

$$\text{with: } 1 \le i \le N, \quad 1 \le j \le N$$

These matrices represent the influence of the control variables in time step i on the state variables at the end of time step j. Using the Q-matrices, the gradient can be calculated as follows:

$$\frac{\partial F}{\partial \underline{u}(i)} = \frac{\partial L(i)}{\partial \underline{u}(i)}.\Delta t + \left[\frac{\partial \underline{x}(i)}{\partial \underline{u}(i)}\right]^T \cdot \frac{\partial L(i+1)}{\partial \underline{x}(i)}.\Delta t +$$

$$+ \left[\frac{\partial \underline{x}(i)}{\partial \underline{u}(i)}\right]^T \cdot \left[\frac{\partial \underline{x}(i+1)}{\partial \underline{x}(i)}\right]^T \cdot \frac{\partial L(i+2)}{\partial \underline{x}(i+1)}.\Delta t + \ldots +$$

$$+ \left[\frac{\partial \underline{x}(i)}{\partial \underline{u}(i)}\right]^T \cdot \left[\frac{\partial \underline{x}(i+1)}{\partial \underline{x}(i)}\right]^T \cdots\cdots \left[\frac{\partial \underline{x}(N-1)}{\partial \underline{x}(N-2)}\right]^T \cdot \frac{\partial L(N)}{\partial \underline{x}(N-1)}.\Delta t +$$

$$+ \left[\frac{\partial \underline{x}(i)}{\partial \underline{u}(i)}\right]^T \cdot \left[\frac{\partial \underline{x}(i+1)}{\partial \underline{x}(i)}\right]^T \cdots\cdots \left[\frac{\partial \underline{x}(N)}{\partial \underline{x}(N-1)}\right]^T \cdot \frac{\partial \phi(N)}{\partial \underline{x}(N)} =$$

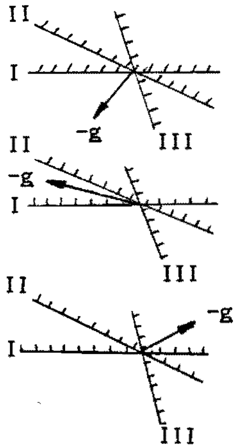
$$= \frac{\partial L(i)}{\partial \underline{u}(i)}.\Delta t + \sum_{j=i+1}^{N-1} Q_i^j \cdot \frac{\partial L(j+1)}{\partial \underline{x}(j)}.\Delta t + Q_i^N \cdot \frac{\partial \phi(N)}{\partial \underline{x}(N)} \qquad (2.24)$$

The Q-matrices can be evaluated in forward time and have a dimension s*m, where s and m are the number of state and control variables respectively. These matrices indicate the extent to which a control vector has influence after a number of time steps. If the elements of Q_i^j are zero, or at least << Q_i^{i+1}, any further influence of the control vector for time steps j'>j can be neglected (provided that the derivative ∂L(j+1)/∂x(j) remains of the same order of magnitude for all time-steps, and this holds for the systems considered here), and it is not necessary to evaluate $Q_i^{j'}$ any further. Besides, it is easy to keep track of the significant columns in Q, which makes it possible to apply special techniques for sparse matrices.
Thus, the calculation of the gradient with these forward-time relations combines a better interpretability with a saving in computer memory use and CPU-time.

2.4.3 Projection of the gradient

The active set strategy

To prevent the control variables from leaving their domain, the search direction has to be projected on the active set of constraints.
If the number of active constraints exceeds the number of control variables (a situation that is sometimes encountered in the problems considered), we have an overdetermined situation, and the projection is not unique. In thise case constraints are removed from the active set depending on the position of the constraint with respect to the gradient direction, as illustrated in Fig. 2.6.



(a) all constraints are removed from the active set

(b) constraint I remains active
II and III become passive

(c) all constraints remain active
→ finish

Fig. 2.6: Removal of constraints in the overdetermined case.

After this, the gradient is projected on the intersection of the planes expanded by the active constraints

$$gp = P * g \tag{2.25}$$

where $P = P[i,j]$ $(1 \leq i \leq m,\ 1 \leq j \leq m)$ is the projection matrix, given by

$$P = I - A\,(A^T A)^{-1}\,A^T \tag{2.26}$$

and $A = A[i,k]$ $(1 \leq i \leq m,\ 1 \leq k \leq a)$ is a matrix obtained by taking all active constraints from the constraint matrix C.

To avoid the calculation of the inverse $(A^TA)^{-1}$, a formula of Rosen, well-known in matrix theory, is used to calculate P if one active constraint is added to (or removed from) the active set [JON82, MEE86]:

$$\left[\begin{bmatrix} A^T \\ \hline \underline{n}_i^T \end{bmatrix} * \left[A \mid \underline{n}_i \right] \right]^{-1} = \left[\begin{array}{c|c} A^TA & A^T\underline{n}_i \\ \hline \underline{n}_i^TA & \underline{n}_i^T\underline{n}_i \end{array} \right]^{-1} =$$

$$= \left[\begin{array}{c|c} B & \underline{b} \\ \hline \underline{b}^T & \beta \end{array} \right] \qquad (2.27)$$

where:

$[A \mid \underline{n}_i]$ = a matrix obtained from A by adding or removing a new constraint with normal vector $\underline{n}_i$, which contains the i-th row of the constraint matrix C.

$$\beta = (\underline{n}_i^T\underline{n}_i - \underline{n}_i^TA(A^TA)^{-1}A^T\underline{n}_i)^{-1} = (\underline{n}_i^T(I - A(A^TA)^{-1}A^T)\underline{n}_i)^{-1}$$

$$\underline{b} = - \beta * (A^TA)^{-1}A^T\underline{n}_i$$

$$B = (A^TA)^{-1} + \left(\frac{1}{\beta} \right)*\underline{b}*\underline{b}^T$$

Along with the projection matrix P, the Lagrange multipliers, which are used in the optimality test, are calculated:

$$\underline{\lambda} = (A^TA)^{-1}A^T* \underline{g}, \qquad \underline{\lambda} = (\lambda_1,\ldots,\lambda_a) \qquad (2.28)$$

Incomplete projection of the gradient

The active set strategy incorporates a complete projection of the gradient on the active constraints, irrespective of the search direction associated with that gradient. This means that even if the search direction points into the control domain, first the extremum on the active set has to be determined before the constraint can be abandoned. However, in our experience an incomplete projection strategy may improve convergence. This incomplete projection refers to the projection of only those components of the gradient that would result in a search direction pointing outside the domain.
As indicated in the scheme of the optimisation method, this incomplete

projection strategy can be used as an alternative to the active set strategy. If one of these strategies does not lead to satisfying results, the other strategy is applied.

2.4.4 The optimality test

In the optimality test it is checked whether the control is optimal with respect to a gradient criterion, related to the accuracy of the criterion function in a manner proposed by Gill et al. [GIL81], which reflects the necessary condition for a sufficient approximation of an optimum:

$$||gp|| \leq \sqrt[3]{10^{-d}}\,(1 + |F^{(k)}|) \qquad (2.29)$$

where d is the number of significant decimals in the criterion function value, and $F^{(k)} = F(\underline{u}^{(k)})$.

If criterion (2.29) is satisfied, and if the active set strategy is applied, the Lagrange multipliers are considered, as mentioned before. If these multipliers do not fulfill the condition for a removal of active constraints, the optimisation procedure stops if the following convergence criterion is satisfied:

$$|F^{(k)} - F^{(k-1)}| \leq 10^{-d}\,(1 + |F^{(k)}|) \qquad (2.30)$$

In Section 2.4.9 some aspects of convergence are discussed in more detail with regard to the characteristics of the processes considered.

2.4.5 Determination of the direction of search

If the active set is not changed and the reset number of iterations (see Section 2.3) is not exceeded, $\underline{p}^{(k)}$ is calculated with the Fletcher and Reeves formula (2.14), but now applied to the (incompletely or completely) projected gradients:

$$\underline{p}^{(k)} = -\,gp^{(k)} + \frac{gp^{(k)^T} . gp^{(k)}}{gp^{(k-1)^T} . gp^{(k-1)}} \cdot \underline{p}^{(k-1)} \qquad (2.31)$$

Otherwise, the steepest descent direction $-\,gp^{(k)}$ is chosen as the new search direction.

2.4.6 Maximum step size in search direction

Given the search direction $\underline{p}^{(k)}$ and the constraint matrix C, the maximum step size α_{MAX} is calculated so that $\underline{u}^{(k)} + \alpha_{MAX}\, \underline{p}^{(k)}$ just does not violate the constraints. This procedure is illustrated in Fig. 2.7.

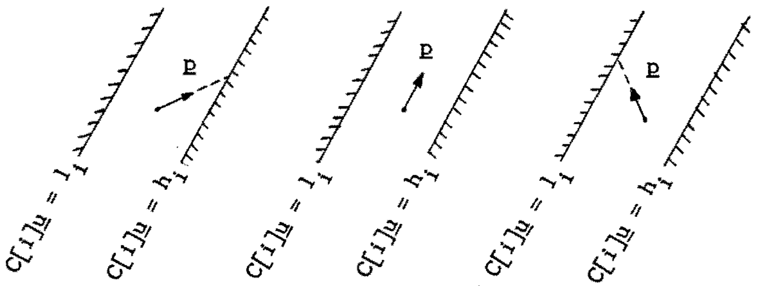


Fig. 2.7: Determination of the maximum step size in the search direction.

a. constraint $C[i]\underline{u} = h_i$ determines $\alpha_{MAX}[i]$.

b. the domain is open in the search direction; $\alpha_{MAX}[i]$ is given a default maximum value.

c. constraint $C[i]\underline{u} = l_i$ determines $\alpha_{MAX}[i]$.

Only the passive constraints in $\underline{u}$ are screened, and:

$$\alpha_{MAX} = \min_{1 \le i \le r-a} (\alpha_{MAX}[i]) \tag{2.32}$$

where $\alpha_{MAX}[i]$ is the maximum step size with regard to the i-th passive constraint, and r-a is the number of passive constraints.

2.4.7 The line search procedure

In the line search procedure the step size $\alpha_{MIN} \in [0, \alpha_{MAX}]$ that minimises F along the search direction, is determined:

$$F(\underline{u}+\alpha_{MIN}*\underline{p}) = \min_{\alpha \in [0,\alpha_{MAX}]} F(\underline{u}+\alpha*\underline{p}) \tag{2.33}$$

We write the functional temporarily as:

$$F'(\alpha) = F(\underline{u}+\alpha*\underline{p}) \tag{2.34}$$

The starting point for the line search, $F'(\alpha_1)$ with $\alpha_1=0$, is already known from the previous iteration. Next, two points on the line are evaluated:

$$\Delta\alpha = \alpha_{MAX}/20$$
$$F'(\alpha_2) = F'(\alpha_1+\Delta\alpha) = F'(\alpha_{MAX}/20) \tag{2.35}$$
$$\Delta\alpha = 2\alpha_{MAX}/20$$
$$F'(\alpha_3) = F'(\alpha_2+\Delta\alpha) = F'(3\alpha_{MAX}/20) \tag{2.36}$$

a) If $F'(\alpha_1)\geq F'(\alpha_3)$ and $F'(\alpha_2)\geq F'(\alpha_3)$, a new step $\Delta\alpha=2\Delta\alpha(old)$ is taken and a new $F'(\alpha_3) = F'(\alpha_3(old)+\Delta\alpha)$ is calculated. The old $F'(\alpha_3)$ and $F'(\alpha_2)$ become $F'(\alpha_2)$ and $F'(\alpha_1)$ respectively, and the relation between $F'(\alpha_1)$, $F'(\alpha_2)$ and $F'(\alpha_3)$ is again evaluated. In this way the search interval $[\alpha_1,\alpha_3]$ is shifted with an exponentially growing step. The maximum number of evaluations of F' per line search is thus limited to 5.
   If α_3 exceeds α_{MAX}, α_3 is put equal to α_{MAX}, and the curvature of the parabola through $F'(\alpha_1)$, $F'(\alpha_2)$ and $F'(\alpha_3=\alpha_{MAX})$ is calculated. If the curvature is positive, quadratic interpolation gives α_{MIN}, else $F'(\alpha_{MAX})$ is accepted as the line minimum.
b) If $F'(\alpha_1)>F'(\alpha_2)$ and $F'(\alpha_2)<F'(\alpha_3)$ the minimum $Fmin'(\alpha_{MIN})$ is determined by quadratic interpolation.
c) If neither a) nor b) is the case, a bisection method between the points $F'(\alpha_1)$ and $F'(\alpha_2)$ (with $F'(\alpha_2)>F'(\alpha_1)$) is applied to search for a minimum. This method is limited to 6 steps. If it does not lead to a criterion function value $F'(\alpha_{MIN})<F'(\alpha_1)$ the search direction has to be reset or modified in another way. These "emergency measures" are generally application-dependent, and they will be given attention in Section 2.4.9.

2.4.8 Scaling

It is assumed that the optimisation procedure works with scaled control variables and a scaled criterion function. The aim of scaling (which is strictly-spoken a system-dependent step and therefore not a part of the optimisation procedure) is twofold:
- the gradients are balanced: the influence of every control variable

in every time-step is approximately of the same order of magnitude, which means that, given a certain convergence criterion, the accuracy of the minimisation in every direction is also of the same order of magnitude.
- the gradients are scaled correctly with regard to the convergence criterion, thus preventing the optimisation procedure from terminating too early or not at all.

The relevant domain of control variables and criterion, defined as the domain that is covered during the optimisation process, is projected between -1 and 1. The linear scaling formula is given by (2.37):

$$u_i = \frac{2\,u_i^*}{h_i - l_i} - \frac{h_i + l_i}{h_i - l_i} \qquad (2.37)$$

where: u_i = the scaled variable (control variable or criterion)

u_i^* = the variable to be scaled

h_i = upper boundary of the relevant domain of u_i

l_i = lower boundary of the relevant domain of u_i

2.4.9 Some aspects of convergence

The numerical optimisation procedure, as discussed in the previous sections, was found to be robust and reliable, especially if the criterion function had a mathematically "decent" behaviour. But this does not guarantee convergence to the global optimal solution. In addition, for non-smooth problems the procedure can get stuck, because one of the criteria of the optimality test cannot be satisfied.

In the beginning of this chapter some of the problems to be kept in mind when applying dynamic optimisation were indicated. They are reformulated here in the following questions:
- Given the differences in time and efforts, do we want a better control or the global optimal control ?
- How accurately do we want to determine the control ?

or, in other words:
- Does the iterative method combined with the stopping criteria provide us with the solution we want ?

This section reflects on the answers to these questions by discussing some aspects of convergence, and what can be done to overcome convergence problems. The following two issues can be identified:
- what is necessary to make a method of dynamic optimisation applicable to realistic problems.
- what extra criteria are needed, apart from the mathematical convergence criteria, to obtain the result "that we want".

This section first discusses the mathematical convergence criteria and some special measures for the optimisation of non-smooth functions, followed by some reflections on global convergence and the concept of "physical convergence".

Mathematical convergence

For all optimisation methods including the iterative method discussed in this chapter the necessary condition for a (local) optimum is:

$$\underline{gp}^{(k)} = \underline{0} \text{ or } \leq \underline{eps_1} \qquad (2.38)$$

This provides a criterion for quitting the iterative loop. Of course in practical cases the gradient is never exactly zero. Therefore the condition is moderated by introducing a tolerance, which is related to the accuracy of the criterion function, as given in Eq. 2.29. The above mentioned condition is based on some assumptions about the behaviour of the functional to be optimised. But in the case of a non-smooth criterion function with an minimum in a sharp "valley", a point satisfying condition (2.38) may be difficult to obtain. Therefore the extra criterion based on the comparison of criterion function values in successive iterations is used:

$$|F^{(k+1)} - F^{(k)}| \leq eps_2 \qquad (2.39)$$

where eps_2 is also related to the accuracy, cf. Eq. 2.30.
The set of stopping conditions (2.29) and (2.30) is also recommended by Gill et al. for the solution of non-linear optimisation problems with linear inequality constraints [GIL81]. However, the optimisation of non-smooth functionals requires extra "emergency measures", which were already indicated in Fig. 2.5, and some of which are discussed below.

Minimisation of non-smooth functions

Numerical calculation of the gradient with the two-step formula given in Eq. 2.16 allows detection of situations with sharp "valleys" in the criterion function. This is particularly helpful if, due to the inaccurate line search, a convergence-slowing "zigzagging" between the walls of the valley occurs. In that case the optimisation procedure applied in this thesis is modified: the components of the search direction pointing in the direction of the walls of the valley are put equal to zero, thus enabling the optimisation procedure to "walk along the bottom of the valley" (see Fig. 2.8). In our experience this has a considerable benificial effect on convergence.

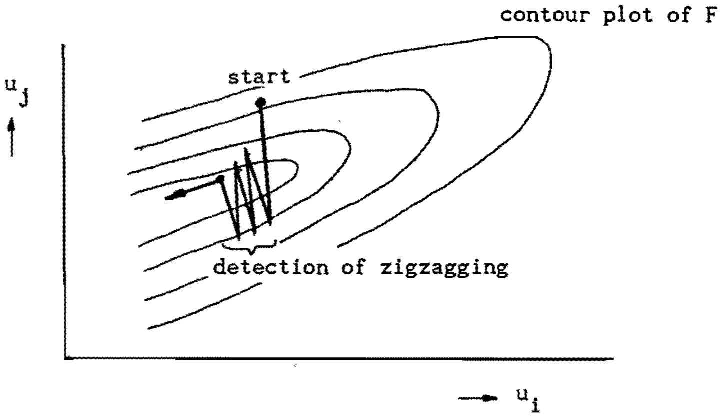


Fig. 2.8: Changing the search direction in the case of a sharp valley in the criterion function.

Another option used in the implementation of the procedure is that the criterion function is made "smooth" at places where the first derivative is known to be discontinuous as a function of a control variable. This is achieved by replacing the actual criterion function by a falsified one (for example: a parabolic segment) in the neighbourhood of this point, as shown in Fig. 2.9. This also has a beneficial effect on convergence: the optimum in the falsified function is found more easily, whereas the approximation of the actual function by the falsified one can be chosen arbitrarily accurate.

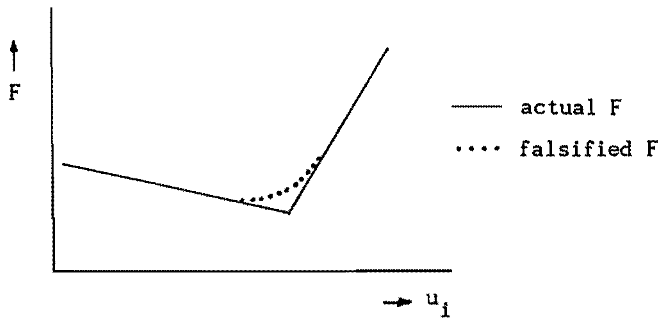


Fig. 2.9: Smoothening the criterion function.

Global convergence

At best, the method discussed here guarantees convergence to a local minimum, which is not necessarily the global minimum. In fact, owing to the relative large number of degrees of freedom for optimal control problems in general, and the resulting large number of variables to be optimised, it is almost impossible to develop a method that guarantees global convergence without the need for an excessive amount of CPU-time.

An estimation of the global optimum in problems with a large number of variables might be found with the aid of Monte-Carlo techniques, applied to zero-order optimisation methods. In that case subsequent criterion function values would be calculated and compared for random control strategies within the domain of $\underline{u}$. However, these techniques were not considered here.

The approach followed in this thesis is that the method is restarted a number of times with a different $\underline{u}^{(0)}$. The control strategy resulting in the best value of the criterion function after the specified number of restarts is accepted as an estimation of the global optimum. The number of restarts and the choice of $\underline{u}^{(0)}$ must be based on a thorough knowledge of the process, and insight into its (modes of) behaviour will then prove very helpful.

Physical convergence; optimisation of the physical performance

As stated in the previous sections, a number of choices are involved in the development of an effective method of dynamic optimisation. These choices may be dictated by numerical or convergence problems, and some of them are empirical and/or related to the physics of the problem.
In general it is of no use to define a convergence criterion without reflecting upon the aims of the optimisation. Especially in control problems the mathematical optimal solution may not be the best solution in practice, because of all kinds of limitations and non-mathematical requirements. For example: the optimal control strategy has rapid fluctuations in the control variables (cf. Section 5.10), whereas a smooth behaviour of these variables may be preferred for the process considered. In practice many of these "additional conditions" occur, which cannot be quantified easily, if at all [RAD88].
Moreover, it is at best of academic interest to calculate the optimal control strategy more accurately than can be realised in practice, or, than would be useful because of model errors or inaccurately known disturbance patterns, unless the optimal control is used as a yardstick for other control strategies (cf. Section 2.1.2).
In this thesis one of the principal aims is to use dynamic optimisation as a tool for arriving at simple but effective near-optimal strategies. In other words: what is actually wanted is not convergence to a dynamic optimal solution, but to one or more practicable, robust control strategies. This suggests another performance criterion which, though it is not possible to formulate it in precise mathematical terms, should be kept in mind. The control should be good enough to serve as a stepping stone to practicable strategies. This will be called "physical convergence" or "physical performance optimisation" in this thesis.
One way of bridging the gap between the mathematical optimal control and a practicable control is to develop suitable adaptation techniques, which are discussed in Section 2.5. Another way is the development of a near-optimal control based on dynamic optimisation results, cf. Section 5.8.3.

2.5 Adaptive Control

2.5.1 Introduction

The beginning of this chapter mentioned the difference between the dynamic optimal control and the control strategy to be applied in practice. Section 2.4.9 briefly discussed the gap between the theory and the practice of dynamic optimisation. In general a dynamic optimal control strategy is not optimal in practice, because of:
- Errors in the model, or in the choice of the criterion.
- Errors in the actual process (other components installed than assumed in the design phase, etc.)
- Differences between the expected disturbance inputs and the actual disturbance inputs. These differences can both be systematic and random.

The first two items may be referred to as "structural errors". Because one of the purposes of this study is to look at a class of systems rather than one specific system already built, these errors are not evaluated within the scope of this thesis.
This section focuses on the adaptation of control strategies to differences in the disturbance inputs.

2.5.2 Conceptual framework

The existence of deviations from the assumed disturbance pattern does not necessarily mean that the original dynamic optimal control has to be changed. If the fluctuations are stochastic but have a mean value equal to the assumed disturbances, and their influence on the criterion function is negligible, no action has to be taken: the control strategy is "robust" with regard to such deviations. Checking for robustness by a form of sensitivity analysis will be discussed in Chapter 5.
If the fluctuations are relatively small, their effect might be eliminated by small variations in the control strategy which do not affect the criterion function value significantly (the first derivative to the optimal control variables being zero, which forms the necessary condition for optimality).
Here we shall concentrate on deviations that may be rather large and lengthy with regard to the optimisation period. Then it may be desirable to adapt the controlled system in one way or another to the deviating conditions.

By adaptive control we understand a control strategy, of which the parameters, the structure or the setpoints are modulated or chosen, based on information on the actual states and the external influences of the system, and reducing a certain cost criterion or obtaining a desired system response [AME84].

In recent years numerous research efforts in control theory focused on adaptive control. However, the practical applications are not very wide-spread, although the potential scope of adaptive control seems very great. It may be applied to non-stationary processes like the ones discussed in this thesis, but it may also to stationary processes, in start-up, tuning, switching between different operational modes, or if the disturbances acting upon the process are very large. In all applications I have studied, controller parameters are tuned to compensate for changes in process behaviour.
A distinction is made between:
- controllers with direct parameter-adjustment: in these controllers no explicit identification of the process behaviour takes place (among others: Model Reference Adaptive Control).
- controllers with indirect parameter-adjustment: in this case the parameters are tuned after a process identification has taken place.

Model Reference Adaptive Control (MRAC) may refer to types of adaptive control using a model, or to the use of a model's responses as a reference. In this thesis the focus is on the latter: the desired response of the system described by a mathematical model, being e.g. its state trajectory $\underline{x}(t)$. If the actual behaviour of the system departs from the desired state trajectory, it is adapted by changing parameters (or the structure) of a controller or by providing additional process input signals (signal-adaptation).

In this thesis the adaptation problem is formulated as follows: An (open-loop) dynamic optimal strategy is calculated up to a certain time-horizon, during which the disturbances acting on the system are assumed to be known a priori. The strategy is applied in practice, and, owing to any of the reasons mentioned in Section 2.5.1, the state trajectory drifts away from the optimal one. The question to be answered is what (control) action has to be taken to improve operation.

As already mentioned in Section 2.1, in this work no control structure is presumed, which means that, unless dynamic optimal control can be approached with some kind of feedforward and/or feedback, the optimal control strategy takes the form of a set of input signals or setpoints at every instant. In this case adaptation comes down to adapting the dynamic optimal control inputs.

The combination of process, assumed disturbance pattern and optimal control inputs in fact constitutes a mathematical model describing a desired optimal state trajectory $\underline{x}^{opt}(t)$. However, the difference with the conventional concept of MRAC is that the optimal control refers to the assumed disturbance pattern. For any other pattern the optimal control, and thus the desired state trajectory, will be different.

In this context, the adaptation problem may be tackled in several ways:
1) Using a one (or more)-step-ahead predictor and calculating a new control strategy. If the number of prediction steps equals the number of time steps in dynamic optimisation, this comes down to a repeated dynamic optimisation over a shifting horizon.

2) Guiding the system back to the optimal trajectory (presuming that this trajectory is, on the average, the best). This comes to Model Reference Adaptive Control.
3) A combination of 1) and 2): calculating a new control strategy over a specified horizon but with the constraint that some "terminal" state approaches the optimal terminal state of 2).

Fig. 2.10 gives an impression of the 3 approaches.

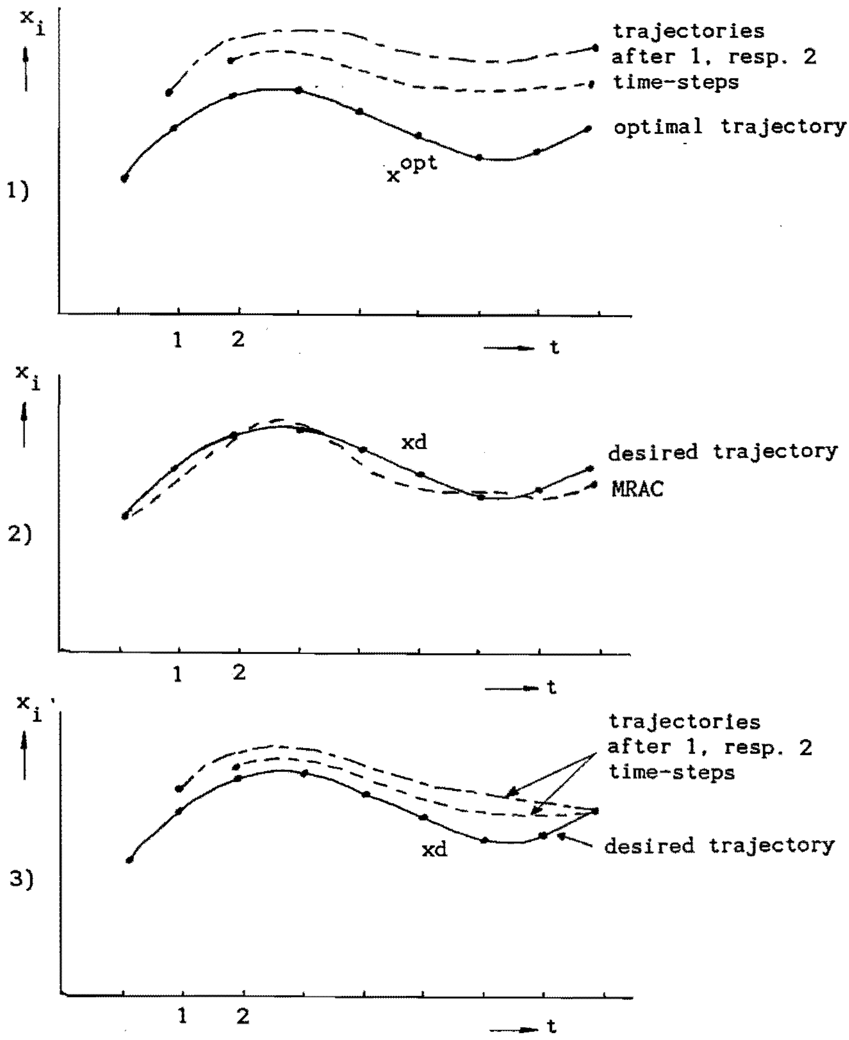


Fig. 2.10: Three basic approaches to the adaptation problem in this thesis.

2.5.3 Numerical solution

From the above it might be clear that the adaptation problem comes close to the dynamic optimisation problem, the basic differences being the use of actual information of the process for the purpose of adaptation, together with a (possibly) different interpretation of the criterion. In essence, it may be regarded as an adaptation of the dynamic optimisation process.

For solution methods 1 and 3 mentioned in Section 2.5.2 the criterion is equivalent to the one used for the dynamic optimisation, with an optional term:

$$P(\underline{x}^{opt}(N)-\underline{x}(N)) \tag{2.40}$$

if the terminal constraints are satisfied using penalty function techniques.

In the case of adaptation to a desired trajectory (MRAC), the criterion chosen to be optimised is:

$$\sum_{n=1}^{Na} (||\underline{x}^{opt}(n)-\underline{x}(n)|| * W(n))^2 \tag{2.41}$$

where $W(n)$ is a weighting function and Na is the number of adaptation steps.

It should be pointed out that this approach could be refined if we knew the influence of the actual disturbances on the dynamic optimal trajectory, or, in other words, if we knew the the changes in $\underline{x}^{opt}$ as a result of the actual disturbances. However, evaluating this influence, numerically or analytically, is very elaborate for the processes in this thesis, and therefore this refinement was omitted.

Another way of guiding the system back to the desired trajectory is to linearise the system equations around this trajectory, and to solve the associated optimal control problem (with a quadratic criterion) in a state feedback form. However, again the nature of the processes considered (in particular the non-linear behaviour and the magnitude of the fluctuations in the disturbance signals) do not allow such a "linear-quadratic" approach.

The adaptive control problems considered here can be treated as an embedded form of dynamic optimal control. The numerical method described in Section 2.4 can thus be applied with minor modifications, discussed in Chapter 4.

3 Description of the thermal energy systems

3.1 Introduction

In Chapter 1 a short description of the processes discussed in this thesis is given. The present chapter provides a treatment of this general class of thermal energy systems, emphasizing the characteristics of the systems from the point of view of systems engineering. In the next chapter the connection is made between the application and the optimisation approach of Chapter 2.
The components of the systems can be divided in the following categories:
- supply components: collectors for solar or ambient heat and other heat exchangers.
- transfer components: heat pump, heat exchanger.
- storage components: short-term or long-term; various storage media.
- demand components: heat distribution system, heat exchangers.

These components, together with their mathematical models and the assumptions are discussed in Section 3.2. except for the heat exchanger: although various system configurations with heat exchangers have been part of the investigations, the results of these will not be highlighted in Chapter 5, and hence a treatment of this component has been omitted.
Section 3.3 treats the sizing and the interconnection of the components and some general system characteristics, together with the simulation method.

3.2 Modelling of the components

3.2.1 Introduction

In this section a description is given of the components that may be applied, emphasizing their dynamics and control variables.
The mathematical models describing their behaviour are discussed briefly. In general these models have to meet two requirements:
- providing a satisfactorily accurate description of the processes with a reasonable computational effort.
- providing an insight into the component's behaviour.

In principle a model may be based exclusively on the input-output relationships (a "black-box" model) obtained with some identification technique. Then the model structure and the parameters usually have no physical meaning, i.e: they cannot be explained on the basis of physical laws or quantities.
In this thesis so-called "white models" are used, i.e. models that are based on physical relationships between input, intermediate and output variables. Reasons to prefer white to black-box models are, for example:

- better interpretability of the results.
- white models can be made in the design phase, whereas black-box models can only be developed for an existing process, or, if white models are already available.
- explicit incorporation of design variables in white models.

The latter reason is illustrated with an example: a heat pump can be modelled using a (black-box) polynomial approach in which the outlet temperatures are described as a function of the inlet temperatures, rotation speed and flow rates. The model parameters have to be determined every time the value of a design parameter (like the condenser heat exchange area) is varied, unless the influence of this parameter is also described in the polynomial (introducing extra identification efforts). Using the quasi-stationary model described in Section 3.2.2, which is based on the physics of the component, the influence of design parameters, being explicit parameters in this model, is directly taken into account.

The models to be discussed are typical examples of so-called "optimisation models". The main characteristic of an optimisation model is the speed of calculation: an optimisation procedure requires a large number of evaluations of the system equations, thus imposing restrictions on the allowable computational effort. As a result, the accuracy cannot be as high as in detailed simulation models.
The general idea behind the models chosen was to provide a realistic description of a component while ignoring secondary effects. All models used have been validated by experiments [DEL87a], from which it was concluded that the requirements were met.

A description of a model without an explicit treatment of the assumptions made is scientifically not valid. Some of these assumptions discussed in the next sections may seem rather severe, but must be seen in the light of the aim to describe the behaviour of <u>a</u> class of systems, and not of a <u>specific</u> process already built.
In the following sections first the reality is discussed, then the model together with the assumptions is described, followed by an enumeration of control, design and state variables associated with that component.

3.2.2 Heat pump

In a heat pump heat from a relatively low temperature heat source is transferred to heat at a higher temperature using the thermodynamic Carnot proces. Fig. 3.1 gives a schematic view of the heat pump with the relevant symbols.

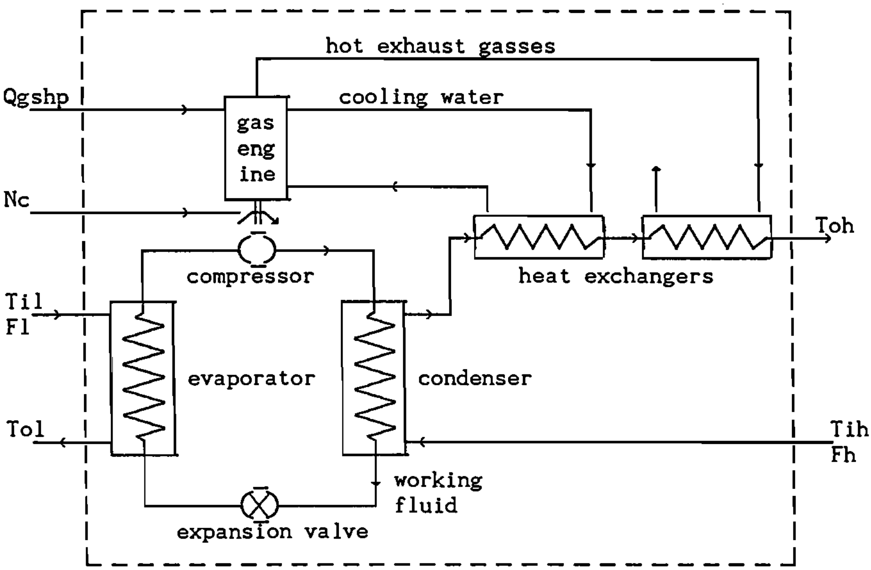


Fig. 3.1: Schematic view of a gas driven heat pump.

In the case shown here, the heat pump is driven by a gas-fired piston engine. The evaporator extracts heat from an external stream with low inlet temperature Til, and flow rate Fl, cooling it to Tol, the heat evaporating a working fluid (up till now usually halogenated hydrocarbons are applied, but there is a strong tendency towards the development of other working fluids, for environmental reasons) at low pressure and temperature Tev, raising this fluid to a higher temperature. The vapour is compressed to a higher pressure and temperature and fed to the condenser, where it is cooled and condensed at temperature Tco, heating an external stream having high inlet temperature Tih and flow rate Fh, to the outlet temperature Toh. The condensed working fluid is returned to the evaporator through an expansion valve. Heat from cooling water and exhaust gas is recovered via two heat exchangers after the condenser output.

A coefficient of performance is defined by:

$$COP = Qhp/Qgshp \qquad (3.1)$$

where:
Qhp is the power delivered by the condenser and the two heat exchangers.
Qgshp is the power consumed by the engine.

In characteristic operational conditions the COP increases with increasing Fl, Fh and Til, and decreases with increasing Nc and Tih.

Slenders [SLE81, SLE85] has developed a calculation model for the steady state conditions of a heat pump. This model is composed of a set of 25 non-linear equations (energy-balances etc.) which has to be solved iteratively. The independent variables in this model are the rotation speed of the heat pump compressor Nc, the flow rates Fl and Fh, and the temperatures Til and Tih. The model is used to calculate the values of Tol, Toh and Qgshp.

$$Tol = Tol(Til, Tih, Fl, Fh, Nc) \tag{3.2}$$

$$Toh = Toh(Til, Tih, Fl, Fh, Nc) \tag{3.3}$$

$$Qgshp = Qgshp(Til, Tih, Fl, Fh, Nc) \tag{3.4}$$

If any of the input temperatures is not known explicitly (e.g. because it is related to Tol or Toh via another component), the (linear or non-linear) relationship between that input temperature and the output temperature (e.g. Til = b0+b1*Tol) is used as an extra equation in the iterative process instead of the input temperature, so that the set of equations is always solvable.

The following assumptions are made:
- evaporator and condenser are counter-flow heat exchangers with constant overall heat transfer coefficients.
- heat losses from heat exchangers and connecting pipes to the surroundings are negligible.
- there is no pressure loss in heat exchangers, compressor and connecting tubes.
- compression is purely polytropic.
- there is no subcooling of the refrigerant in the condenser.
- expansion is isenthalpic.
- the energetic efficiencies of compressor and gas engine are constant.
- the recovery efficiency of heat from exhaust gas and cooling water is constant.

The control variables of the heat pump are the rotation speed of the compressor and the evaporator and condenser fluid flows. Design variables are the heat-exchanging areas of condenser and evaporator (Aco and Aev) and the swept volume of the compressor Vc.

3.2.3 Collectors

There are various types of collectors, ranging from high efficiency evacuated tubular solar collectors to simple ambient heat exchangers. An intermediate range type of collector is the flat plate solar collector, in which a fluid like water is led through small pipes or other kinds of channels in a plate that absorbs solar radiation.
Equation 3.5, a simple quasi-stationary equation referred to in the literature [DUF80] is used to describe the relationship between inlet and outlet temperature. The assumptions made are:
- no conduction of heat in the direction of the flow.
- the temperature in the collector is uniform perpendicular to the flow direction in any plane parallel to the absorber plate.
- the heat losses are proportional to the temperature difference between collector plate and the surroundings.
- heat transfer during a time-step is constant.
- no freezing or boiling of the fluid occurs.
- the efficiency factor is equal to unity.

$$Toc = Hc*Tic+(1-Hc)*Teq \qquad (3.5)$$

where: Toc = collector outlet temperature
Tic = collector inlet temperature
Hc = $\exp(-Uc*Ac/(\gamma w*Fc))$
Uc = collector heat loss coefficient
Ac = collector area
γw = specific heat collector medium
Fc = collector flow rate

Teq is the equivalent ambient temperature [RON80], combining the effects of absorbed solar irradiation and ambient temperature, and is defined by:

$$Teq = Ta+Qs/Uc \qquad (3.6)$$

where: Ta = ambient temperature
Qs = absorbed solar irradiation

The control variable for a collector is the flow rate Fc, design variables are the collector area Ac, and the heat loss coefficient Uc, the latter being related to the type of collector (e.g. Uc $\approx$ 2 $W/m^2/K$: evacuated tubular collector; Uc $\approx$ 15: energy roof).
For given values of Fc, the design variables and the thermal properties, Eq. (3.5) represents a simple linear relationship between inlet and outlet temperature, which is used for the calculation of the equilibrium temperatures in the system.
From Eq. 3.5 it can be derived that the power withdrawn from the collector is at a maximum if Fc is maximal, provided that the inlet temperature is constant.

3.2.4 Long-term heat storage

By long-term heat storage I mean the storage of heat for a period of at least six months. A typical example is the seasonal heat storage, a type of which is treated here. The idea of a seasonal heat storage is to store the summer heat surplus for use in winter. There are various alternatives for seasonal heat storage, like rock caverns, aquifers, and heat exchangers in the soil. In this thesis the focus is on underground heat storage via a heat exchanger.
The seasonal heat storage considered here consists of a cylindrical storage volume with coaxial rings of pipes vertical in the ground (see Fig. 3.2).
Hot water is circulated through pipes in the ground, thus heating the surrounding ground. Owing to the very slow conduction of heat in the ground, and if the size of the storage is sufficiently large, it is possible to extract in winter 70 to 80 % of the heat that was injected in summer (see, for example, [LUN84a], and various papers in [PRO81, PRO82, PRO83, PRO85]).

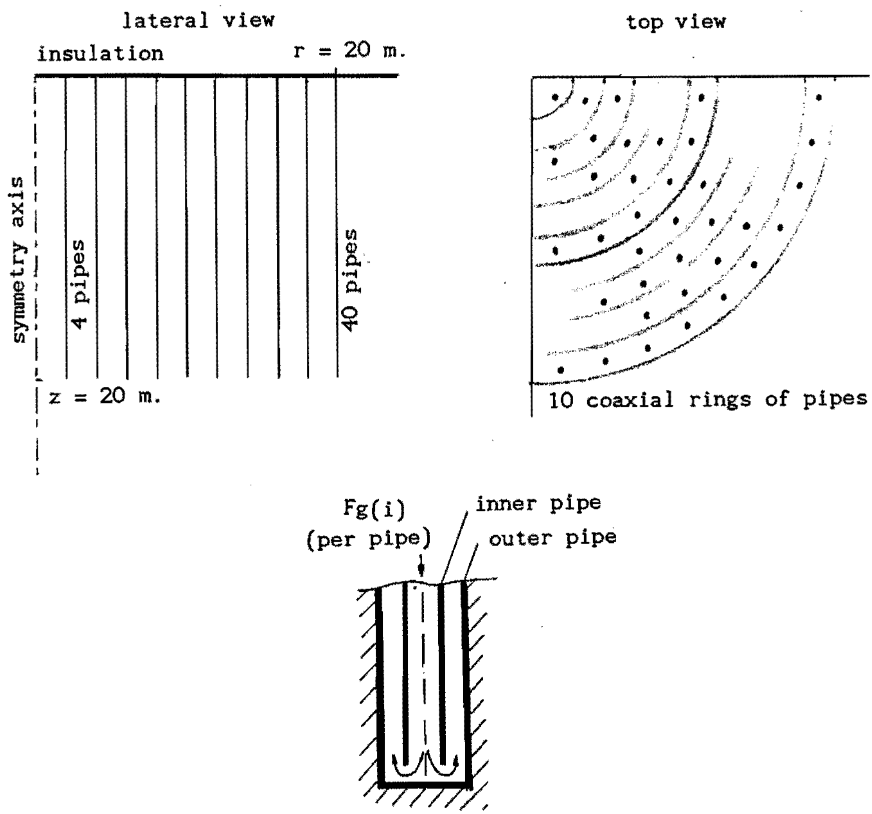


Fig. 3.2: Schematic view of a seasonal heat storage.

A calculation model for this configuration was developed in the System and Control Technology Group, and is described in [SAN84] and [DEL86]. The heat transfer phenomena in a heat exchanger pipe during a time-step are approximated by a semi-analytical (finite-element type of) method, which yields source terms representing the heat exchanged between pipes and ground.
The heat conduction equation for the ground with source terms for the pipes is solved using an Euler-explicit finite-difference method and a typical time step of 1 hour or 1 day.
The assumptions are:
- apart from the source terms only heat conduction is taken into account, the effects of ground water flow can be neglected [DEL85].
- the temperature profile in the ground is rotation-symmetric around the vertical axis through the center of the storage.
- no freezing of the ground, nor evaporation of the ground water occurs.
- the ground is homogeneous and isotropic.
- the insulation on top of the storage is perfect.

Within one time step, the input-output temperature relationship of the pipe model is linear for given values of flow rates and ground temperatures, and hence the following relationship for the ground heat exchanger as a whole, under the assumption that the inlet temperature is equal for all pipes, may be written as:

$$\overline{Tog} = Ag + Bg \times Tig \qquad (3.7)$$

where: $\overline{Tog}$ = average outlet temperature of the heat exchanger pipes
Tig = inlet temperature ground heat exchanger
Ag = constant depending on flow rates and ground temperatures
Bg = constant depending on flow rates

Like the collector equation (3.5), this equation is used for the determination of the equilibrium temperatures, which is explained in Section 3.3.3.
Control variables are the flow rates per sector of pipes (radius-dependent), a sector being composed of one or more coaxial rings. State variables are the temperatures of the discretised segments in the ground (Tg(n)). Principal design variables are the number of pipes, their length, their mutual distance, their distance from the axis, and hence also the volume of the storage.

3.2.5 Short-term heat storage

The short-term storage serves as a buffer against variations in heat supply and demand during upto a few days.
In this thesis the storage is assumed to be a vessel containing a fluid like water. If heat is supplied to, or withdrawn from, the vessel, the thermal stratification of the water in the vessel is taken into account. This means that the temperature difference between the water supplied to the vessel and the place where it is supplied is minimised. Likewise, if heat is to be withdrawn at a specified temperature, the temperature difference with the place of withdrawal is minimised. It is assumed that:

- the vessel has no heat losses to the surroundings.
- the temperature stratification is perfect, in other words, there is no mixing or heat conduction between layers of different temperature.

In the calculation model of this storage the temperature stratification is simulated by assuming that the vessel is built up from a number of so-called "registers" [RAD88], each register containing a quantity of water with the temperature that is associated with that register (see Fig. 3.3).

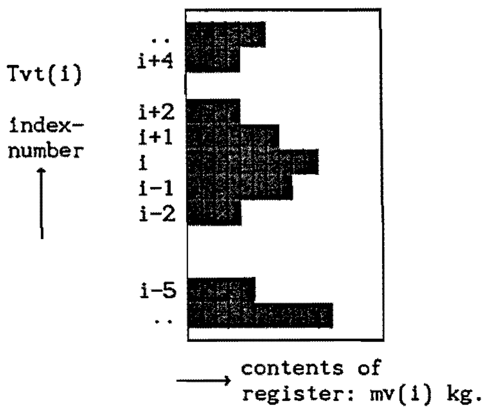


Fig. 3.3: Modelling of the thermal stratification in the short-term storage vessel. Register model.

The temperature Tvt(i) of a register containing mv(i) kg water is chosen to be proportional to the number of the register:

$$Tvt(i) = 100*i/Nreg \qquad 1 \leq i \leq Nreg \qquad (3.8)$$

where Nreg is the number of registers

In this thesis Nreg is chosen to be 100, so the vessel model covers all integer temperatures from 1 ^{o}C to 100 ^{o}C. These integer tempe-

ratures are in fact the average temperatures between Tvt(i-0.5) and Tvt(i+0.5).
If the desired temperature on the demand side of the system exceeds the maximum temperature available in the vessel, auxiliary heating (Qgsau) is necessary.
If the demand temperature is lower than the minimum temperature available, water from the vessel is mixed with water returning from the heating system, or from the heat exchanger. This situation is called "bypass", and the bypassed mass of water is denoted by Mbyp.
It is assumed that the outlet fluid flowing to the supply side of the system is extracted from the bottom of the vessel, i.e. at the lowest temperature possible. This has a positive effect on the efficiency of heat withdrawal if the supply circuit consists of a collector and/or seasonal storage. However, if a heat pump is used, situations may occur in which a higher condenser inlet temperature favourably affects the overall energy consumption. This would suggest that extraction from the bottom is not always the best, in other words, that it is useful to optimise the place of extraction. This extra degree of freedom is discussed briefly in Section 5.8.2.

Modelling of the short-term storage with registers means that the computational effort is small compared to a conventional (height-discretised) type of storage model, but also that the order of operations (extraction or injection of heat) becomes important. The demand side is chosen to be processed first, when necessary resulting in auxiliary heating or bypass (see Fig. 3.4 and Section 3.2.6). After that the supply side is processed, starting with extraction at the bottom. As a consequence, there is a time-lag of one time-step between the moment of charging and the moment of discharging of a particular quantity of heat. The reason for this can be found in the possibility of calculating the gradient of the criterion function to the control variables analytically in this way.

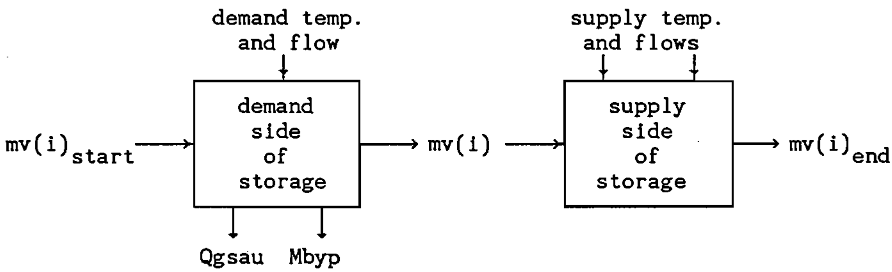


Fig. 3.4: Block diagram of the short-term storage calculation process.

Possible control variables are the flows into and out of the vessel. State variables are the masses mv(i) of each temperature in the vessel. A design variable is the total storage mass Mv.

3.2.6 Space heating demand circuit

For applications like industrial process heat and domestic hot water usually a heat exchanger is applied. However, if the system is used for space heating purposes, the demand circuit is influenced by a disturbance variable that may also play a role in the supply circuit: the weather pattern. Therefore this case gets a separate treatment.
The demand circuit comprises:
- the building(s), in which a specified indoor temperature Tb is required.
- the heating system that is used to meet the space heating demand.

The heat demand Qd can be calculated with:

$$Qd = Cb*(Tb-Ta-\Delta Thb) \qquad (3.9)$$

where: Cb = heat transfer coefficient building(s)
Tb = required indoor temperature
Ta = ambient temperature
ΔThb = indoor temperature rise because of heat sources (lamps, human beings, etc.)

under the assumptions that:
- the heat transfer coefficient from building(s) to surroundings is constant.
- Cb and ΔThb are constant.

The first assumption implies that building dynamics are neglected. This is a severe assumption, which can only be justified if the required indoor temperature is constant throughout the day. To a large extent, this condition is fulfilled in well-insulated houses, where experimental studies have shown that it is of little use to lower Tb during the night.
The heating system is assumed to consist of conventional radiators with a design maximum inlet temperature (Td) of 70 ^{o}C and outlet temperature (Tod) of 50 °C (Tb = 20 ^{o}C, ΔThb = 5 ^{o}C, Ta = -12 ^{o}C). The relationship between inlet and outlet temperature is described by the following quasi-stationary equation:

$$Tod = Hd*Td+(1-Hd)*Tb \qquad (3.10)$$

where: Td = inlet temperature of heating system = demand temperature
Tod = outlet temperature of heating system
Hd = $\exp(UAd/(\gamma w*Fd))$
UAd = heat transfer coefficient heating system
γw = specific heat of the heating fluid
Fd = flow rate heating fluid

In deriving Eq. (3.10) it is assumed that:
- the heat transfer coefficient is constant.
- the heat transfer between heating system and building(s) is constant.

If the heating system satisfies the heat demand:

$$(Td-Tod)*\gamma w*Fd = Qd \qquad (3.11)$$

the demand temperature Td can be calculated from (3.10) and (3.11):

$$Td = Tb + \frac{Qd}{(1-Hd)*\gamma w*Fd} \qquad (3.12)$$

If the temperature of water coming from the short-term storage cannot meet the required temperature of the heating system, an auxiliary heater supplies the deficit. It is assumed this heater is gas-fired, like the heat pump, and that its energetic efficiency is constant and equals 80 %.

Fig 3.5 gives a schematic view of the space heating system.

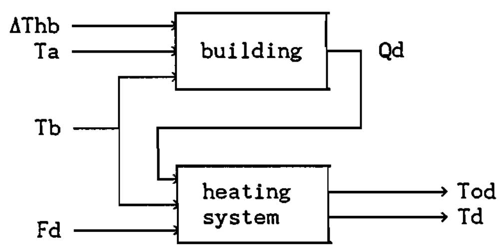


Fig. 3.5: Block diagram of the space heating system.

The space heating demand circuit is considered as prescribed, so it makes no control and design variables available for optimisation purposes.

3.3 System aspects

3.3.1 Configurations

The components described in the previous sections can be interconnected in several ways. The general principle of the class of systems under study is the transfer of heat from one or more specific heat sources (supply) to a heat sink (demand) at a desired temperature level, via alternative routes including temporary storage and heat pump facilities. Possible configurations can be classified as follows (in increasing order of complexity):

- systems with a heat source and a heat sink both operating at prescribed temperatures.
- systems with a heat source at a fixed temperature but with a fluctuating heat sink temperature. An example of these might be a system employing industrial waste heat for space heating of buildings.
- systems with a fluctuating heat source and a constant desired heat sink temperature. An example is a system with solar or ambient heat input for domestic hot water applications, or for industrial process heat.
- systems with heat source and heat sink temperatures both varying as a function of time.

Fig. 3.6 shows one of the many possible configurations. It is a system with a heat pump, collector and short-term storage, for space heating purposes. In this thesis the so-called series configuration is chosen for this kind of system, which is representative for many installations in Europe. In the U.S.A. parallel configurations are often preferred [DUF80], but the series configuration allows the collector to operate at lower temperatures. This permits the use of a collector with a comparatively high heat loss coefficient (a type of collector which is able to produce heat even if the equivalent ambient temperature is comparatively low), which is interesting from an economic point of view.

In this system hot water from the solar collector can be used as a heat source for the heat pump, and/or be stored in the short-term storage, while the (optional) presence of a seasonal storage provides an alternative for injecting or extracting heat. The space heating demand is met in first instance by the short-term storage vessel. The auxiliary heater comes into operation if the storage temperatures cannot provide the demand temperature.

The system of Fig. 3.6 poses an interesting operational alternative: a part of the collector heat can be used to preheat the flow through the heat pump condenser, which was found to be a clever mode under certain circumstances [SLE84]. Several such hybrid modes are possible.

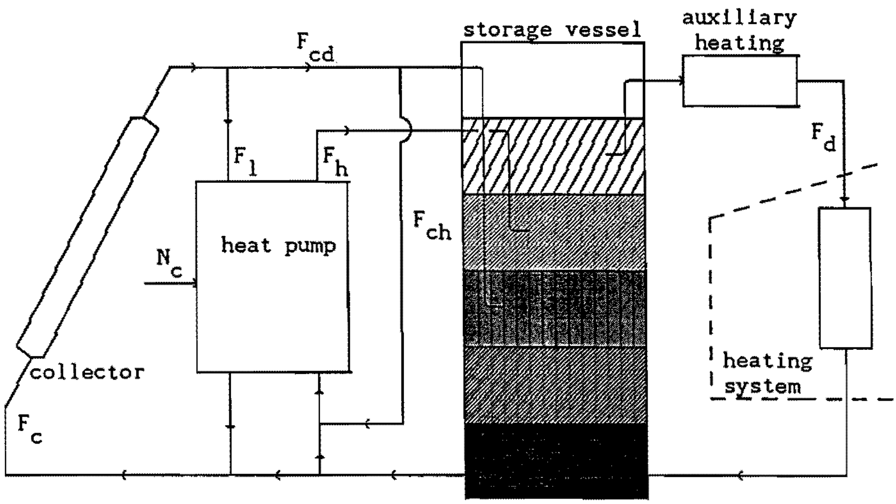


Fig. 3.6: Solar assisted heat pump system with short-term storage.

3.3.2 Dimensioning

This section gives the reference values for the dimensioning parameters of the various components. These values serve as a basis for the investigation of the control aspects in Chapter 5, and as a starting point for studying the design aspects, at the end of Chapter 5. Table 3.1 gives the most important sizing parameters of the reference systems.

To start with, we refer to the configuration of Fig. 3.6. The maximum space heating demand load is assumed to be 600 kW at Ta = -12 °C (Cb = 22222 W/K, UAd = 15325 W/K, Fd = 7.1 kg/s), which is approximately equivalent to 100 well-insulated houses.
It is assumed that the desired indoor temperature is 20 °C throughout the day, and that the temperature rise because of internal heat sources is 5 °C.

The heat pump is designed to deliver 300 kW under average circumstances, which is 50 % of the maximum heating load. For economical reasons, there is a tendency to choose an even smaller fraction of the maximum heat load to be installed in heat pump power. But for the system considered here, the design conditions of the heat pump are not satisfied if the heat demand is at a maximum, because at these moments the heat supply by ambient heat is at a minimum. Therefore it was decided to take a 300 kW heat pump. The heat pump components are sized according to Slenders' unity sizing [SLE81].

For systems without seasonal storage and with a heat pump, a collector area of 1000 m^2, with a heat loss coefficient of 15 $W/m^2/K$, was found to be the best to serve as a heat source [BAZ88].

The short-term storage mass is 100000 kg of water, which is enough to store heat for several hours, given the characteristics of the demand system (cf. Section 3.2.6).

For systems with long-term storage the layout and dimensioning of the components is basically the same, the main difference being the connection of the long-term storage parallel to the collector (see, for instance, Fig. 5.14), a consequence being that the only possible

Table 3.1: Sizing parameters of the reference systems

collector area	Ac	1000 m^2	(without seas. stor.)
		1500 m^2	(with seas. storage)
		2500 m^2	(with seas. storage without heat pump)
collector heat loss coefficient	Uc	15 $W/m^2/K$	(without seas. stor.)
		5 $W/m^2/K$	(with seas. storage)
		2 $W/m^2/K$	(with seas. storage without heat pump)
long-term storage volume	Vg	25000 m^3	
number of pipes	Npipe	220	
length of pipe	Lpipe	20 m	
delivered power under design conditions	Qg	150 kW	
heat pump output power under design conditions	Qhp	300 kW	
short-term storage mass	Mv	100000 kg	(without seas. stor.)
		400000 kg	(with seas. storage)
max. heat demand	Qd,max	600 kW	
aux. heating capacity necessary to meet Qd,max	Qaux	300 kW	(with heat pump)
	Qaux	600 kW	(without heat pump)

mode of operation to heat up the storage is provided by the direct input of collector input. Other possibilities are: using the heat pump to achieve a higher storage temperature; using the short-term storage to spread the heat input in the long-term storage over the day. But these modes have not been part of the investigations in Chapter 5.
The long-term storage volume is 25000 m^3, with heat-exchanging pipes inserted vertically in the soil at a mutual distance of 2 m. The pipes are 20 m. long, and the total number of pipes is 220. This results in a ground heat exchanger which delivers approximately 150 kW under design conditions [DEL86, DEL87a], which is ideal to serve as a heat source for the heat pump.
Simulation studies over operational periods of several years [MOU88, SCH88] showed that to enable a desirable temperature rise of the long-term storage during the charging period, a collector heat loss coefficient of 5 $W/m^2/K$ is necessary, and therefore this type of collector was chosen, with an area of 1500 m^2. But it must be stressed that this is highly dependent on factors such as the possible operational modes during the discharging period, and the presence of a heat pump. For a configuration without a heat pump, it was concluded from simulation studies that a collector heat loss coefficient of 2 $W/m^2/K$ (which refers to high-efficiency evacuated tubular collectors) and an area of 2500 m^2 were satisfactory.

3.3.3 Disturbances

The disturbances acting upon the systems studied are defined as external variables that cannot be influenced themselves in any way for a given design (cf. Section 2.1).
The disturbance variables identified in the previous sections are:
- The ambient temperature Ta, influencing the demand temperature in the case of space heating, and the collector temperature in the case of (solar or ambient heat) collectors;
- The absorbed solar irradiance Qs, influencing the collector temperature.

Although it might seem curious to speak of disturbances if these variables contain the heat source for the systems studied (ambient and/or solar heat), the term "disturbances" will be used throughout this thesis, in agreement with their definition in Section 2.1.

For the application of optimisation techniques it is necessary to have a priori knowledge, or a sufficiently accurate estimate, of these disturbances. The weather variables Ta and Qs form a special kind of disturbance in various respects:

- in systems with space heating, the heat demand is at a maximum when the heat supply is at a minimum, introducing the well-known dephasing in supply and demand, which makes a storage component desirable for efficiency reasons.
- both variables have a deterministic component, caused by day/night and seasonal variations. but also a very strong stochastic component with a large amplitude.
- For climates comparable to the one in The Netherlands, variations in Ta and, to a lesser extent, in Qs can be predicted quite accurately over a relatively short period (1 to 3 days), but it is impossible to obtain reliable predictions for periods longer than about 5 days (because weather changes may originate from random micro-effects in the atmosphere). It is presumed (on an intuitive statistical basis, without proof) in this thesis that the best prediction over a horizon longer than about 5 days is a tendency of the weather towards the average weather in that time of the year.

In this study the patterns that are used for Ta and Qs come from representative hourly Dutch weather data (the so-called KNMI-reference year). The reference year is based on hourly data of the Royal Dutch Meteorological Institute (KNMI), and is representative for the Dutch climate. It is used in a large number of applications in The Netherlands, and contains realistic values of ambient temperature and solar irradiation, including periods of severe frost as well as heat waves.

In many applications discussed in the literature, stylised weather data are used, obtained by realistic weather data fitted to a sinusoidal function with a periodicity of one year, superimposed by sinusoidal variations to account for day/night cycles. The amplitude of the day/night cycle in the case of solar irradiation is then also sinusoidal with a one year period. Although working with synthetic weather data has some advantages like the ease of calculation and the possibility to examine certain effects in the frequency domain, I prefer to use the reference year because:
- the stylised weather evokes no higher order effects; the weather is always "smooth", or, in other words, apart from the daily cycles it contains no high frequencies.
- most systems reach their (physical or safety) limits at extremely cold or hot days, so it is not justifiable to exclude such days from the analysis.

Van Paassen [PAA81] gives some characteristics of the reference year, together with the generation of a 56-day short reference year having the same statistical properties. From his statistical analysis it is concluded that the coherence between succeeding daily mean values is much stronger for ambient temperature than for global solar irradiation. In general, the mean values of ambient temperature that occurred several days ago still have an effect on momentary values. This effect is stronger in winter than in summer, of course, because the "disturbing" effect of solar irradiation on ambient temperature is weaker in winter. The ambient temperature spectral analysis shows peak values at frequencies 1/12 and 1/24 $hour^{-1}$, the latter being more dominant in summer, also owing to the disturbing effect of solar irradiation.

3.3.4 Simulation

The dynamic behaviour of the systems considered can be described by a set of equations, that describe the trajectories of the state variables (masses in the short-term storage and/or temperatures in the long-term storage). In general, such a set of equations has to be solved numerically with a discrete-time approach.
For the numerical simulations the following assumptions are made:
- control variables and disturbances are represented by constant values during a time step;
- all processes within a time step are quasi-stationary (see also the assumptions made in the models of the storage components).

The operational mode is defined by the values of the independent control variables. Conventionally, such variables are under on/off control, but my aim is to find the best control strategies first, and then to consider simpler solutions. Therefore, these variables are to be continuously adjustable within a prescribed domain.

In addition, it is assumed that:
- water is used as heat carrier in the system;
- the specific heat of water is constant;
- heat losses and pressure losses in connecting pipes can be neglected;
- the energy consumption of the circulation pumps in the system is a function of the flow rates only, and is assumed to be proportional to the third power of these flow rates.

Consequently, numerical simulation of a system over a certain period amounts to determining the equilibrium temperatures in the system during every time-step; these are the inlet and outlet temperatures of the components that result from an evaluation of the stationary temperature interrelationships dealt with in the previous sections, the initial conditions being given by the values of the control and state variables at the beginning of the time-step.
Then, for each time-step the new values of the state variables are calculated.

The equilibrium temperatures are calculated by combining the input-output temperature relationships of all components given the values of the control and design variables, and the disturbances in that time step. This comes down to the solution of a set of linear or non-linear equations. In the latter case, a secant method is used.
The resulting equilibrium temperatures are used to calculate the heat input and output of the storage components.

The choice of the time-step size is a compromise between accuracy and computational efforts. A small time-step ensures a more accurate calculation of the dynamics of the system, but implies a large computational effort, and introduces the risk of accumulating rounding-off errors. Moreover, the assumptions of stationarity in some of the models are not valid if the time-step is too small.
For systems without long-term storage the time-step is chosen to be 1 hour. If long-term storage is applied, a rather coarse time-step of 4 hours is necessary, for computational reasons discussed in Chapter 4.

As a consequence of the discrete-time simulation approach, another interesting control variable can be defined that is not related to a particular component. This variable is given by the fraction of the time-step that the supply-side of the system is operated:

$$fr = \Delta t^{op}/\Delta t \qquad (3.13)$$

where: Δt^{op} = operating time of the system within one time-step.

This means that the system is considered to be switched on during a period $fr*\Delta t$, and switched off during $(1-fr)*\Delta t$. In this case the discrete-time approach for simulation can better represent reality, where a component can be switched on or off any time during a time-step.

3.3.5 Characterisation in systems engineering terms

The characteristics of the systems can be summarised as follows:

- Rapid dynamics of energy-transferring components: some components, like the collectors and the heat pump, have fast dynamics, that can be neglected when simulating with a one-hour time-step.
- Slow dynamics of long-term energy storage components: the heat conduction processes in the ground are very slow (although switching the flow from one sector of pipes to another will cause a short-term effect, cf. Section 4.4.1).
- Non-linear influence of control variables (for example: fluid flows): the systems are non-linear with respect to the control variables and in general the performance index is not a quadratic expression, which means that many special optimisation techniques suggested in the literature (cf. Chapter 2) are not applicable. As already mentioned, this led to the development of a dedicated optimisation method.
- Mode-switches: the performance index can be non-smooth, due to mode-switches. With regard to the system configuration, one can even speak of system-switches (yes/no installing a heat pump, yes/no long-term storage, etc.).

- The systems can be influenced by disturbances with uncommon properties: the weather and (weather-related) heat demand pattern, as treated in the previous sections.
- The number of independent control variables (being the number of control variables per time-step times the number of time-steps) can be very large (>100). This was an important consideration in the choice of the optimisation method, as mentioned in Chapter 2. The number of state variables depends strongly on the configuration and the required accuracy, but can range from less than a dozen to several hundreds.

In this and the previous chapter the fundamentals have been treated of the methods to be applied and the systems to be investigated. Before turning to a presentation of the results, the next chapter combines the method and the application, poses the optimisation problems to be solved, presents a new design method for thermal energy systems and compares it with other approaches.

4 Dynamic optimisation of thermal energy systems

4.1 Introduction.

The aim of this chapter is twofold. First, the focus is on the coupling of the optimisation method and the system simulation. In order to obtain useful results for various configurations, some system-dependent modifications in the optimisation method were developed. These are described in this chapter.
In Section 4.2 the optimisation problem for this class of systems is posed. Special features in the optimisation procedure are dealt with in Sections 4.3 and 4.4. In Section 4.5 the important translation step from dynamic optimal control to practicable control strategies is treated. This serves as a step-up to Section 4.6 where, after a discussion of the optimisation of design variables, a new design method for thermal energy systems is presented.
Second, to emphasize the differences between the approach dealt with in this thesis and the approaches taken thus far, Sections 4.7 to 4.9 discuss the state of the art concerning optimal control, adaptation and design of thermal energy systems. This also provides a basis against which the results discussed in Chapter 5 can be judged.

4.2 Formulation of the optimisation problem

4.2.1 Control variables and their constraints

In Chapter 3 the control variables for the components discussed have been identified. These are in general the fluid flows between the components, the switch-on fraction fr (cf. Section 3.3.4) and, in the presence of a heat pump, the rotation speed of the piston compressor.
Another possible control variable which was already mentioned in Chapter 3 is the place of extraction from the short-term storage on the supply side. In Chapter 5 this variable is also investigated.
For a given configuration only a limited number of fluid flows can be chosen independently, the others satisfying mass balances at Tee-pieces etc.
All fluid flows have to satisfy the following inequality constraints:
- The flow must be larger than or equal to zero.
- The flow cannot exceed a maximum value, imposed by the scale of the system (see Table 3.1 of Section 3.3.2) and the dimensioning of the circulation pumps. This value is 25 kg/s.

Exceptions to these rules exist, for computational reasons or because of model-validity:

- For systems incorporating a seasonal heat storage the flows through this storage can have both positive and negative values, corresponding to charging, c.q. discharging the storage. This is done for computational reasons only and can be interpreted as the use of this component "in two directions", whereas in the other components the flows have a fixed direction.
- Another exception for computational reasons is imposed by the short-term storage. The mass of water extracted from the short-term storage on the supply side in one time-step Δt must be smaller than the total mass of the storage. Therefore the flow is limited to $Mv/\Delta t$.
- The last exception is the lower boundary of the heat pump flows. If the heat pump is in operation these flows must have a minimum value, to avoid boiling or freezing effects, which where assumed not to take place in the development of the heat pump model. The minimum value of the flow in this case is 2.5 kg/s.

The rotation speed of the heat pump is limited to a maximum value of 1500 rpm.
The switch-on fraction fr has a lower boundary which is imposed by the assumption of quasi-stationarity in some of the components. For a one-hour time-step the minimum acceptable value of fr is 0.25.
Table 4.1 gives the constraints in the control variables:

Table 4.1: Constraints in the control variables.

(in)dependent flows	$0 \leq F \leq Fmax$
condensor flow	$Fmin \leq Fh \leq Fmax$
evaporator flow	$Fmin \leq Fl \leq Fmax$
flows in seasonal storage rings ($\sum Fg(i) = Fgtot$)	$-Fmax \leq Fgtot \leq Fmax$
flow extracted from short-term storage	$0 \leq Fv \leq Mv/\Delta t$
rotation speed	$0 \leq Nc \leq Ncmax$
switch-on fraction	$0.25 \leq fr \leq 1$
Fmin = 2.5 kg/s, Fmax = 25 kg/s, Ncmax = 1500 rpm	

The dependent flows can be written as a linear combination of the independent ones. The general form of the constraints is:

$$\underline{l} \leq C\underline{u}(n) \leq \underline{h} \qquad 1 \leq n \leq N \qquad (4.1)$$

where $\underline{u}(n)$ is a vector containing the independent control variables in the n-th time-step. For the constraints in these variables the matrix C is a simple unity matrix. The linearly dependent variables introduce extra rows in C, and therefore the projection on the constraints is not trivial, as discussed in Section 2.4.3.

For design variables (to be considered as time-independent control variables) also upper and lower boundaries have to be satisfied. It is assumed that the design variables can be adjusted independently. The constraint matrix becomes a simple unity matrix and introduces no complications for projection. The numerical values of these constraints are given in Section 5.9.2.

4.2.2 State variables and their constraints

As mentioned before, the state variables are the temperatures and/or masses in the storage components. Together with the values of the control variables and the disturbances, these state variables determine the equilibrium temperatures in a time-step.
This section discusses the constraints on the state variables and the associated equilibrium temperatures.

Inequality constraints

The model chosen for the short-term storage can only handle temperatures within a prescribed interval, but it is assumed that the equilibrium temperatures (like the temperatures injected in the storage) remain within this interval during normal operation.

A problem (with a physical interpretation) arises if the set of non-linear equations for the calculation of the equilibrium temperatures is not solvable. In systems with a heat pump this happens if the temperature of the heat source is high compared to the temperature entering the condenser. In this situation the heat pump cycle is not able to transfer heat from evaporator to condenser. If this is detected the heat pump is switched off, and thus the control strategy for that time-step is changed. Although an explicit treatment of this state constraint would be more elegant, the switch-off approach was preferred because in this way the rather complex task of coping with a non-linear inequality constraint could be avoided.

The assumptions in the model of the seasonal storage imply that the temperatures in the ground are bounded. The lower boundary arises from the fact that freezing of the ground is not taken into account. The upper boundary is necessary because the effects of natural convection are not taken into account, and they can play an important role if the temperature differences in the ground are relatively large. However, it is assumed that during normal operation of the system these constraints are not violated, and therefore they are not treated explicitly in the optimisation procedure.

Equality constraints

In Section 4.3 the idea of periodic optimisation is dealt with. Speaking in terms of state constraints this means that in this approach it is required that:

$$\underline{x}(N) = \underline{x}(0) \qquad (4.2)$$

Of course it is also possible to impose general restrictions on the terminal state of the system, which are not related to the initial state:

$$\underline{x}(N) = \underline{x}d \qquad (4.3)$$

This type of constraint, referred to as the terminal state constraint, is also discussed in Section 4.3.

4.2.3 Performance index

In the literature on thermal energy systems there is no consensus on the choice of the criterion to be optimised.
For a given system configuration and layout, the criteria are usually energetic ones, such as:

a - components (e.g. heat pump) operating at maximum efficiency
b - maximum fraction of heat load satisfied by the supply side of the system, which comes down to minimising the input of auxiliary energy.
c - minimum use of energy for heat pump, auxiliary heating etc.
d - maximum input of "free" heat in the system

Previous work in the System and Control Technology Group showed that criteria a and d are only suitable for optimising a component, but owing to interactive effects they are not equivalent to the optimisation of the system as a whole [RAD81a, SLE84].
Criteria b and c are equivalent for systems without a heat pump, but again it can be shown that in specific cases for heat pump systems, b and c are not the same. Slenders showed that for space heating purposes a combined operation of heat pump and auxiliary heating can be energetically more attractive under certain circumstances [SLE84].
This leaves c as the only logical criterion for an energetic optimal system under varying conditions. For the systems discussed this comes down to the minimisation of the energy consumption of heat pump, auxiliary heating and circulation pumps over a given period, the performance index PI being denoted by the criterion function F:

$$\min_{\underline{u}} F = \min_{\underline{u}} \sum_{n=1}^{N} (Qgshp + Qgsau + Qpump)\, \Delta t \qquad (4.4)$$

$$= \min_{\underline{u}} (IQgshp + IQgsau + IQpump)$$

If design variables are optimised, the costs associated with the components involved are taken into consideration, and the criterion becomes an economic one. For economic criteria several standard formulas can be applied. With a prescribed pay-back period, the criterion used in this work can be formulated as:

$$\min_{\underline{u},\underline{p}} F = \min_{\underline{u},\underline{p}} (\text{total costs} - \text{total savings}) \qquad (4.5)$$

4.2.4 Statement of the problem

The dynamic optimisation problem can now be formulated:

Consider a control vector $\underline{u}(1:N)$ containing the values of the independent flows, the rotation speed of the heat pump, the switch-on fraction, and additional control variables, in every time-step:

$$\underline{u}^T = [\ Fl,\ Fh,\ \ldots\ ,\ Nc,\ fr,\ etc.] \qquad (4.6)$$

Consider a state vector $\underline{x}(0:N)$ containing the values of the masses in the short-term storage and/or the temperatures in the seasonal storage:

$$\underline{x}^T = [\ mv(1),\ \ldots\ ,\ mv(Nreg)\ ,\ Tg(1)\ ,\ \ldots\ ,\ Tg(Ngrid)\ ] \qquad (4.7)$$

with Nreg is the number of registers in the model, and Ngrid is the number of grid points for the solution of the heat conduction equation in the ground volume.

Consider a design parameter vector $\underline{p}$ containing the values of the design parameters:

$$\underline{p}^T = [\ Ac,\ Uc,\ Hp,\ Mv,\ Npipe,\ Vg,\ etc.] \qquad (4.8)$$

Consider a disturbance vector $\underline{z}(1:N)$ containing the values of the disturbance parameters, usually the weather pattern or other uncontrollable external infuences:

$$\underline{z}^T = [\ Qs,\ Ta,\ etc.] \qquad (4.9)$$

Find the values of $\underline{u}(1{:}N)$ and/or $\underline{p}$ that minimise:

$$F = \sum_{n=1}^{N} L(\underline{x}(n-1), \underline{u}(n), \underline{p}, \underline{z}(n), n)\Delta t \tag{4.10}$$

subject to the following constraints:

$$\underline{x}(n) = \underline{f}(\underline{x}(n-1), \underline{u}(n), \underline{p}, \underline{z}(n)) \qquad 1 \leq n \leq N \tag{4.11}$$

$$\underline{l} \leq C\underline{u}(n) \leq \underline{h} \qquad 1 \leq n \leq N \tag{4.12}$$

$$\underline{lp} \leq \underline{p} \leq \underline{hp} \tag{4.13}$$

where L is the momentary cost function, in this case referring to the total energy consumption per unit time, or, if design variables are optimised, the total costs minus the total savings per unit time, and (4.11) is the discrete-time version of the system equations.

This problem formulation refers to dynamic optimisation. Fig. 4.1 gives a schematic representation.

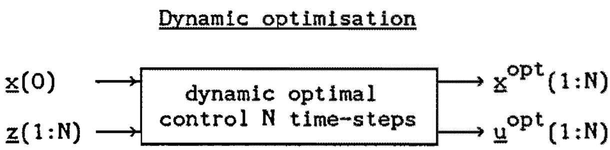


Fig. 4.1: Schematic representation of dynamic optimisation.

The other types of optimisation discussed in this thesis are:
- static optimisation;
- momentary optimisation;
- adaptive control (also a type of optimisation, cf. Section 2.5);
- periodic optimisation and optimisation with terminal state constraints (to be discussed in Section 4.3);
- hierarchical optimisation (to be applied to systems incorporating seasonal storage, and discussed in Section 4.4);
- simultaneous optimisation of control and design variables (to be discussed in Section 4.6).

For static optimisation the problem is basically the same, apart from the fact that in this case the control variables in every time-step have the same value (unless the system is switched off, cf. Section 5.2.2), and thus the time-index n in the formulas above can be omitted for the control variables (see Fig. 4.2).

Static optimisation

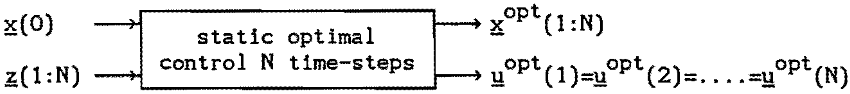


Fig. 4.2: Schematic representation of static optimisation.

For momentary optimisation (which in this case means optimisation of the control in one finite time-step), the system equations are not relevant, but the order of calculation if a short-term storage is present (first the demand-side, then the supply-side of the vessel, cf. Section 3.2.5) has to be changed to allow a direct use of supplied heat in the demand circuit. The criterion is the minimisation of L as defined above. In the following, momentary optimisation over an interval [tb,te] is defined as the momentary optimisation in every time step nΔt of that interval, the starting conditions being:

$\underline{x}(0) = \underline{x}0$ in the first time-step

$\underline{x}(0) = \underline{x}opt(n-1)$ for the n-th time-step, with $\underline{x}opt(n-1)$ is the state at the end of the previous time-step, resulting from the application of the momentary optimal control within that time-step.

This is illustrated in Fig. 4.3:

Momentary optimisation

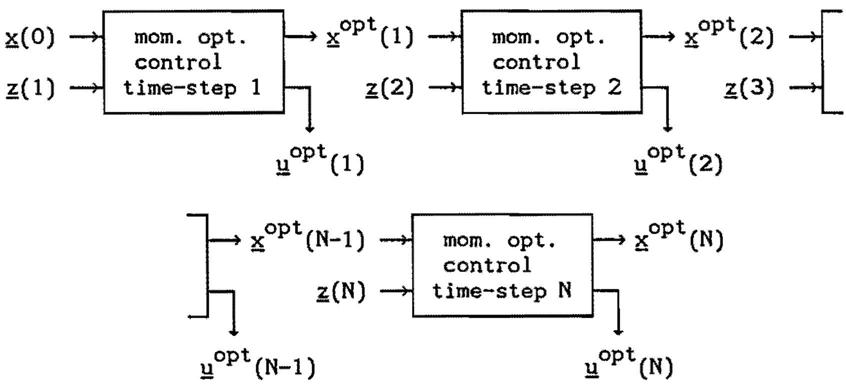


Fig. 4.3: Schematic representation of momentary optimisation.

As mentioned before, adaptive control can be regarded as a form of dynamic optimisation, possibly with an extra expression in the criterion function (see Section 2.5). For model reference adaptive control the procedure is illustrated in Fig. 4.4.

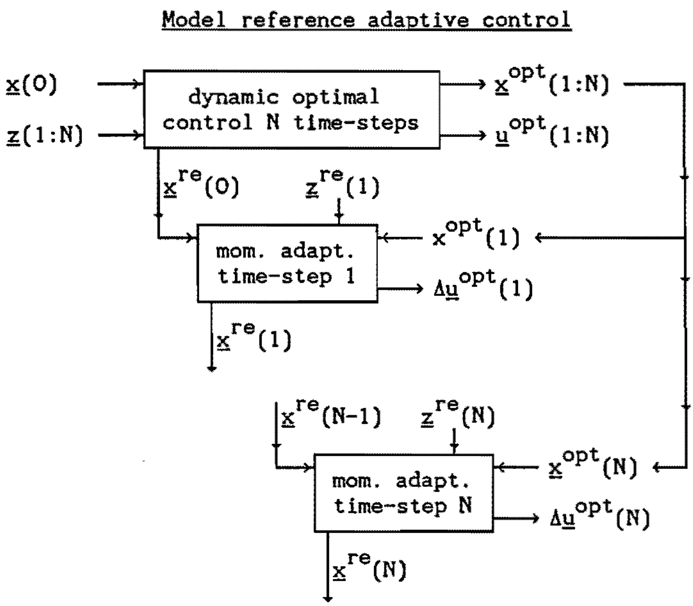


Fig. 4.4: Schematic representation of model reference adaptive control.

In Fig. 4.4 the reference trajectory is $\underline{x}^{opt}(1:N)$, the actual states of the system are given by $\underline{x}^{re}(n)$, and the actual disturbances by $\underline{z}^{re}(n)$. Every momentary adaptation box contains an optimisation over Na adaptation steps, as indicated in Section 2.5.3.

Fig. 4.5 gives a representation of adaptive control with the aid of dynamic optimisation.

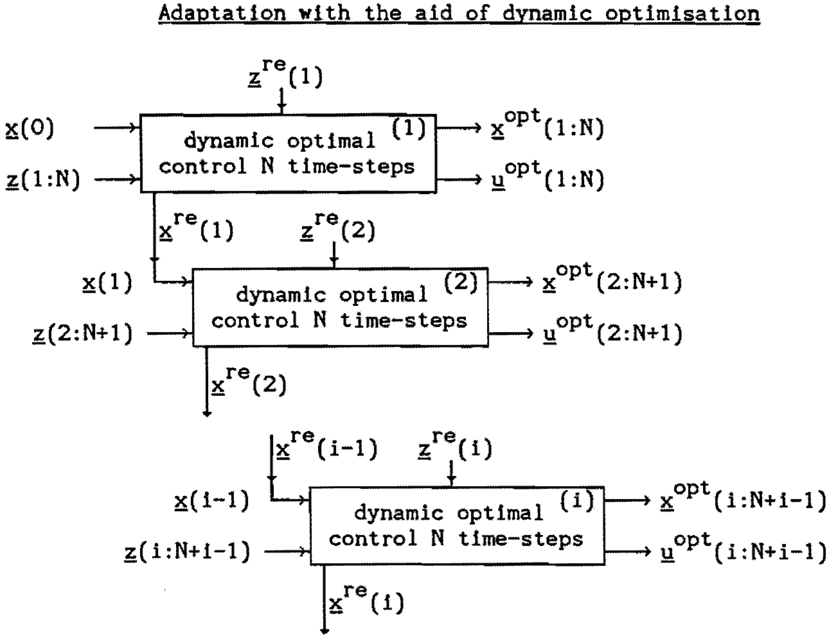


Fig. 4.5: Schematic representation of adaptive control with the aid of dynamic optimisation.

In this figure N denotes the adaptation horizon, and the index i refers to the actual time-step.

For periodic optimisation the so-called periodic constraints (Eq. 4.2) have to be satisfied. The solution method is discussed in Section 4.3. For terminal state constraints (Eq. 4.3) the situation is slightly different, and is also described in Section 4.3. Figs. 4.6 and 4.7 illustrate the problems schematically.

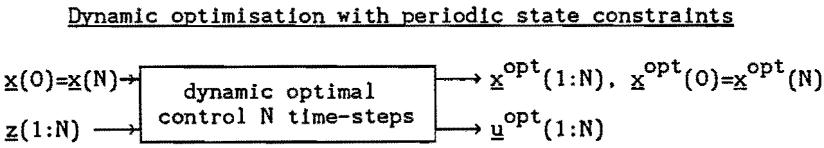


Fig. 4.6: Dynamic optimisation with periodic state constraints.

Dynamic optimisation with terminal state constraints

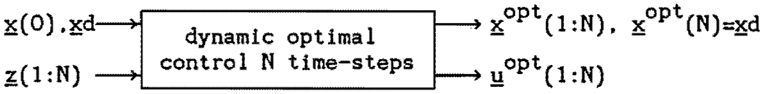


Fig. 4.7: Dynamic optimisation with terminal state constraints.

For hierarchical optimisation the problem is comparable to dynamic optimisation, the only difference being that some control variables are fixed in the successive steps (see Section 4.4). For design optimisation a similar modification has to be made (see Section 4.6).

4.3 Optimisation with state equality constraints

4.3.1 Introduction

In the treatment of the general dynamic optimisation problem the concept of "end costs" is introduced as being the costs associated with the state of the system at the end of the optimisation interval. For the thermal systems in this work it is hardly possible to obtain an explicit expression for the end costs without arbitrary assumptions. Therefore these end costs are simply neglected. This means that, in a system with a short-term storage, the storage would be thermodynamically "as empty as possible" at the end of the optimisation period, irrespective of the heat content of the storage at the beginning of this period. This however is not a realistic situation, because the heat content at the end is the same as the heat content at the beginning of the next period in practice, and starting with an "empty" vessel will usually result in an increase in energy consumption in that period.
A way to overcome this problem is to optimise with periodic state constraints, already formulated in Eq. 4.2.
The dynamic optimal control strategy satisfying these periodic state constraints has an interesting aspect if the disturbance pattern for which the strategy was determined has a repetitive nature. This is because the dynamic optimal control for a series of identical periods can be obtained by repeatedly applying this periodic optimal strategy.

4.3.2 Methods of periodic optimisation

The concept of periodic optimisation for thermal energy systems is discussed by a few authors. Dorato [DOR79a] gives a method based on Fourier analysis. An optimal control strategy (using a quadratic performance index, cf. Section 4.2.3) for a simple configuration is derived in terms of Fourier coefficients as a function of the coefficients of the periodic disturbance signal. However, for complex, non-linear systems this method leads to rather elaborate expressions and is therefore not considered here.

From a strict mathematical point of view a way of dealing with equality constraint (4.2) is to consider the state variables $\underline{x}(0)$ as extra control variables and to use a penalty function or a gradient projection technique to ensure (4.2).
To avoid complications that would arise if the number of control variables increases with the number of registers in the storage model, an ad hoc method is used.
Before turning to the ad hoc method, we first discuss an alternative approach: Another method to satisfy (4.2) is to perform an ordinary dynamic optimisation over a period [tb.te], and to use the terminal states $\underline{x}(N)$ as the initial states of a next optimisation. The process is repeated until the equality constraint is satisfied. Although convergence of this method is mathematically difficult to prove in all cases, it is felt (for physical reasons) that this procedure will work in all practical situations. But the procedure shows an important drawback: dynamic optimisation will still result in a storage that is as "empty" as possible at the end of the optimisation period, and thus the next optimisation period will always start with a "cold" storage. It is evident that, although (4.2) is satisfied, this need not be the global optimal solution. The "cold start" of the storage may introduce auxiliary heating at the beginning of the period. Operating the storage at a higher temperature level can be energetically more efficient, but these solutions will not be detected with this method.
Thus it can be concluded that condition (4.2) is not enough to obtain the global periodic optimal solution. The effects of the terminal states on the initial states of the next period have to be taken into consideration, as is done in the ad hoc method.

The main principle of the ad hoc method is that for a given control strategy and disturbance pattern over an optimisation period, condition (4.2) is always satisfied. This is realised by an extension of the simulation procedure. Normally in this procedure the states of the system and the criterion are calculated for given $\underline{u}(1:N)$, $\underline{z}(1:N)$ and $\underline{x}(0)$. This procedure is replaced by an iterative one in which the terminal states $\underline{x}(N)$ are used as the initial states for the next iteration, until (4.2) is satisfied. This procedure converges for all realistic situations, except one [BAZ88]. This exception refers to a

situation in which an overproduction of heat from the supply circuit takes place. In that case successive substitution leads to a monotonically increasing heat content of the storage. However, an overproduction of heat can never be a periodic optimal situation. So if overproduction is detected, a penalty is introduced to force the control strategy towards a situation in which the heat produced matches the heat demand.
Fig. 4.8 gives a schematic view of the procedure for periodic optimisation.

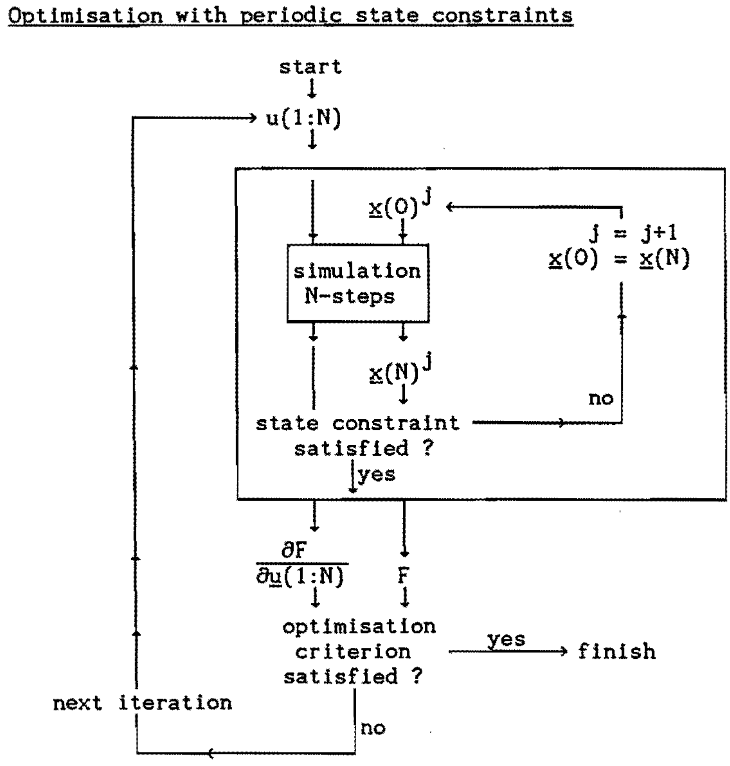


Fig 4.8: The procedure for periodic optimisation.

Another way to handle the end costs is to impose requirements upon the terminal state of the system, irrespective of the initial state (Eq. 4.3). These requirements may be induced by various reasons (see, for example, the concept of Model Reference Adaptive Control in Section 2.5.2). The optimisation procedure for this type of constraint is basically identical to the dynamic optimisation method: The terminal constraint is fulfilled by adding a penalty function to the criterion function (4.10), which forces the control to minimise the difference between $\underline{x}(N)$ and $\underline{x}d$. Again it must be pointed out that there is a mathematically more elegant method to satisfy this constraint: a gradient projection technique in which the direction of search is projected on the state constraint [JON82]. However, this leads to computational problems owing to the non-linear behaviour of the systems considered and to the assumptions made in the short-term storage model. Therefore the approach of using a penalty function was preferred.

4.4 Hierarchical optimisation

4.4.1 Introduction

For systems incorporating a seasonal storage an optimisation period of one or more years is necessary to include charging and discharging. If the stored heat is provided by solar or ambient heat collectors, and/or used for space heating purposes, the time-step for calculation of the system equations must be small enough to allow realistic variations in the weather pattern. This results in a time-step of one to four hours. Keeping in mind that in every time-step the control variables can be chosen independently, the number of variables for a one-year period will be in the order of 10000 to 100000. This introduces two problems:

- a dimensionality problem: the optimisation of systems with this number of variables requires enormous CPU-times and memory usage.
- a sensitivity problem: the effect of one control variable in one time-step on the criterion function is very small, which makes it necessary to calculate in (at least) double precision.

Apart from a number of pilot studies in the System and Control Technology group, no results have been reported concerning the dynamic optimisation of seasonal heat storage in the literature thus far. In these pilot studies the problems mentioned have been solved by taking a very coarse time step for the whole system, thus neglecting all short-term effects [HEM83, LIN83]. In another pilot study, the short-term effects were considered by applying a sub-optimal control strategy for the hourly collection of solar heat. The heat was collected in an artificial "buffer" and after each seven-day period the heat from the buffer was injected in the ground. Discharging the storage happened in a similar way [RIJ85].
The tendencies in the control strategies for the seasonal storage were basically the same. However, for reliable statements on the optimal

control strategy an approach is necessary which takes the short-term effects into account without introducing artefacts like charging and discharging buffers. This is because the long-term storage also has a short-term dynamical effect: per time-step the rings of the storage can be used independently, and switching from one sector of rings to another will cause a rapid change in outlet temperature. A possible procedure developed here is dealt with in the next section.

4.4.2 A method of hierarchical optimisation

The problems and experiences discussed in Section 4.4.1 lead to the following requirements for the method:
- a strong reduction in the number of variables;
- calculating the seasonal dynamic behaviour while maintaining the sensitivity to short-term effects.

The idea of the method is a partial decoupling of the long-term and short-term dynamics. The system is optimised over a number of periods that are characteristic for different parts of the year. The control strategy of the seasonal storage then serves as a boundary condition. Subsequently, the long-term strategy is optimised with the short-term control strategies as boundary conditions.

The assumptions made are:
- The short-term dynamics of the system are represented in 12 characteristic days. These days are obtained by taking monthly averaged weather data.
- For each of these days the periodic optimal control strategy is determined, the periodic constraints referring to the states in the short-term circuit only. The total flow through the seasonal storage, and its distribution among the various rings, is fixed for every time-step.
- A month consists of 30 identical characteristic days.
- The source terms representing the heat transferred to or from the seasonal storage in the same hour of each day do not change significantly from day to day, within each month [MOU88].
- The source terms from each characteristic day are accounted for in the ground 30 times, so as to represent the effects of one month.
- The effect of the average delay-time of 15 days thus introduced is negligible.
- The only control variables in the long-term optimisation over a year are the flows in the seasonal storage during the 12 characteristic days.

It should be noted that the criteria for short-term and long-term optimisation are conflicting to a certain extent. Whereas the long-term optimisation will result in a maximum storage of the heat collected in summer for use in winter, the short-term optimisation will undoubtedly decide that it is of no use to inject heat in the

ground. This is one of the reasons to decide to perform only a limited number of iterations in both long-term and short-term optimisation. A maximum number of iterations (kmax) in the order of 5 to 15 was found to give the best overall results.
The procedure for hierarchical optimisation is given schematically in Fig. 4.9.

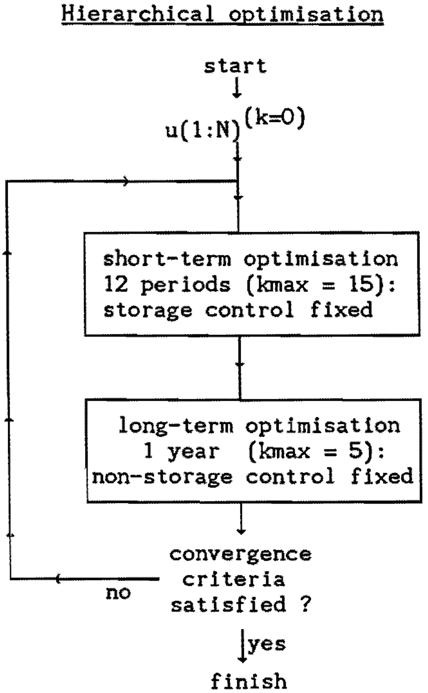


Fig. 4.9: Procedure for hierarchical optimisation. "Storage control" refers to the flows in the seasonal storage.

4.5 Translation of optimal control strategies into practicable, near-optimal strategies

Having determined the dynamic optimal control for various configurations and supply and demand patterns, the question arises how this control is to be implemented in practice, where an exact future knowledge of variations in supply and demand is not available (especially if supply and demand are influenced by weather variables).

In this context, practical implementation only refers to the determination of the input signals in a practical situation, and not to the associated hardware (sensors, actuators, microprocessors).

The first step in this process is to investigate the extent to which the optimal control strategy is robust to realistical fluctuations in the disturbances. The approach taken, together with a number of illustrative results, is described in Section 5.6.
As mentioned in Chapter 2, adaptation of the control strategy to the changing circumstances is a possible approach if the control strategy is not satisfactorily robust. Some results on adaptation will be discussed in Section 5.7.
This section first highlights other approaches that may be followed to obtain a practical control strategy based on dynamic optimal control.

The approaches can be divided in the following categories:

1 - The translation of the optimal control strategy into near-optimal, robust control policies (perhaps on/off): For each optimisation period it is determined what disturbance pattern is the most probable, and the control policy associated with that pattern is applied. In the case of weather disturbances, these patterns can be divided according to various parameters, such as:
- time of the year;
- expected duration of solar irradiance;
- expected "amplitude" of solar irradiance;
- expected ambient temperature and associated demand curves.

This approach is by far the simplest to implement, but has an important and clear drawback:
- robustness is a relative concept: if the deviations from the assumed disturbance pattern are structural, the application of the near-optimal control might prove to be very disadvantageous. The use of adaptation, or a momentary optimal approach, might then lead to better results.

2 - Using the optimal controls to detect static or dynamic relationships with measurable quantities in the system, such as the state variables and the disturbances, together with their evolution in time. These relationships are used to obtain one or more feedback control laws covering all possible situations. This approach, however elegant, also has some drawbacks:
- the essential characteristic of dynamic optimisation (controlling a system by looking not only at momentary effects on the performance, but at future effects as well) is not reflected in this approach.
- the detection of these relationships and translating them to control laws was found to be an extremely difficult task, involving many inaccuracies and arbitrary choices, owing to the non-linearities in general, and the mode-switches in particular.

In Chapter 5 some results are discussed concerning a near-optimal control law for a heat pump system, which was obtained with this approach.

4.6 Simultaneous design and control optimisation

4.6.1 Introduction

Chapter 1 presented an outline of the conceptual framework with regard to the control and design of thermal energy systems. Chapter 2 introduced the use of dynamic optimisation as a design tool. Having treated the dynamic optimisation aspects and the processes under study, it is now time to elaborate on the design optimisation aspects. Section 4.6.2 discusses the simultaneous optimisation procedure for design and control variables.
In Section 4.6.3 the proposed design procedure for thermal energy systems is presented in detail.

4.6.2 Simultaneous optimisation

There are several ways to arrive at an optimally designed and controlled process, e.g.:
- An alternating approach: starting with a chosen set of design variables, control variables and design variables are optimised alternately. The control variables give rise to a dynamic optimisation problem, the design variables to a (comparatively simple) static optimisation problem.
- An integrated approach: the design variables are treated as time-independent "control" variables and optimised simultaneously in the same iterative dynamic optimisation loop.

It may be argued that the integrated approach is more favourable than the alternating approach, because the latter requires the convergence of several dynamic optimisation loops, whereas in the former only one optimisation loop exists. Moreover, in the alternating approach a change in the design variables cannot be combined with a change in control, so the optimal set of design variables after such a step is only optimal in a limited sense, i.e. under the constraints imposed by the control strategy.

A small complication arises if the optimisation period consists of a number of separate disturbance patterns (e.g. in the procedure for hierarchical optimisation, Section 4.4). In every iterative step the control variables for each pattern can be varied independently, but the effect of the design variables in each characteristic pattern has to be combined to a gradient of the total criterion over all patterns (given by Ftot).
The integrated approach is represented in Fig. 4.10, where imax denotes the number of separate patterns.

Simultaneous optimisation of design and control variables

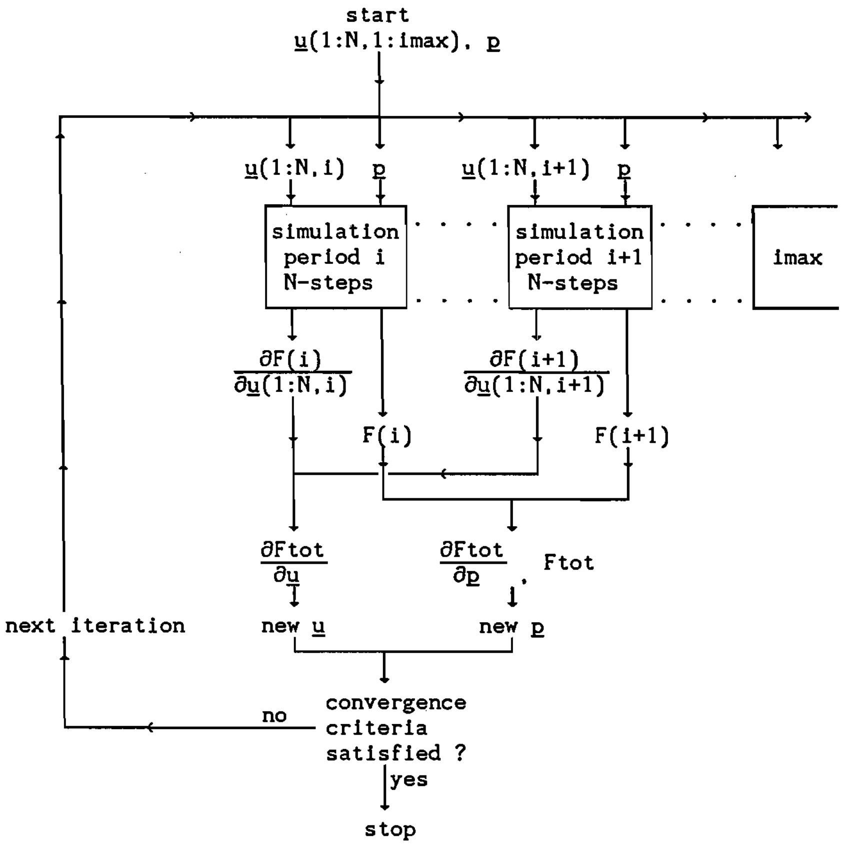


Fig. 4.10: The dynamic optimisation method for both design and control variables.

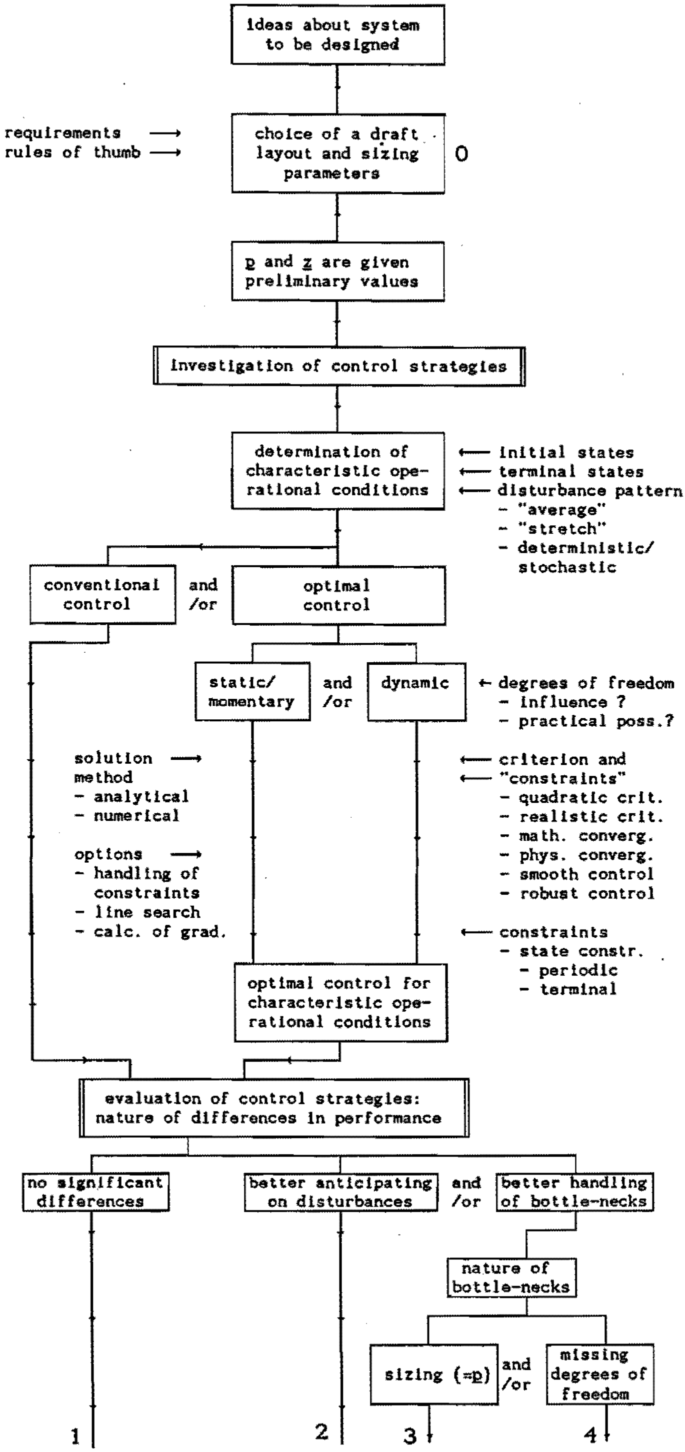
If the criterion function is much more sensitive to changes in design variables than in control variables, and this is the case in the applications treated in this thesis, a modification has to be made which refers to the scaling of the problem. The need for scaling the optimisation problem, i.e. the relevant domain of control variables and criterion, was already mentioned in Section 2.4.8. It would seem logical to scale design variables also between -1 and 1 over the relevant domain. But if the relevant domain of a design variable is comparatively large (for example a short-term storage mass between

10000 and 150000 kg.) the influence of this variable on the criterion is dominant, owing to the effects on the total costs of the system. In practical situations this simply means that first the optimal value of the design parameters is chosen, while the control variables hardly change. After that the control variables are tuned, but if the changes are significant the influence of the design parameters will become dominant again. In this way the procedure is nearly equivalent to the alternating optimisation approach mentioned above.
A way to overcome this problem is to scale design and control variables according to their influence on the criterion function. In this way, the search direction will no longer have a preference to point predominantly in the direction of the design parameters, and a balanced trade-off will be made between design and control effects.
Another approach is to reduce the relevant domain of the design variables so that the change from a maximum to a minimum value causes a change in criterion function comparable to the influence of control variables.
Both techniques have been developed for obtaining the results discussed in Section 5.8.

4.6.3 A design procedure for thermal energy systems

In this section I propose a new design procedure for thermal energy systems, including the whole design process from the initial problem statement to the operation of an existing process.

The first steps in this design procedure (see Fig. 4.11) are comparable to existing procedures: based on a set of requirements and/or according to proven rules of thumb, a draft system layout is chosen, and the sizing of the components is determined using rules of thumb or other forms of prior knowledge.
Next, the control aspects are investigated: starting with a determination of characteristic operational conditions, a number of control alternatives is examined. Fig. 4.11 also shows some of the choices that have to be made when using an optimal control approach. Afterwards, the possible differences in control performance have to be examined more closely, which may lead to the conclusion that the draft system layout should be changed (causing a feedback loop in the procedure).


ideas about system to be designed
requirements
rules of thumb
choice of a draft layout and sizing parameters
0
p and z are given preliminary values
investigation of control strategies
determination of characteristic operational conditions
initial states
terminal states
disturbance pattern
- "average"
- "stretch"
- deterministic/ stochastic
conventional control
and /or
optimal control
static/ momentary
and /or
dynamic
degrees of freedom
- influence ?
- practical poss.?
solution method
- analytical
- numerical
options
- handling of constraints
- line search
- calc. of grad.
criterion and
"constraints"
- quadratic crit.
- realistic crit.
- math. converg.
- phys. converg.
- smooth control
- robust control
constraints
- state constr.
- periodic
- terminal
optimal control for characteristic operational conditions
evaluation of control strategies: nature of differences in performance
no significant differences
better anticipating on disturbances
and /or
better handling of bottle-necks
nature of bottle-necks
sizing (=p)
and /or
missing degrees of freedom
1
2
3
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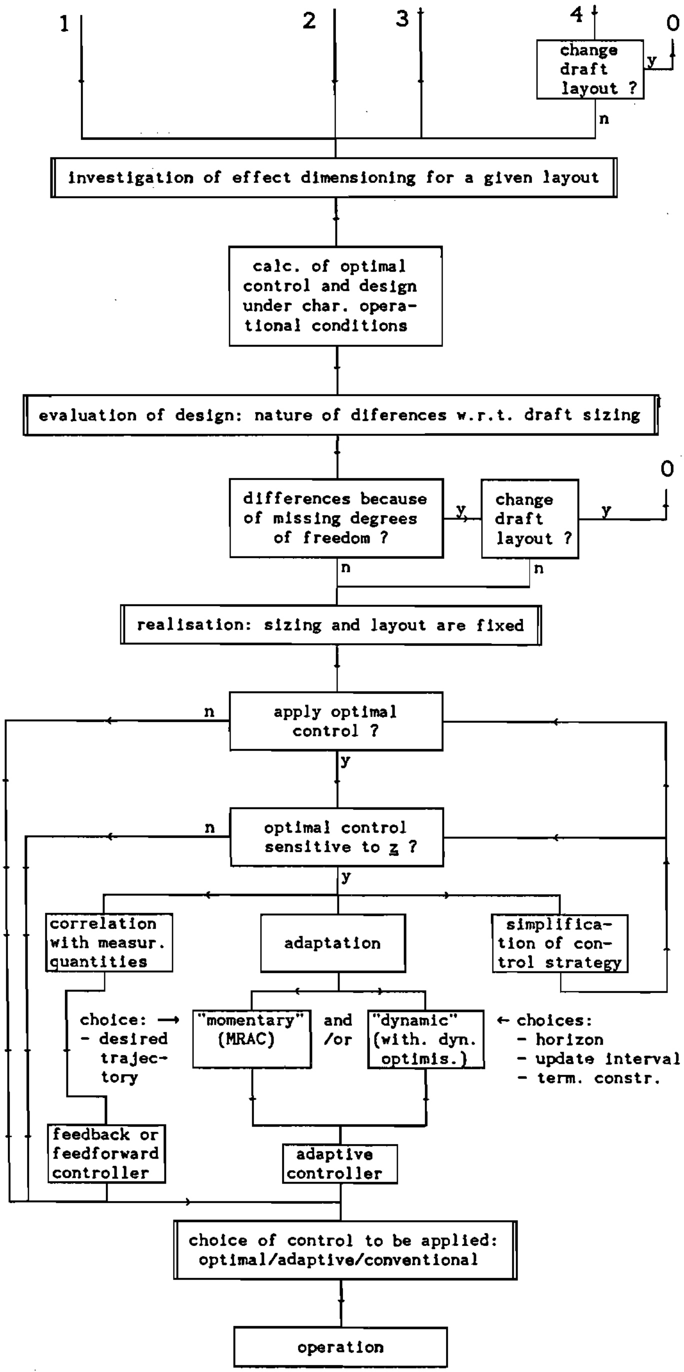


Fig. 4.11: The design procedure for thermal energy systems.

The next main step is the investigation of the effects of sizing for a given layout. Here the simultaneous optimisation procedure for control and design variables, as discussed in the previous section, is the most important tool. The results from this procedure are evaluated and compared with the initial sizing parameters which were chosen in the beginning of the procedure. This also may lead to a change in the draft layout.
The final step is the practical realisation of the system, including system control. If a non-conventional type of control is applied, matters like robustness and reliability require extra attention. It may be useful to apply adaptive control.

Thus far I deliberately have not mentioned any specific application in this section. Although the development of the design procedure treated here was fully based on our experiences in the field of thermal energy systems, it is felt that the general ideas of the procedure can easily be translated to other classes of dynamical processes.

4.7 State of the art: optimal control

4.7.1 Introduction

This section gives an overview of the state of the art with regard to optimal control of the systems dealt with in this thesis. Relevant published research on adaptive control and design optimisation is dealt with in Sections 4.8 and 4.9.
The references can be divided on the basis of the systems studied, the optimisation techniques and the criteria. To provide a basis against which the optimal control approaches can be judged, conventional ways of control are considered first.

4.7.2 Conventional control

It is beyond the scope of this thesis to discuss the large number of conventional control strategies suggested in the literature (see, for example, the proceedings cited in the reference list). The most important characteristics are:
- Most strategies have a "momentary" nature; Based on actual information on supply and demand variables and the states of the system, an operational strategy is chosen for the interval until the next update.
- Most strategies are limited to on/off control only.
- The selection between different operational modes is based on rather arbitrary criteria.
- The choice of these criteria is a problem in itself, and the use of "empirical" criteria such as:

- minimisation of the difference between storage temperature and momentary demand temperature.
- maximum heat input in the storage until it is "full"

is probably the most striking characteristic. Often quadratic criteria (quadratic expressions in control and state variables) are used, even if the aim is to minimise a non-quadratic quantity like the momentary auxiliary heating (cf. Section 4.2.3).

In general it can be concluded that conventional control strategies at best use a certain knowledge of deterministic variations in supply and demand patterns. The reaction of the control strategy to stochastic fluctuations is mostly on the safe side [DOR79b].

4.7.3 Research on optimal control

In earlier papers on solar thermal applications, the system is nearly always equipped with a fully mixed storage. The system is approximated by equations which are unnecessarily simple, allowing an analytical approach to be applied (Pontryagin, cf. Section 2.2.2), and resulting in on/off control strategies, partly based on measurable system states, and partly on future weather knowledge [ORB79, DOR79b, DOR83, WIN79]. For systems with thermally stratified storage some authors report optimal control under restrictive assumptions, for example the tempe- rature of the fluid entering the collector being constant throughout the day.

Only a few authors discuss the control of systems incorporating a heat pump [PRO82 and PRO85 give an overview], and in some papers the control of seasonal storage systems is discussed [LUN84a, LUN84b]. But this is mainly done by comparing several, fixed, control strategies, overlooking the possibilities of optimising the independent control variables.
The criteria most frequently used are quadratic, allowing for the application of special optimisation techniques, but again it must be pointed out that this comes down to solving the wrong problem, the primary interest being of an economic or energetic nature, and thus non-quadratic.
In recent years a tendency may be noticed towards criteria with a somewhat more realistic physical or economical meaning. The correct formulation of criteria, however, is still a topic of discussion among many authors [various papers in PRO82, PRO84 and PRO87b], and this often leads to confusion and difficulties in the intercomparison of results (cf. Section 4.2.3 for an evaluation of some of these criteria).
At the end of Chapter 5, where a comparison is made between the optimisation results of this thesis and previous work, some of these previous results are discussed in more detail.

It is concluded that the optimal control of thermal energy systems is not yet very thoroughly studied, especially for systems with more operational modes.

4.8 State of the art: design tools

4.8.1 Introduction

This section focuses on some existing design rules and tools for thermal energy systems. The design tools range from simple on-the-back-of-an-envelope methods to elaborate programme packages and can be divided on the basis of the following criteria:
- flexibility: what configurations can be studied ?
- degrees of freedom: what parameters can be optimised and how ?
- assumptions: are they (too) restrictive ?

The design tools discussed have in common that they are all developed for more or less general use, and are not site-specific or configuration-specific.
To start with, Section 4.8.2 is devoted to conventional design rules.

4.8.2 Conventional design rules

For specific applications and climatic conditions quite a few design rules are given in the literature, providing the sizes of the components using a fixed conventional control strategy. In Chapter 3 already some of these rules were used for the development of reference systems.
This section describes some of these design rules, which are, to a certain extent, "established" or "conventional wisdom" in this field, thereby focusing on two systems for space heating purposes.

- Solar energy systems with short-term storage for space heating

The first "generation" of these systems was designed to cover a relatively large part of the heat demand [e.g. PRO84]. This resulted in systems which were "optimal" from the point of view of energy consumption, but nearly always overdimensioned, and thus very uneconomical. The explanation to this fact is that because during the greater part of the year only a small part of the installed capacity is actually needed, the extra investments associated with collectors, storage ducts, etc. resulted in economically unattractive pay-back periods (it should be pointed out that in these economic evaluations the environmental effects are not taken into account).
Second generation systems for North-West European climates are generally designed according to a rule which implies that the collector-storage system should be able to produce about 30 % of the maximum heat demand [PRO84], thus covering 70 to 80 % of the total space heating load. The required collector area depends on the type of collector (see Section 3.3.3), and the storage volume is related to the collector area and type. For flat-plate collectors a short-term storage volume of 50 kg/(m^2 of effective collector area) is considered to be sufficient.

- Solar assisted heat pump systems with short-term storage for space heating

For systems incorporating a heat pump, similar experiences are described in the literature [PRO82, PRO85], indicating that the total power installed at the condenser side should be 25 to 30 % of the maximum space heating load. It is stressed that this refers to the system configuration of Fig. 3.6. In the U.S.A. solar assisted heat pump systems are also used for cooling purposes, which accounts for the fact that many advocates of other configurations (with their own design rules) can be found there.
The required heat source power at the evaporator side capacity depends primarily on the installed heat pump power.

4.8.3 Programme packages

The TRNSYS package is developed mainly for (dynamic) simulation purposes [KLE78, TRN78]. The components (all possible variations of collectors, heat pumps, storage systems etc.) are described in separate modules, coupled via a simulation handler. The emphasis is on the dynamics of the system under varying conditions, but the package is not very well suited to the variation and optimisation of control variables. For the optimisation of design variables general optimisation routines are employed.
The MINSUN package also permits an optimisation of design variables [INT83]. This is done by a bi-directional search procedure in every degree of freedom. A penalty function technique is used to handle constraints in the design variables.
The F-chart method and its direct successors were developed as a short-cut method for the design of (a limited class of) solar energy systems [BEC77].
Other packages treated in the literature are: SIMSOL, SUNSYST, NORSOL [INT83]. They were all mainly developed for a specific site or configuration, and thus their applicability is very limited.
All these design tools have the main drawback that is mentioned in the general discussion on design tools in Chapter 2. They presume a fixed control strategy or fixed values for the control variables, and thus the resulting optimal design is actually not optimal at all. Moreover, they sometimes yield quite different results, owing to the assumptions made.

From this it is concluded that the design tools already available have some important drawbacks with regard to the assumptions made, the incorporation of more advanced control strategies, and the criteria used. This formed the background for developing a new design procedure.

4.9 Applications of adaptive control

This section deals with some of the key references with regard to the application of adaptation to thermal processes related to the ones discussed in this work, the uncertainty in system parameters and future disturbance patterns being one of the main issues in thermal energy systems control. In literature two approaches are discussed:

- a probabilistic approach, using techniques for optimal control of stochastic systems. The system must be optimised in some "statistical" sense, resulting in a performance that is only optimal "on the average" (i.e. the operational modes are usually on the safe side), and in actual situations the system performance under this type of control may be quite poor [DOR83].
- an adaptive control approach, which is focused in this section.

Farris et. al. [FAR78, FAR80] (see also [DOR83]) discuss the application of adaptive optimal control to a model of a solar heated and airconditioned laboratory. An approximate linear model of the system is estimated over an identification interval. An optimal linear-quadratic control problem is solved via on-line solution of a Riccati equation [ELG67], using the most recently estimated values of the parameters in the linear model. Then an updated optimal feedback gain is implemented, and the whole procedure is repeated. A 28 percent reduction in auxiliary heating is claimed for this system compared to a simple on-off control. However, these papers suffer some methodological flaws, because the initial conditions were not the same in the comparison, and the comparison took place for one specific weather pattern only. Moreover, apart from being not realistic, the quadratic criterion function also had a number of arbitrary weighting factors.

A model reference adaptive control system for the temperature control of large buildings is discussed by Baars et al. [BAA87]. In this work the aim is to track a desired temperature trajectory by controlling the heating system. The trajectory is divided in 5 zones. After determination of the actual zone, followed by a linearisation within the zone, a "knowledge-based" system is used to determine the structure of the feedback controller and the adjustment of the controller parameters. The method works well for specific trajectories, although some questions remain unanswered, for example the effect of a change in the desired trajectory, or the influence of the choice of zones. For the problems dealt with in this thesis this approach is not suitable, because it is impossible to incorporate switches of operational mode.

It is concluded that the adaptive control of thermal energy systems is still a more or less uncovered subject.

5 Results

5.1 Introduction

In this chapter the optimisation results for both design and control parameters of a number of configurations are discussed. To illustrate the feasibility of the approach, some representative points in the multi-dimensional configuration space given by the components of Chapter 3 have been chosen. It is beyond the scope of this work to scan this configuration space completely, but it is stressed that the dynamic optimisation approach as presented in this thesis is not limited to the configurations treated.
The systems discussed in this and the following sections are:

A - a heat pump with collectors and short-term storage for space heating (see Fig. 3.6).

B - collectors with short-term and long-term storage for space heating (Fig. 5.17).

C - a heat pump system with collectors, short-term and long-term storage for space heating (Fig. 5.14).

From the point of view of optimal control, configuration B is relatively simple because of the small number of control variables and operational modes. Configuration A and C represent the relatively complicated situation of a system with various operational modes and with disturbances affecting both the supply and the demand side.

Also a number of systems incorporating a heat exhanger has been studied. The results, however, showed no significant differences with the systems treated here: if the heat exchanger is used to interface with the surroundings of the system, the quasi-stationary behaviour is more or less comparable to a collector; if the heat exchanger is placed, for example, between collector and heat pump, the optimal flow rates at both sides of the heat exchanger nearly always have the same ratio, and this confirms results of Rijk [RIJ85]. Therefore this component will not be discussed in this thesis, the emphasis being on the configurations A, B and C.

The layout of this chapter reflects the schematic representation of the design procedure treated in Section 4.6.3., the only difference being the discussions of sensitivity, adaptation and translation to near-optimal controls, which are treated here before turning to the design aspects.
In the first part of this chapter the design parameters are considered as prescribed and the focus is on the control aspects. Each system is considered to have fixed dimensions, more or less according to existing design rules. The demand circuit, the heat pump, the short-term and long-term storage, are all sized according to Table 3.1 of Section 3.3.2. For the collectors a heat loss coefficient of 15 $W/m^2/K$ and an area of 1000 m^2 is chosen, unless indicated otherwise.

In Sections 5.2 to 5.4 the focus is on configuration A. Section 5.2 treats the conventional, static and momentary optimal control. In

Section 5.3 the dynamic optimal control strategy is discussed, whereas in Section 5.4 the effects of state constraints are dealt with. An important topic in dynamic optimisation is the choice of characteristic disturbance patterns, which is discussed in Section 5.4.4.
Results of the hierarchical optimisation procedure for configurations B and C with both short-term and long-term dynamics are presented in Section 5.5.
Section 5.6 discusses the sensitivity of the optimal solutions to variations in the assumed disturbance patterns. In Section 5.7 the most important results on adaptive types of control are summarised.
In Section 5.8 a near-optimal control for configuration A is developed, based on the dynamic optimal control results. Furthermore, results from previous research and the results presented here are compared, and some design considerations for different configurations are treated.
In the second part of this chapter the design parameters are taken into consideration. To illustrate one of the most important characteristics of the new design method developed in this thesis, Section 5.9 presents results of simultaneous optimisation of control and design variables, the cost functional being an economic one rather than an energetic one.
Section 5.10 is devoted to an evaluation of some computational aspects of the optimisation method with regard to the application to thermal energy systems.

To permit an intercomparison of the results, most of the optimal control strategies to be discussed in this chapter were obtained under the same conditions regarding optimisation interval, disturbance patterns and initial states of the system. The few exceptions are treated separately in Sections 5.4.4, 5.5, and 5.7.3.
For the purpose of illustration, the optimisation interval is restricted to 24 hours. The weather pattern consists of so-called characteristic days obtained by taking the monthly average of the hourly data of Ta and Qs from the reference year. Only the results for the characteristic days of January, April, July and October are shown. The use of "averaged" weather data in the (non-linear) system considered here can only be justified if the effects of deviations from these average patterns are investigated, as will be done in Section 5.6. Although these characteristic days may not be representative for the effects of the various control strategies under all conceivable disturbances (cf. Section 5.4.4), they reflect the most important phenomena.
The characteristic days all start at 6.00 am, which allows heat supply to the storage under relatively favourable circumstances, for later use during the night. Fig. 5.1 gives the weather data Ta and Teq, and the demand temperatures Td and Tod, for the characteristic days considered. From this figure it can be concluded that these characteristic patterns are rather "smooth". The effects of the choice of these smooth patterns are discussed briefly in Section 5.6.2.
It also follows from Fig. 5.1 that the maximum in Teq always occurs a few hours before the maximum in Ta, reflecting the realistic time-lag

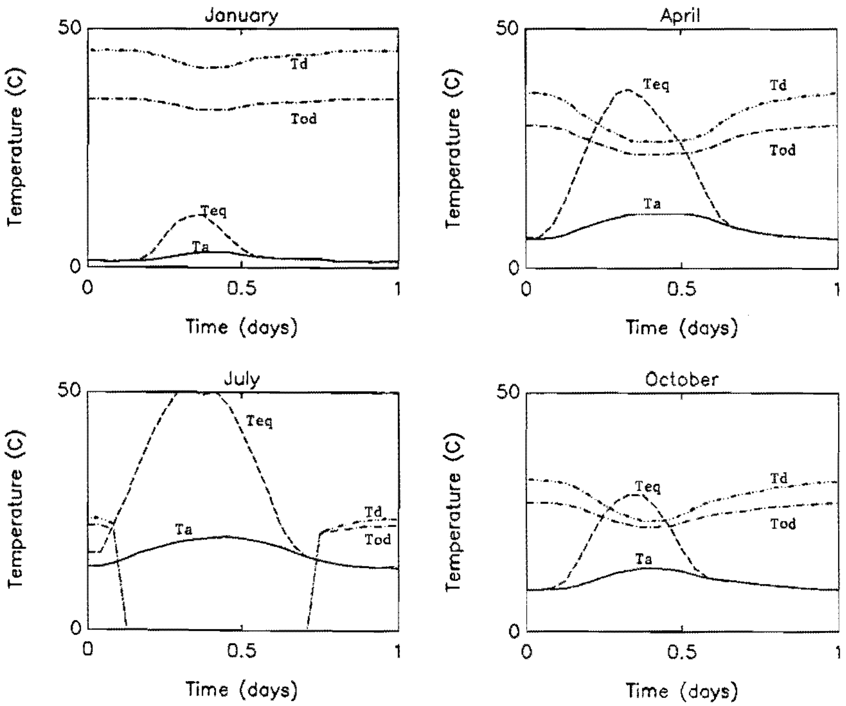


Fig. 5.1: Characteristic weather and demand patterns for January, April, July and October.
Time-axis: 0 is 06.00 a.m., 0.25 is noon.

between solar irradiation and ambient temperature. Td and Tod are directly related to Ta (cf. Section 3.2.6).
The control variables are the rotation speed of the heat pump compressor, Nc, the flows Fl, Fh, Fcd, Fch (cf. Fig. 3.6) and the switch-on fraction fr. Except in Section 5.5, this set of control variables is used throughout this chapter.
Another choice to be made is the initial state of the system, in this case this comes down to the temperature distribution of the short-term storage. For the characteristic day of January, April and October the storage is assumed to have a uniform temperature of 30 °C at the beginning of the optimisation period, which is representative for that time of the day. For July this temperature is chosen to be 20 °C: A higher temperature would result in a situation without the need for charging the short-term storage, owing to the very small heat demand in this characteristic day.
The initial states for systems with long-term storage are discussed in Section 5.5.

Presentation of the results

In the following sections the most important optimisation results are presented graphically or in tabular form. Detailed information concerning these results can be found in Appendix A, to be used as a reference.
For the short-term storage the temperature distribution is illustrated by the average temperatures of four horizontal layers in the storage, each with the same mass: Tvt1 represents the bottom layer and Tvt4 is the top layer of the storage.

For each time-step the following variables, if relevant, are depicted:
- the weather pattern, the equivalent ambient temperature being related to solar irradiation and ambient temperature in Eq. 3.6 of Section 3.2.3;
- control variables (if a component, for example the heat pump, is not operated during a time-step, the control variables fr, Fl and Fh are put to zero, in spite of their lower boundary in Table 4.1);
- the momentary criterion value, which is the integrand of the criterion function (the pumping power is usually not depicted, its contribution to the total energy consumption mostly being relatively small);
- (an indication of the) storage temperatures;
- required temperature and return temperature on the demand side.

For the optimisation period as a whole the following quantities are given:
- averaged efficiencies of various components;
- total energy flows in the system;
- the value of the criterion function;
- the difference in heat content of the storage components before and after the optimisation interval.

5.2 Conventional, static and momentary optimal control

5.2.1 Introduction

This section discusses the results for conventional, static and momentary optimal control of configuration A.

In Section 4.7.2 it was pointed out that most of the conventional control strategies are on/off strategies, the switching points generally being determined on the basis of momentary criteria. To allow a realistic comparison with optimal control, a conventional strategy is chosen in which, based on momentary measurements, the operational mode is selected. The fraction of the time-step that this mode is applied is determined via a momentary criterion. Thus the reality of a continuously operating conventional control is translated to the discrete time-step used in optimisation in the best possible way. In words this strategy comes down to:

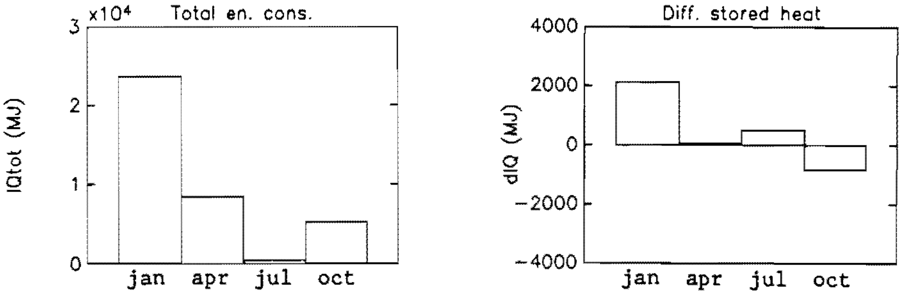
- The storage is charged if the temperature distribution at that moment does not permit a delivery of heat during 3 hours at a required maximum temperature level, characteristic for the season.
- If charging of the storage is necessary, the mode of operation is chosen according to the momentary values of the output temperature of the storage at the supply side, Tov, and the equivalent ambient temperature Teq. If Tov is below Teq-5, only the collector is in operation, with a constant flow rate (Fcd = 5 kg/s). If Tov exceeds Teq-5, the collector is used together with the heat pump, with constant values of the rotation speed and the flow rates (Nc = 1000 rpm, Fl = Fh = 5 kg/s). In this case no preheating of the condenser is allowed (Fch = 0). The fraction fr is chosen so as to minimise the difference between the actual heat content in the storage and the heat content required for 3 hours of maximum heat demand in that part of the year. ($0.25 < fr < 1.00$).
- In summer the heat pump is not used.

The static optimal (on/off) control strategy is determined via the approach described in Chapter 4. An important difference between static optimal and conventional strategies lies in the (dynamic !) optimal choice of the on/off switching points.

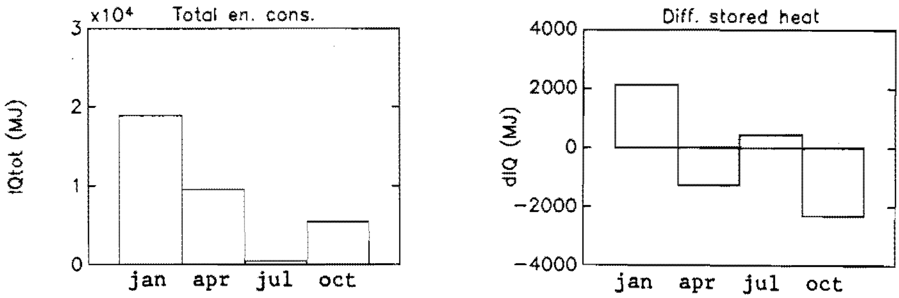
The momentary optimal control to be presented is actually of minor interest for systems with storage components, because in this type of control it is useless to store heat for future use. But the momentary optimal control gives an insight in the choice of efficient operational modes under varying conditions, and is therefore useful for an interpretation of dynamic optimisation results.

5.2.2 A comparison of control strategies

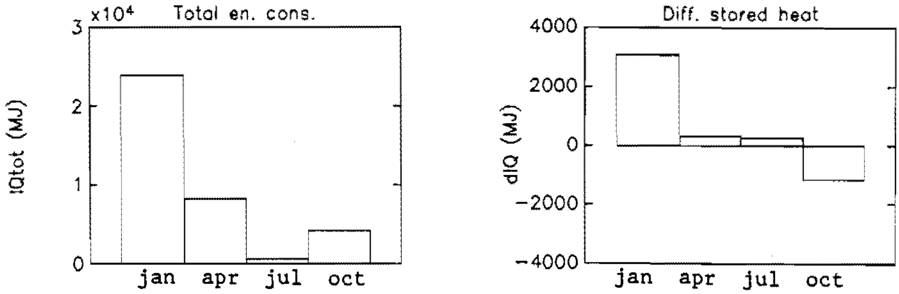
Fig. 5.2 presents for 3 types of control the energy consumption IQtot and the increase in heat content of the storage from the beginning to the end of the 24-hour interval, dIQ. The total energy consumption over the four characteristic days, IQtot(year), interesting for an evaluation of the differences in performance over a year, is also given. The total heat demand IQd(year) equals 46.49 GJ. More detailed information can be found in Appendix A.
From this figure it can be concluded that the differences in control strategies mainly occur in the characteristic periods of October and April, which are periods with a rather small discrepancy between supply and demand. In cold winter days the system is always operated at full "speed" in the same operational mode. In summer days with a lot of ambient heat and a small heat demand the operational mode without the heat pump is always favoured.



Conventional control. IQtot(year) = 37.98 GJ.



Static optimal control. IQtot(year) = 36.73 GJ.



Momentary optimal control. IQtot(year) = 34.34 GJ.

<u>Fig. 5.2:</u> Results of conventional control compared with static and momentary optimal control.

Except for January, which will be discussed later on, the momentary optimal control is always inferior to the static one and the conventional control. The performance of the momentary optimal control is especially worse in April and October, because in these months storage is more important than in January, where the heat demand is constantly high and the system is always operated at maximum capacity, and in July, with a very small heat demand.
In April the conventional strategy comes close to the static one with regard to the total energy consumption, but the static strategy results in a considerably larger heat content of the storage at the end of the day. Of course this effect has to be taken into consideration when comparing these strategies, because the heat content in the storage for the next day will strongly affect the energy consumption in that day.
The small difference between static optimal and conventional control, although the heat pump is operated at very different speed, can be explained by looking at the numerical results in Appendix A: Under conventional control the heat pump is operated at a lower Nc, which results in a better COP and a better collector efficiency.

In January a start-up phenomenon can be discerned which results in a momentary optimal control with a better performance than the static one: this is because in momentary optimisation the supply circuit has to be calculated first (cf. Sections 3.2.5 and 4.2.4), as opposed to static and dynamic optimisation where first the demand circuit is calculated in a time-step. Therefore the need for auxiliary heating in the first time-step is much smaller, thus reducing the total energy consumption. The large difference between static and momentary control in this period can thus be regarded as a computational artefact. As a result, the yearly performance, represented by IQtot(year) is 7 % better compared to static optimal, and nearly 11 % better compared to conventional control.
For the same reason the momentary optimal control shows operational conditions which are not "full speed" at times when the heat supply via Teq is at a maximum, and this is indicated in Appendix A where the control strategies and other important data for the four weather patterns under different types of control are given.

To examine typical differences between the various control strategies in more detail, Fig. 5.3a to c give the results for the characteristic day of April.

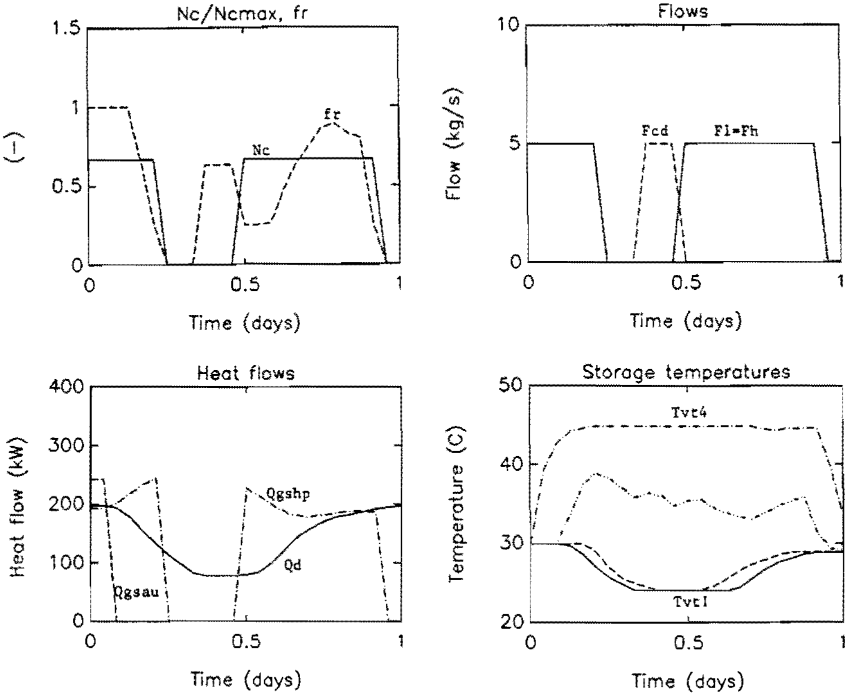


Fig 5.3a: Results of conventional control, April.

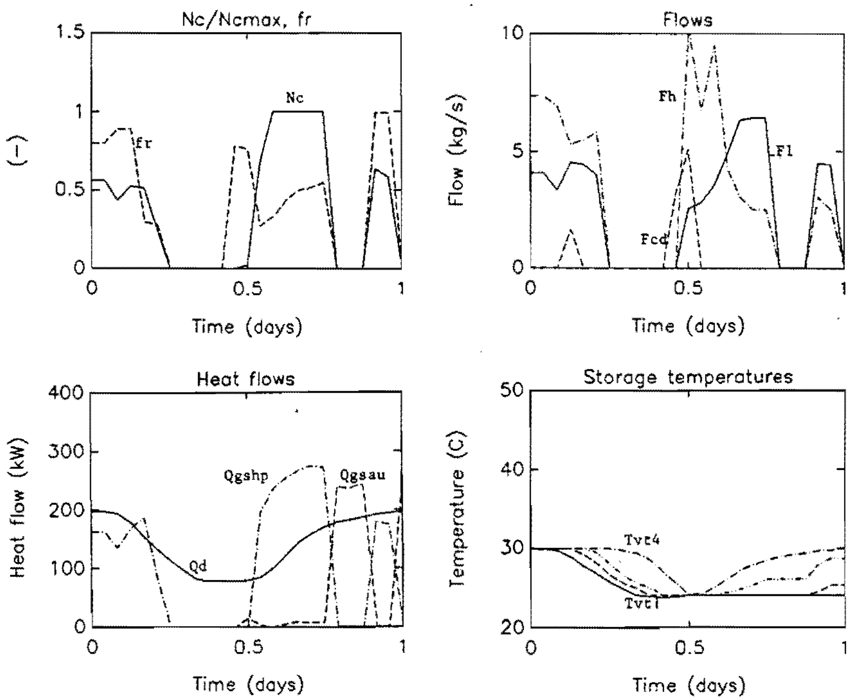
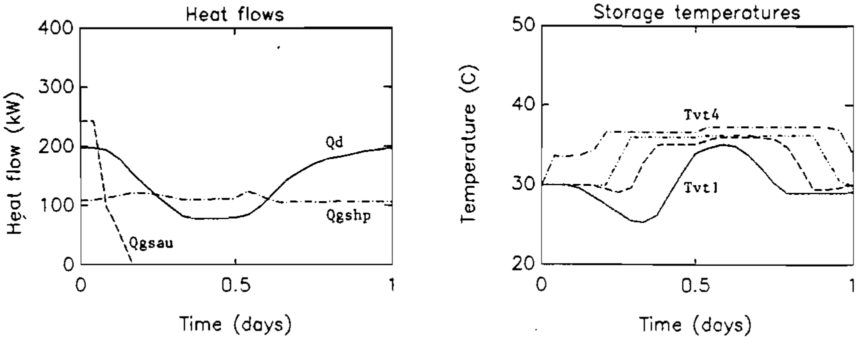


Fig 5.3b: Results of momentary optimal control, April.



Nc = 1098, fr = 0.74, Fl = 4.08, Fh = 4.71, Fcd = 2.62, $4 \leq n \leq 12$

Fig 5.3c: Results of static optimal control, April.

The conventional control strategy of April shows a smooth pattern. First the heat pump is operated (see Nc), and if Teq is sufficiently high the bypass mode (Fcd) is used. If the heat pump is in operation, the switch-on fraction (fr) more or less follows the pattern of the heat demand (Qd).
The storage temperatures (indicated by the average temperatures Tvt1 to Tvt4) are high enough to make auxiliary heating unnecessary, except during the first time-step.
Under static optimal control (Fig. 5.3c), the heat pump is operated at a relatively high Nc of 1098, with a switch-on fraction of 0.74, for those time-steps of the day where Teq is high, thus collecting heat in the most efficient way, given the constraint that only one mode of operation (apart from being switched off) is allowed in this case. Although the storage temperatures are not as high as with conventional control, the amount of auxiliary heating is still very small.
Under momentary optimal control (Fig. 5.3b), the behaviour is slightly more complicated. Both heat pump and collector are not employed at the times when operation would be most efficient, i.e. when Teq is high. This is because, at that moment, there is no need to operate the supply-side of the system, the heat demand being covered by the contents of the storage. As a result, the storage temperatures in the second half of the day are too low to meet the heat demand, and a considerable amount of auxiliary heating is necessary, which illustrates the non-anticipating behaviour of momentary optimal control.
The operational mode provided by Fch (cf. Fig. 3.6) was not used in static and momentary optimal control.

5.3 Dynamic optimal control

This section presents the dynamic optimal control strategies for configuration A, focusing on the differences with the other types of control discussed in Section 5.2.2.
In Fig. 5.4 the values of three key variables are given for the reference weather patterns, together with a comparison (by means of IQtot(year)) of the four types of control discussed thus far. Detailed numerical results can be found in Appendix A.

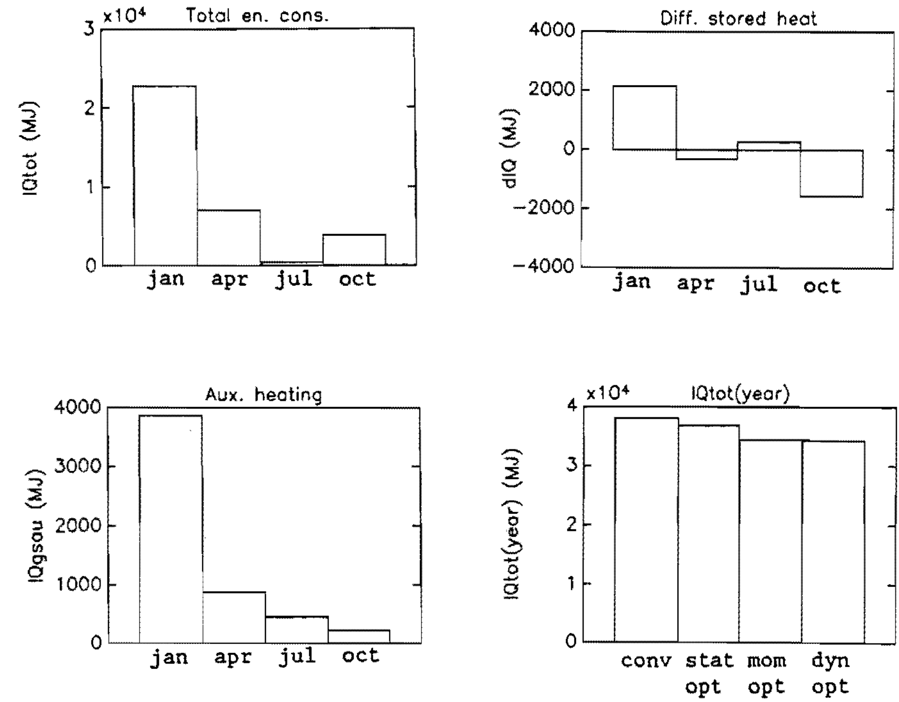
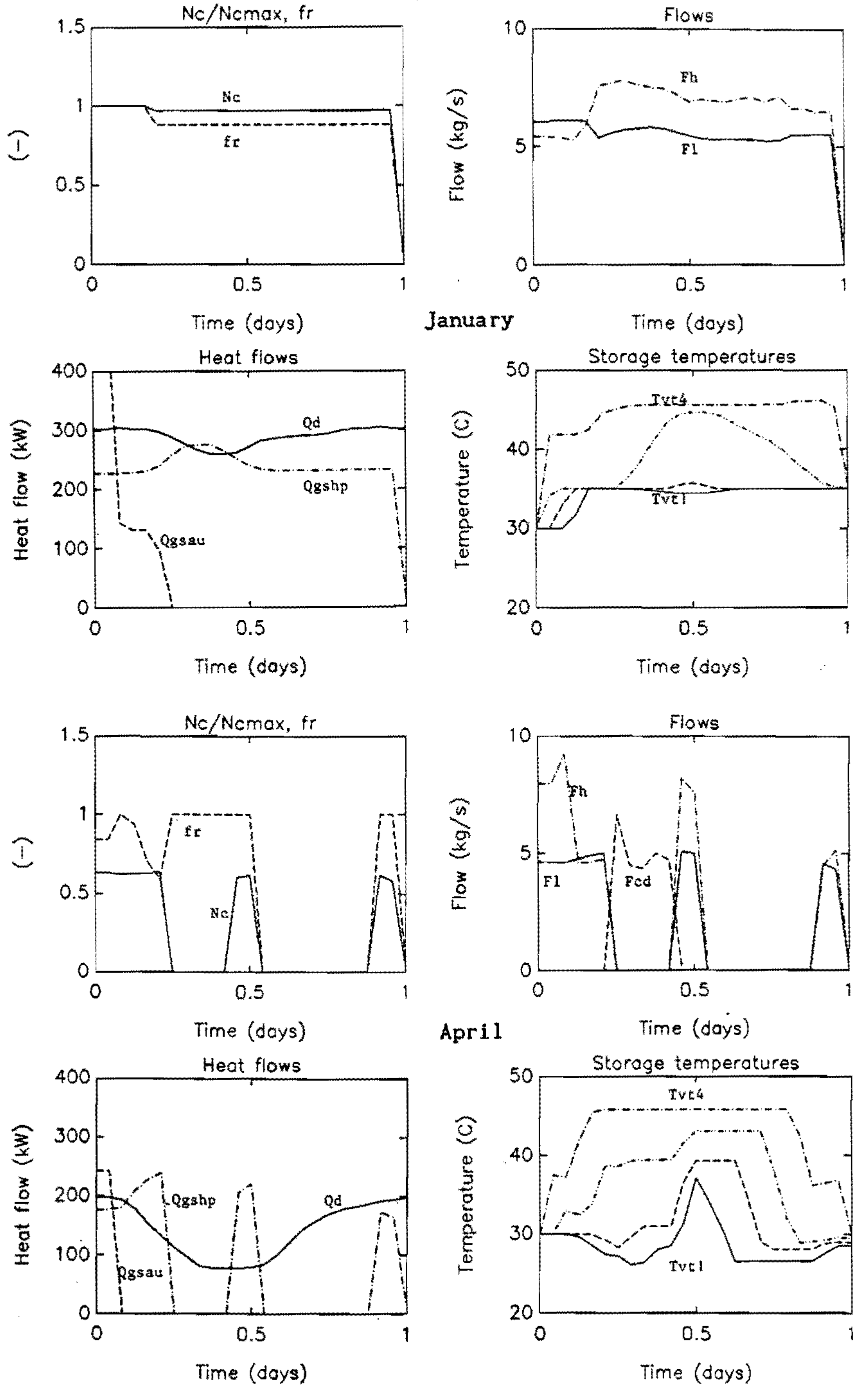


Fig. 5.4: Results with dynamic optimal control.
IQtot(year) = 34.23 GJ.

A comparison with Fig. 5.2 shows that dynamic optimal control achieves a significant reduction in energy consumption as compared to the other types of control, of up to 10 % when compared to static optimal control, and from 5 to 20 % when compared to conventional control (the only exception is the start-up artefact under momentary optimal control discussed in Section 5.2.2). In terms of IQtot(year), the reduction is 11 % with respect to conventional control and 7.3 % as compared to static optimal control. These reductions are of the same order of magnitude as obtained by Slenders [SLE84], under slightly different circumstances (cf. Section 5.8.2).
These differences may seem small, but it is stressed that the numbers are highly influenced by the results of January, where the positive effect of dynamic optimal control is very small. However, the differences are still significant with respect to the accuracy of the criterion function, which is 0.2 %.
Fig. 5.5a and 5.5b show the most important data for the characteristic days.
The dynamic optimal controls of January and July show a pattern which could be expected on the basis of Section 5.2.2: In January the heat pump is operated at full speed, in July only the collector is used.
In April and October, different operational modes are applied, depending on the momentary value of Teq. If Teq is sufficiently high, either only the collector is used (April) or the combined operational mode is applied (collector and heat pump operating simultaneously, with a part of the collector fluid flow bypassing the heat pump (Fcd), as in October).
This is an indication of a direct relation between the dynamic optimal mode of operation and the momentary value of Teq, which I will use for the development of near-optimal control strategies discussed in Section 5.8. A similar relationship is also reported by Slenders and Van Stiphout [SLE84, STI83] (see Section 5.8.2). An important difference between their work and the results presented here is the fact that their conclusion with regard to the output temperature of the heat pump condenser is not supported here (see Section 5.8.2: they concluded that in the dynamic optimal case this temperature was always a few degrees below the demand temperature).
The operational mode provided by Fch is again not used in this type of control. It may be concluded that this extra degree of freedom is superfluous for the system considered.
The numerical results given in Appendix A reveal the differences between the control strategies in more detail: Dynamic optimal control generally leads to higher collector efficiencies and higher, but not necessarily maximal, COP-values, and this, combined with the more efficient use of the thermal stratification in the storage, accounts for the reduction in total energy consumption.



<u>Fig. 5.5a:</u> Results of dynamic optimal control strategies applied to a system with heat pump and collectors. Weather patterns of January and April.

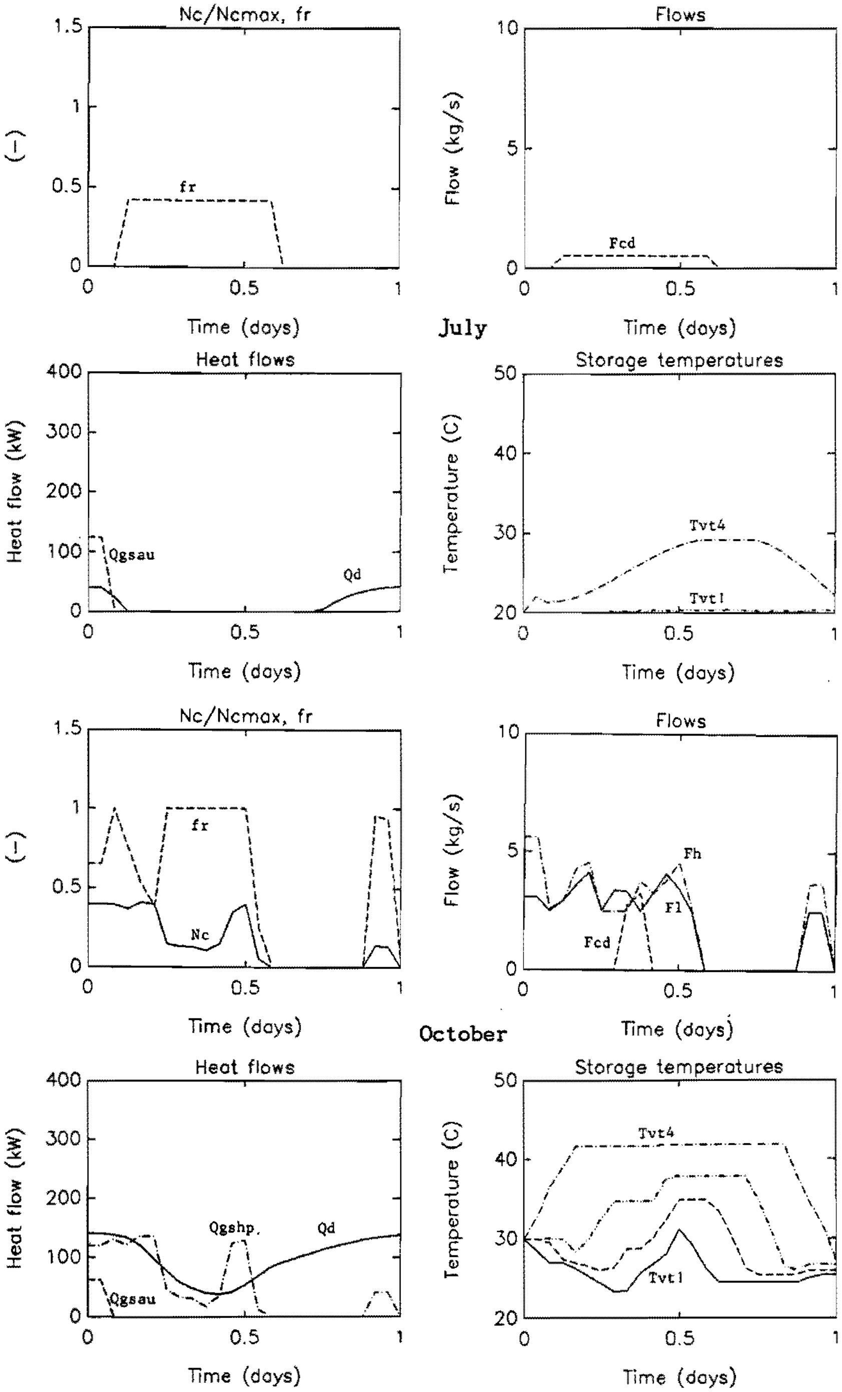


Fig. 5.5b: Results of dynamic optimal control strategies applied to a system with heat pump and collectors. Weather patterns of July and October.

5.4 Optimisation with state constraints

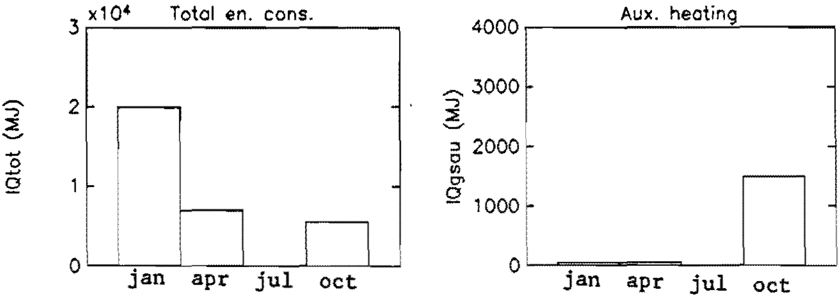
5.4.1 Introduction

In the previous chapters, two types of state constraints were discerned:
- Terminal state constraints: the temperature distribution at the end of the optimisation interval must equal a desired distribution (which implies that this state constraint has to be satisfied using an appropriate expression for the "end costs" (cf. Chapter 2), or using a penalty function method).
- Periodic state constraints: for a system with short-term storage this means that the resulting temperature distribution in the storage at the end of the optimisation interval is equal to the distribution at the beginning of this interval.

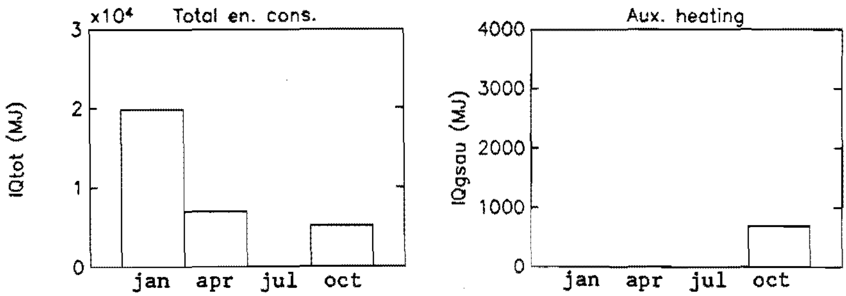
In the following sections some aspects of these constraints are dealt with.

5.4.2 Periodic state constraints

One of the most important reasons to apply periodic state constraints is that the strong influence of the initial and terminal states (cf. Section 5.2 and 5.3) is eliminated. Because optimisation with these constraints provides an approximation of the dynamic optimal control for an infinite series of intervals with identical weather patterns, the resulting optimal state trajectory might be used as a reference trajectory in adaptive control. Moreover, the periodic optimal states for each time-step can be used to serve as terminal state constraints for dynamic optimisation in start-up or transient situations. The latter is illustrated with an example: assume a configuration for which periodic optimisation reveals that the short-term storage should have a certain temperature distribution at 6 o'clock in the afternoon. If the weather shows a tendency towards the average weather pattern in the time of the year (for which the periodic optimal control was calculated), it may be a good (and probably the best practical) strategy to apply the dynamic optimal strategy over a period of, say, one day ending at 6 pm, with as terminal state constraints the periodic optimal state at that time.
In this section the results of periodic optimisation of configuration A are presented.
In Fig. 5.6 the energy consumption and the auxiliary heating is given for the reference weather patterns. Control variables and system dimensions are identical to the previous sections. The periodic state constraints are applied under static as well as dynamic optimisation.



Static optimal control with periodic state constraints.
IQtot(year) = 32.37 GJ.



Dynamic optimal control with periodic state constraints.
IQtot(year) = 31.98 GJ.

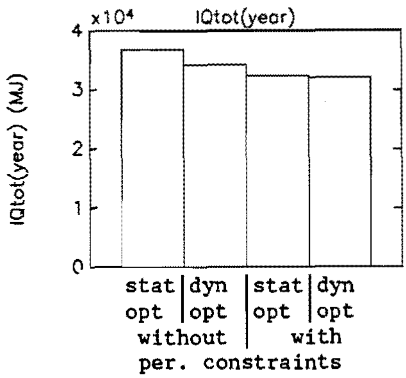


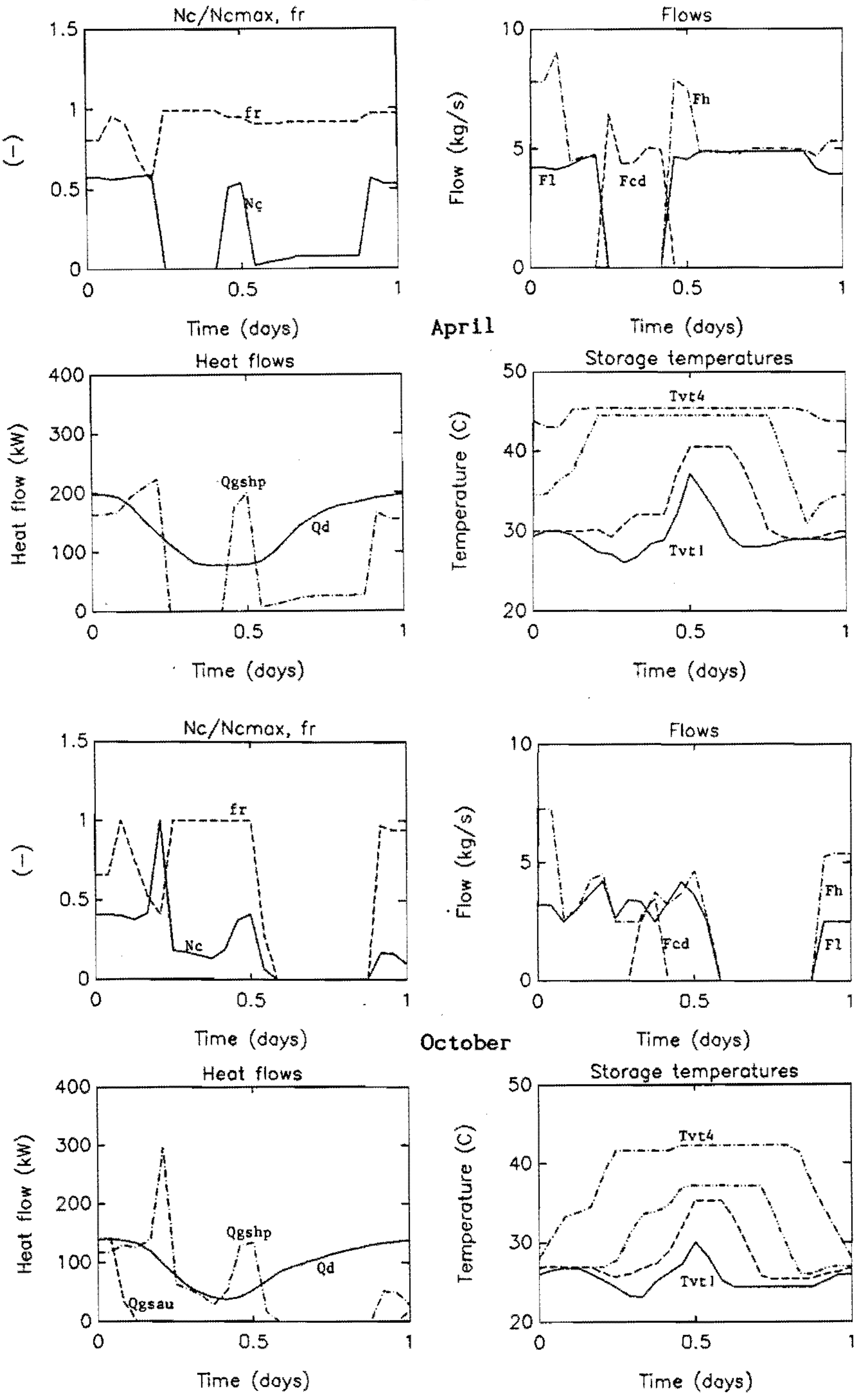
Fig. 5.6: Results of static and dynamic optimisation with periodic state constraints.

From Fig. 5.6 it can be concluded that the differences between static and dynamic optimal control performance are very small in January and April. In July the percentual reduction in energy consumption for dynamic optimal as compared to static optimal control is 40 %, but in absolute terms this is still a very small difference. In October this reduction is 6 %. These small differences can be explained from the fact that the heat demand is "matched" by the periodic optimal heat content of the storage: Except in October, the optimal strategy is to minimise the contribution of the auxiliary heating. For example, the detailed numerical results given in Appendix A reveal that in April static optimisation as compared to dynamic optimal control leads to lower storage temperatures, and less auxiliary heating, the heat pump being operated at a better COP, which results in a barely larger total energy consumption, although the actual control strategy is quite different.

Fig 5.6 also gives a comparison of IQtot(year) with results obtained without periodic state constraints. The reduction of the auxiliary heating leads to an improvement of about 6 % when compared to dynamic optimal control without state constraints.

Fig. 5.7 shows the most important dynamic optimal control data for April and October, those for July and January are not shown because the dynamic optimal control is only slightly different as compared to the results of Section 5.3. In April the initial auxiliary heating, which was found necessary in Section 5.3, disappears completely, because dynamic optimal control keeps the storage at higher temperatures until the end of the day. For April and October the control shows more differences compared to Section 5.3: In April the heat pump is in operation during the night, in order to keep the top layers of the storage at a higher temperature. In October the storage is kept at a relatively low temperature. This introduces the need for some auxiliary heating at the beginning of the period, but has the advantage that better operational conditions for the heat pump are obtained.

The storage temperatures follow typical patterns which are similar to the ones obtained in Section 5.3, suggesting a sort of reference state trajectory which might be used in adaptive control (Section 5.7) or in the derivation of a near-optimal control strategy (Section 5.8).



<u>Fig. 5.7:</u> Results of dynamic optimisation with periodic optimal control strategies applied to configuration A. Weather patterns of April and October.

5.4.3 Terminal state constraints

Section 5.4.2 already mentioned the use of terminal state constraints to arrive at a periodic optimal state trajectory, starting from an arbitrary state. In this section the emphasis is on the following questions:

- starting from a given initial state, what range of terminal states can be obtained under various supply and demand patterns, or in other words: what is the "controllability" of the system for a given interval of, say, 24 hours.
- starting from an initial state, how much time is necessary for the system to reach a prescribed terminal state.

As in the previous section, the results shown are not pretended to give an overall picture, but merely indicate the most significant aspects.

In Fig. 5.8 the energy consumption and the differences in the states of the storage are given for the reference weather pattern of April, and a number of specified terminal states of the storage. The terminal state constraint $\underline{x}d$ is represented here by the value of the average storage temperature $\overline{Tvt}$, ranging from 25 to 50 °C. Detailed numerical results are given in Appendix A.

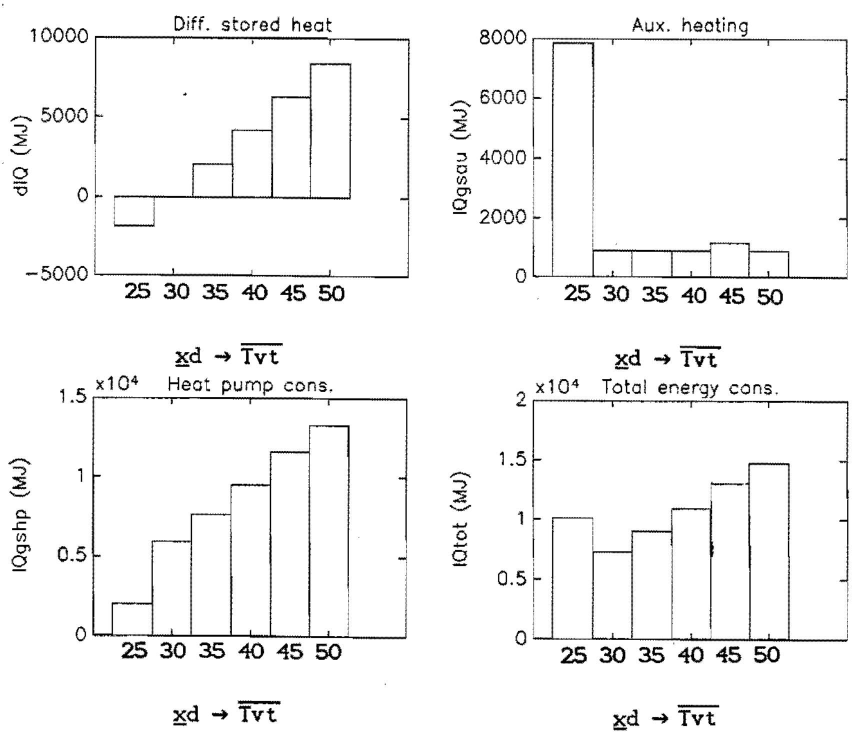


Fig. 5.8: Results with terminal state constraints. Weather pattern of April.

Fig. 5.8 indicates that the specified terminal states can be obtained simply by modulating the total energy delivered by the heat pump. The only bottleneck is given by the return temperature of the heating system. If this temperature is relatively high, a terminal state constraint corresponding to a low average storage temperature cannot be satisfied without applying a very awkward control strategy, with a high rate of auxiliary heating (cf. $\overline{Tvt}$ = 25 °C in Fig. 5.8). This can also be concluded from Fig. 5.9, which shows the most important data for two characteristic situations.

For $\overline{Tvt}$ = 25 °C, as can be seen in Fig. 5.9, the supply side of the system is switched off during the second part of the day, resulting in a storage temperature which is as low as possible under these circumstances, but introducing the need for auxiliary heating. The effect of the return temperature Tod can be identified in the graph of the storage temperatures: The top layer temperature Tvt4 follows the pattern of Tod (cf. Fig. 5.1).

A comparison of the results for $\overline{Tvt}$ = 50 °C to the dynamic optimisation results of Section 5.3 reveals that this state constraint affects the setpoints of the control variables (the heat pump is operated at a higher rotation speed), as well as the operational modes (in contrast to Fig. 5.5a the heat pump is now in operation in almost every time-step).

It can be concluded that under "average" circumstances the system is able to transfer the state variable values over a relatively wide range (given the fact that under Dutch climatic conditions the ambient temperature almost never changes more than about 15 °C in one day), and that the system is satisfactorily fast and flexible with regard to optimisation periods of at least 24 hours. This is an important finding to be kept in mind for hierarchical optimisation, and for the application of adaptation techniques and near-optimal control.

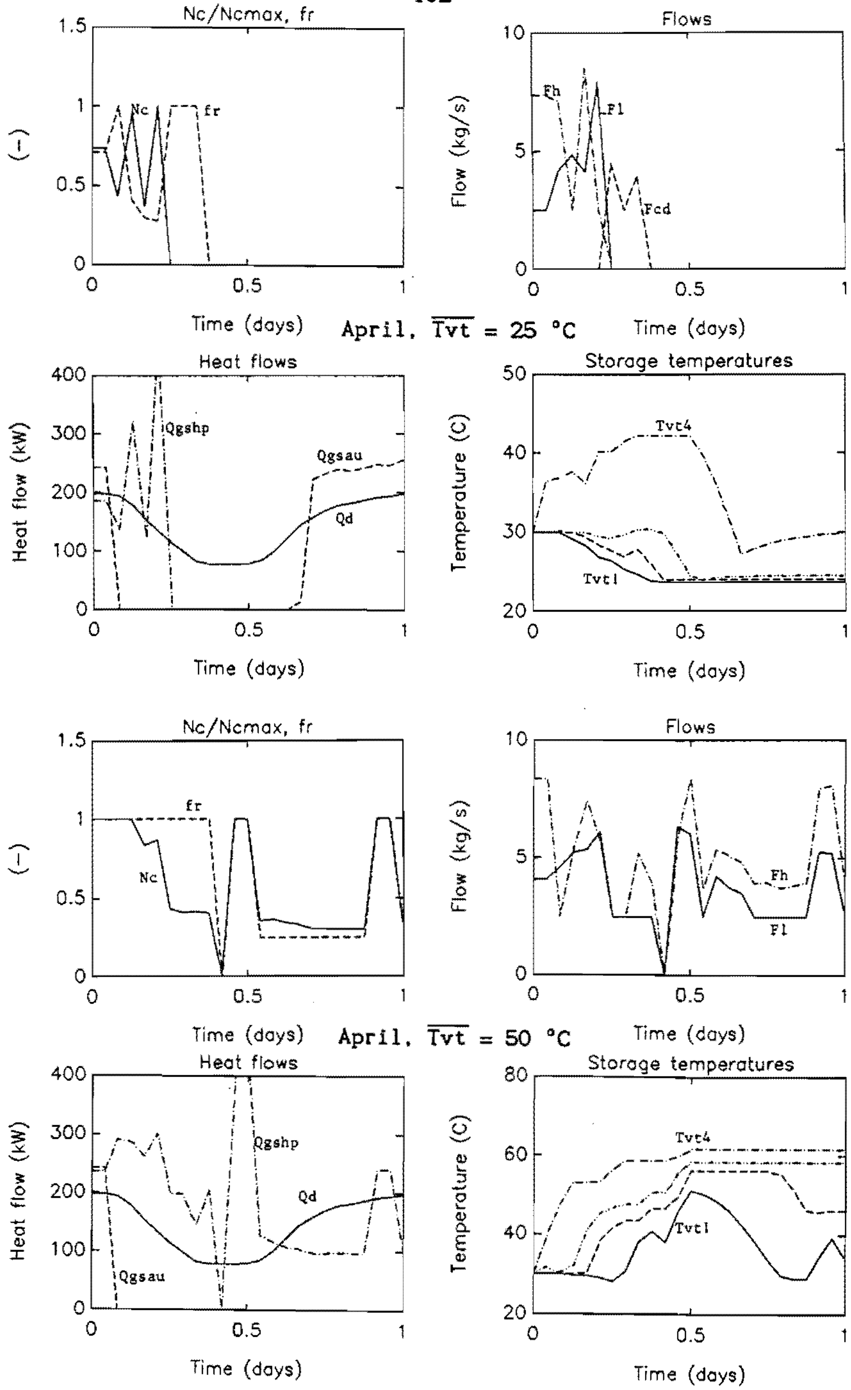


Fig. 5.9: Results of terminal state constrained optimisation applied to a system with heat pump and collectors. Weather pattern of April. Desired average short-term storage temperature: 25 °C and 50 °C, respectively.

5.4.4 The choice of characteristic disturbance patterns

Thus far the discussion of the results was restricted to a 24-hour optimisation interval. Of course this imposes limitations to the applicability of the results.
Periodic state constraints give the optimal solution for a long series of identical intervals. But in realistic situations with weather variables as disturbances (and this is the case in the configurations considered in this chapter) the number of more or less identical 24-hour periods will generally be small.
For the 24-hour optimisations the weather pattern was extracted from the reference year by taking the monthly averaged data, thus obtaining "characteristic days" for each month. But the spread in daily weather patterns within a month is great, and for an accurate description of the behaviour throughout the year this spread has to be taken into consideration. Thus the system is almost never in a periodic stationary situation, but nearly always in a "transient" state. The previous section showed that this system has the ability to respond relatively rapidly to transient conditions.
In this section an impulse is given to a more detailed optimisation approach, by studying the effect of transient conditions, using the concept of a "stretch". Rademaker [RAD88] previously introduced the stretch as an interval between two identical states of the system. In this thesis I extend this definition to intervals between two periodic stationary situations. This is illustrated in Fig. 5.10, where an example of such a stretch is given:

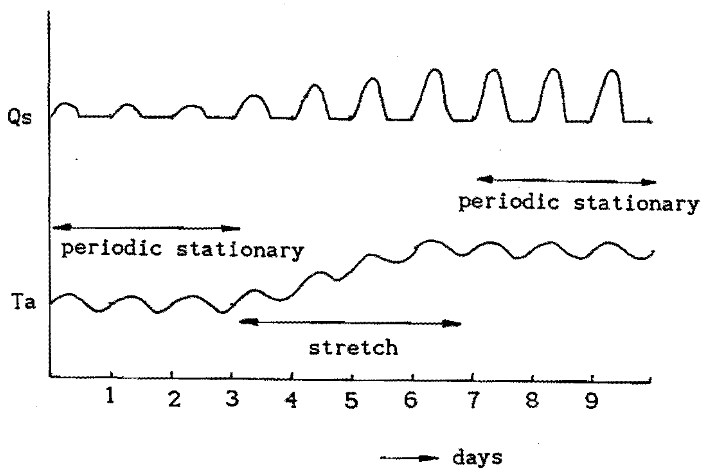


Fig. 5.10: Illustration of the "stretch" concept.

It is evident that the number of possible stretches is infinite. So, if the aim is to make this concept of a stretch workable, some simplifications have to be made. First of all, the length of a stretch can be constrained. For configuration A a stretch length of 3 to 7 days seems sufficient to study transient effects under Dutch weather conditions. Another reduction in the number of stretch patterns can be obtained be assuming that the periodic stationary conditions before and after the stretch are identical, and that the average daily values of Qs and Ta in a stretch can have either one maximum or minimum, or be constant. This is illustrated in Fig. 5.11, which gives a schematic representation of all possible stretch patterns, showing the behaviour of the daily averages of Qs and Ta.

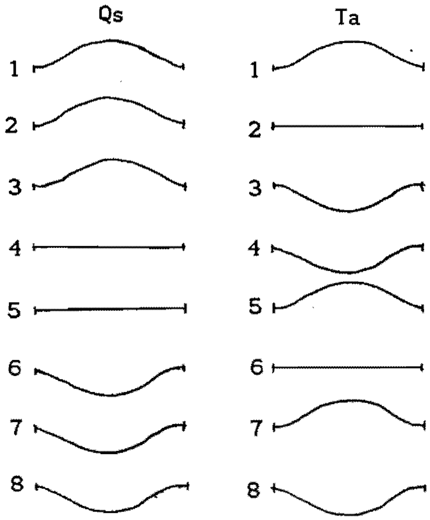


Fig. 5.11: Possible stretch-patterns.

From the above I conclude that a stretch may be useful as a stylised weather pattern. For realistic results it is necessary that the amplitude of Qs and Ta is chosen in accordance with the statistical properties of these quantities.

This means that an indication of the performance of a system under optimal control can be obtained by calculating the periodic optimal controls for the characteristic days in that year (e.g. the monthly averaged days, or one day per season), combined with the determination of the control for the stretch-patterns associated with that characteristic day (see Fig. 5.11). In this way the original problem (obtaining information on the control improvements throughout the year), with an optimisation horizon of 365 daily patterns (or more) may be approximated by a limited number of optimisations over a horizon of a few days. An advantage is that it is not necessary to take the "end costs" (cf. Chapter 2) into account, because the terminal states of the system in the optimisation over a stretch are fixed.

A more detailed analysis (as compared to the use of a small number of characteristic days to represent a year, as in Sections 5.2 to 5.4.2) of the performance improvements with optimal control over a one year period or longer was not found possible within the scope of this study, and therefore the "stretch"-concept was not further developed within the framework of this thesis. But for a detailed design it is necessary to include these "transfer" patterns in the analysis.

The effects of the dynamic optimal control over a number of realistic seven-day stretches have been investigated. Two examples are presented here, taken from realistic weather data for the month of April. Fig. 5.12 and 5.13 give the heat flows, the weather and demand pattern and the average short-term storage temperature of these two stretches. The weather pattern in Fig. 5.12 shows a decreasing amplitude of the ambient temperature and the solar irradiance, represented by Ta and Teq. Fig. 5.13 presents the results obtained with an increasing weather pattern. Detailed results can be found in Appendix A.

Fig. 5.12 and 5.13 illustrate some conclusions that may be drawn from the various investigations, in combination with the periodic optimal solutions of Section 5.4.2. Looking at the average short-term storage temperature of the decreasing stretch (Fig. 5.12), it is striking that this temperature has a pronounced maximum in the middle of the seven-day period. This can be compared with the periodic optimal situation: in that case the storage temperatures are also kept at a high level, so as to minimise the contribution of the auxiliary heating. But the main difference with the periodic optimal situation is the decreasing weather pattern, combined with an increasing heat demand in the course of the week. In the relatively warm, first part of the week, the increase in heat demand is anticipated by heating up the storage to an average temperature far above the momentary demand temperature. Operating the supply side of the system at full-speed, which is unfavourable from an efficiency point of view, can thus be avoided in the cold second part of the week.

For the increasing stretch (Fig. 5.13) the situation is rather different. Here the storage temperature is being decreased, to allow a better collector efficiency and heat pump COP in the second half of the stretch. In spite of the fact that this even leads to some auxiliary heating in the middle of the week, when the heat demand is still relatively high, the total energy consumption is lower.

In general one can also conclude from these examples that the role of the weather forecasts is quite important for the configuration considered: it strongly affects the momentary control behaviour. In Section 5.7.3 on adaptation this role is studied in more detail.

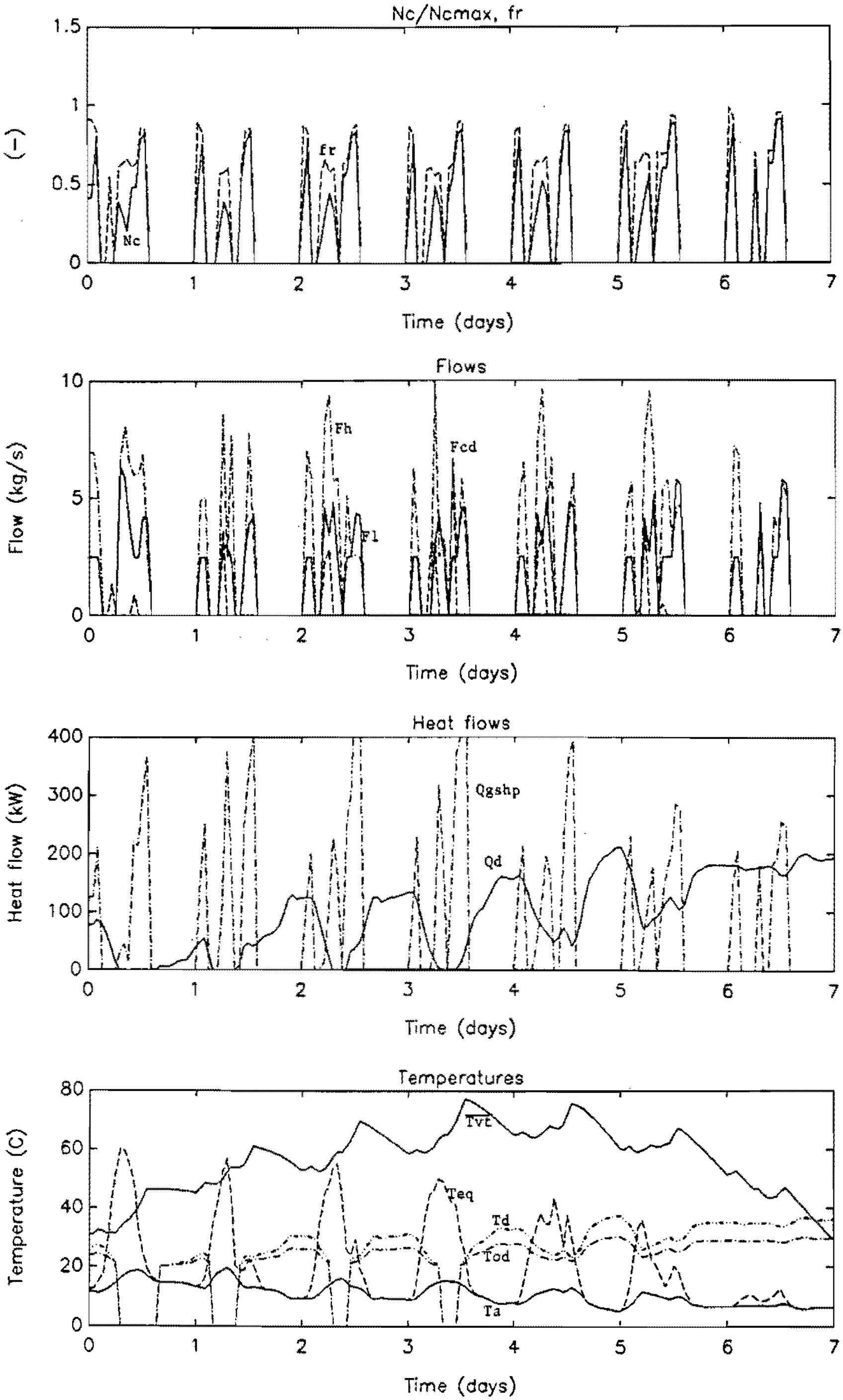


Fig. 5.12: Results of dynamic optimisation over a stretch of seven days with decreasing Ta and Teq.

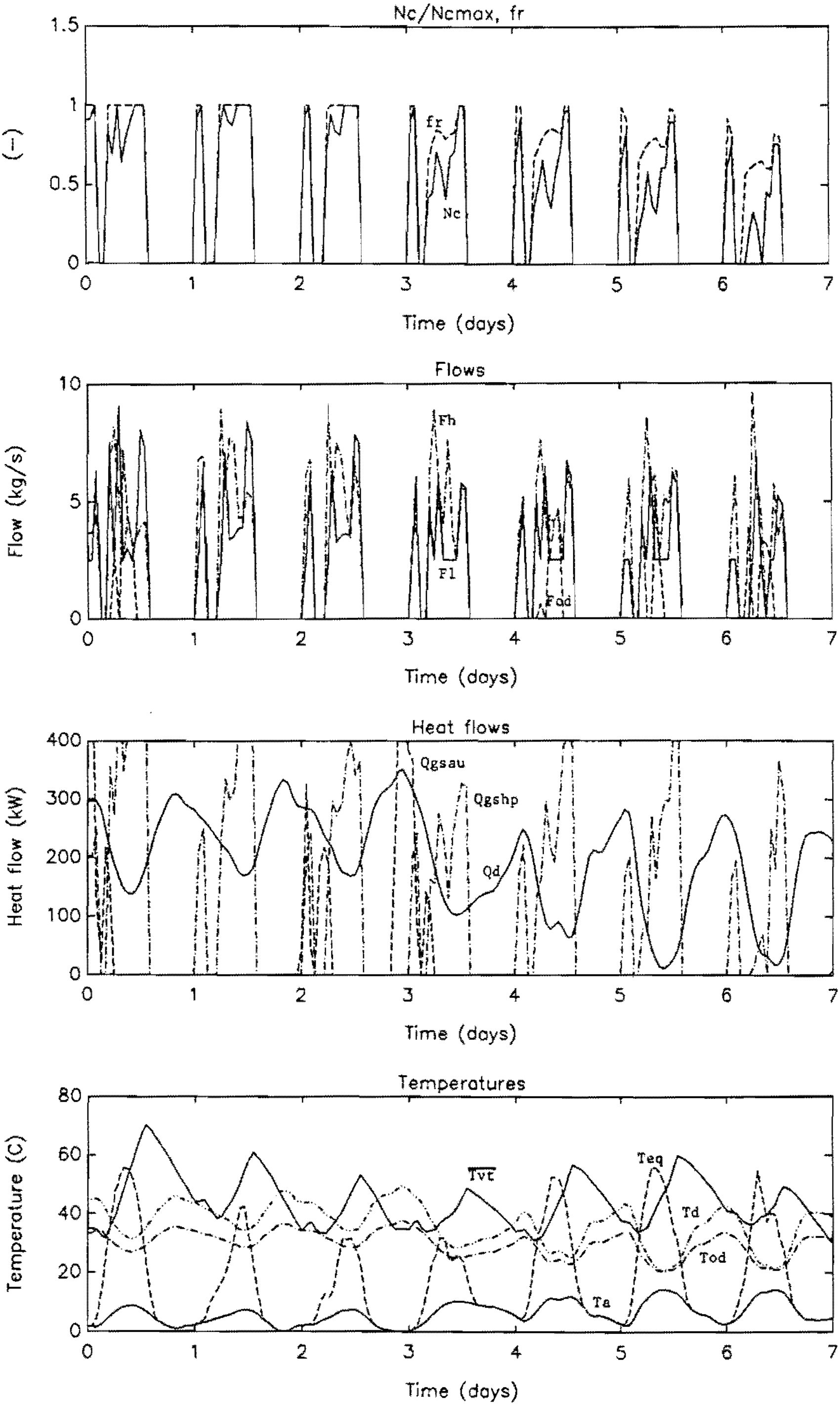


Fig. 5.13: Results of dynamic optimisation over a stretch of seven days with increasing Ta and Teq.

5.5 Hierarchical optimisation

Let us now consider configurations B and C (of Section 5.1), that also employ long-term heat storage. In this case the optimisation problem requires a special solution method, discussed in Section 4.4. This section presents the results of this hierarchical optimisation method, starting with configuration C.

Configuration C with heat pump, collectors, short-term and long-term storage

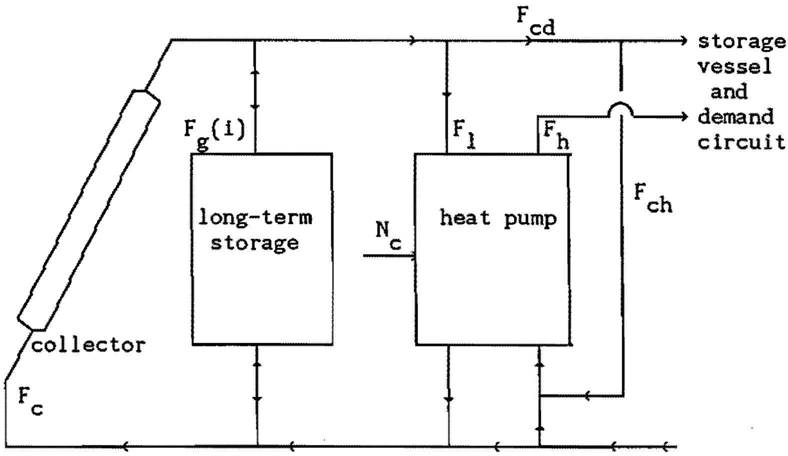


Fig. 5.14: Configuration C with heat pump, collectors, short-term and long-term storage.

Section 3.2.4 discussed the configuration of long-term storage with coaxial rings of pipes. As mentioned before, the control variables in the long-term storage are the flows per concentric ring of pipes, and they have a 24-hour pattern which remains constant during a month. It is assumed that the fluid flow in three sectors of the storage can be adjusted independently. These sectors refer to the 5 inner rings with a total of 60 pipes (control variable Fg(1)), the 2 outer rings with 76 pipes (control variable Fg(3)) and the 3 intermediate rings with 84 pipes (Fg(2)). Thus the number of pipes per sector, and the associated storage volume, is almost equal for all sectors. A positive value of Fg refers to charging the storage, and a negative value to discharging. If the storage is charged, the fluid is first led through the outer pipe down, returning through the inner pipe, whereas in a discharging situation the flow is in the opposite direction.
The switch-on fraction fr is in this case fixed at 1 throughout the year.

The optimisation period is one year, starting with the characteristic day of April, at 8:00 hours. The time-step is chosen to be 4 hours, for computational reasons. This means that the short-term storage volume must be larger in order to obtain realistic charging/discharging patterns. The volume in this case is 400 m^3.

The initial state of the long-term storage is obtained by taking the periodic stationary temperature distribution after simulating the system with a small time-step over several years, with a conventional control strategy [SCH88].

The initial states of the short-term storage in each of the characteristic days are chosen so as to be equal to the periodic optimal states at that time of the day, as obtained in Section 5.4.2. The fact that the results of Section 5.4.2 refer to a different configuration and a different time-step is not taken into account: because the demand circuit and the associated demand pattern is identical, it is assumed that the periodic optimal temperature distribution of the short-term storage will not be radically different for the various configurations.

To allow a reasonable charging of the storage in summer, the collector area is chosen to be 1500 m^2 and the heat loss coefficient 5 $W/m^2/K$.

In Table 5.1 the most important results over the one-year period are summarised. The heat pump COP and the efficiencies ETAdau (the heat input of the auxiliary heating divided by the heat demand Qd) and ETAcol (the actual collected heat Qcol divided by the maximal heat Qe to be collected given the collector inlet temperature and flow rate) are yearly averages. The heat content of the long-term storage is calculated with respect to a reference temperature of 0 °C.

<u>Table 5.1:</u> Results with hierarchical optimisation. System with collectors, heat pump and long-term storage.

IQd	443.4	ETAdau	0.117		
				IQg0	559.5
IQgsau	65.1			IQg1	589.0
IQgshp	185.8			IQig	135.1
IQpump	20.0			IQog	89.1
IQtot	270.9			IQggr	-21.1
				IQggz	-7.9
IQcol	245.7	ETAcol	0.753		
IQhp	300.4	COP	1.617		
dim[IQ...] = 10@10 J.					

The results in this table indicate that under optimal control 70 % of the heat injected in the storage in summer (IQig) is withdrawn in winter (IQog), whereas the heat loss to the surrounding ground (IQggr and IQggz) is about 20 %. As a result, 10 % of the injected heat

remains within the storage ground volume after one year, and this will reduce the energy consumption in the next year until a periodic stationary situation is reached.
In spite of the availability of the long-term storage, which provides an extra heat source in winter, there is still a need for a contribution of the auxiliary heater of about 12 % of the total heat demand.
Another important characteristic is that the presence of a heat pump, which allows heat delivery in winter at a reasonable efficiency, apparently forces the control of the system to store only a small amount of heat (30 % of the total heat demand) in summer.

To display these effects more closely, Fig. 5.15 gives the control strategies and other important data for the characteristic days. For illustrative purposes the data of these 12 characteristic days are drawn as continuous curves. In reality each control strategy for a characteristic day is applied 30 times, so as to represent a month, as pointed out in Section 4.4. Therefore the time-axis is given in months, starting with April.

The flows in the long-term storage show a typical behaviour. During the charging period (from month 0 to 6; i.e. from April to October) the inner rings of the storage have a high flow rate, whereas the outer sector is only used after 2 months, and with a very small flow rate.
In the discharging period the behaviour is more complicated, and this must be seen in the light of an important characteristic of the long-term storage: although the temperature distribution in the storage does not change significantly during one day, the possible extraction temperature can be within a relatively wide range, because the control strategy can switch from one sector of pipes to another instantaneously (cf. Section 4.4.1). The demand circuit dictates the need to deliver heat at a specified temperature level (Td). Depending on the temperature distribution of the short-term storage, this heat can be obtained from either the collector, the 3 sectors of the long-term storage, or not at all, in the latter case introducing the need for auxiliary heating. As a result, the outer sector of the storage is used in the beginning of the discharging period only, and the inner sectors are used alternately until the end of January.
Another complicating factor in the discharging period is the heat pump. The extracted temperature from the long-term storage influences the heat pump COP, and hence directly the energy consumption. A higher storage flow rate means a higher evaporator flow rate, positively affecting the COP. But it also means a lower extracted temperature, which negatively affects the COP. The resulting control strategy per time-step is always a trade-off between these kinds of efficiency-effects, and this contributes to the complicated storage flow behaviour.
In February and March, which are winter months with relatively high insolation levels, the available temperatures in the long-term storage are too low to be competitive with the collectors. This phenomenon again supports the anticipating behaviour of dynamic optimal control.

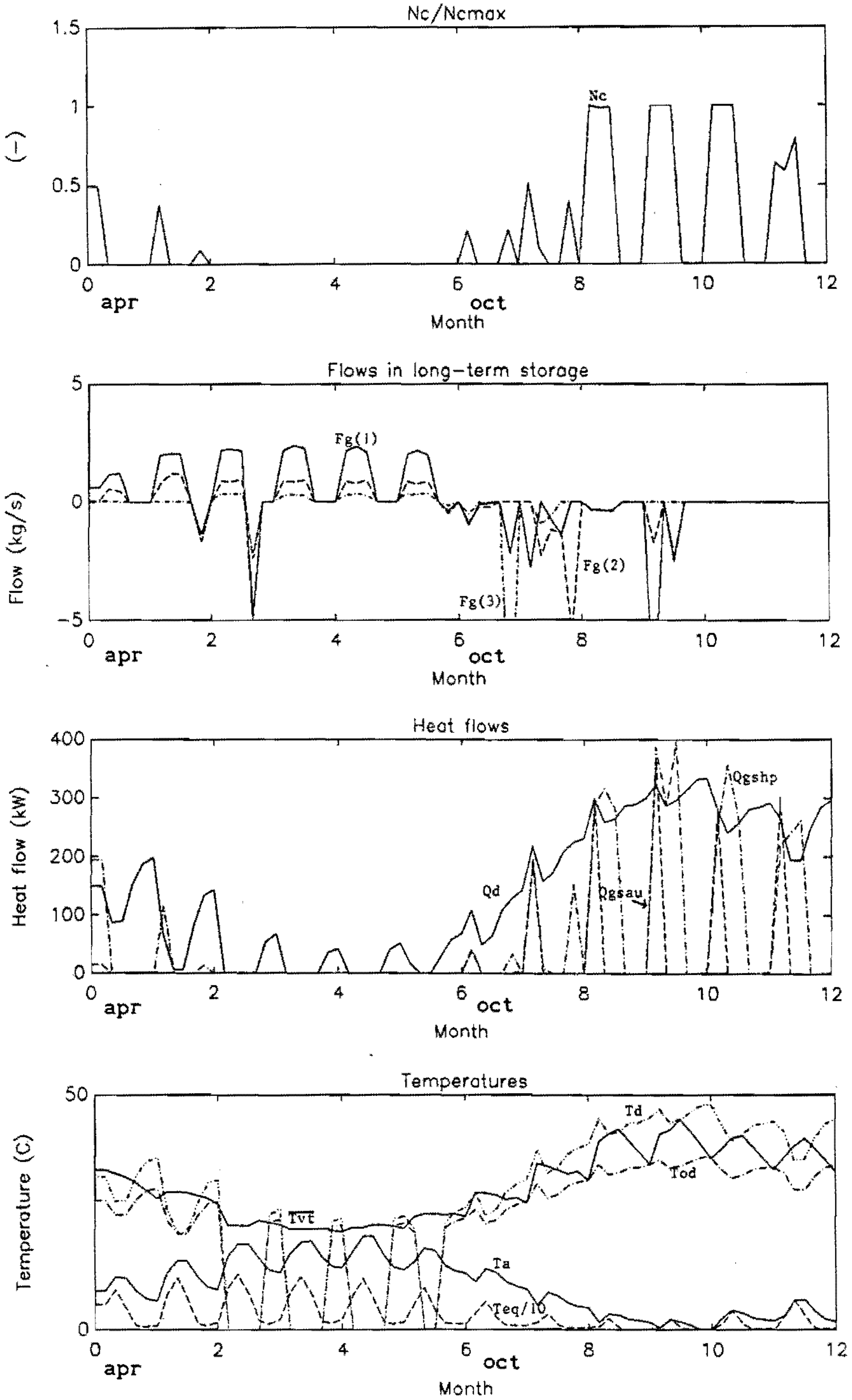


Fig. 5.15: Control strategies, heat flows and temperatures for characteristic days. Configuration C.

Fig. 5.15 can be compared with the results of Sections 5.2 and 5.3, the main difference being the availability of the long-term storage. The patterns of the short-term storage temperatures and the heat pump controls (not depicted in Fig. 5.15) are similar, although Fig. 5.15 reveals that in the beginning of the charging period the average storage temperature does not show a periodic pattern, which was initially assumed.

Fig. 5.16 gives the temperature distributions in the long-term storage for every 6 months. The initial "heat islands" surrounding the storage volume, which resulted from the preceding application of a conventional control, do not return at the end of the one-year optimisation interval. The charging period results in an almost spherical temperature distribution (with a slight preference for the two inner

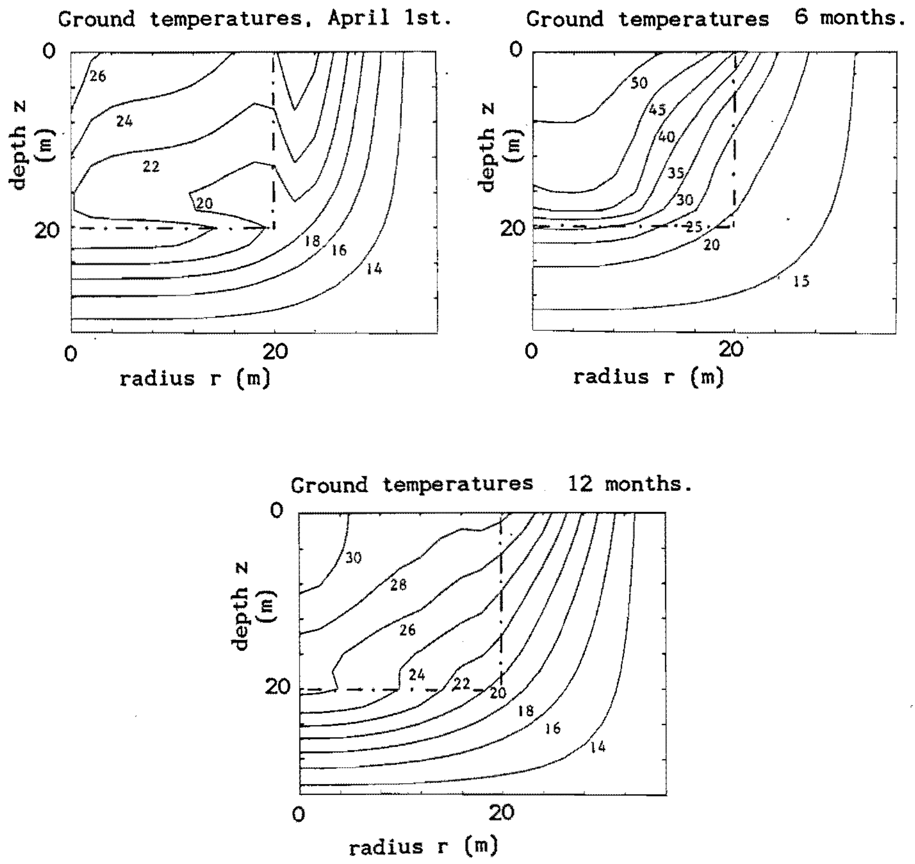


Fig. 5.16: Temperature distribution in the storage volume after 0, 6 and 12 months. Configuration C.

sectors) in the storage, which is favourable from the point of view of conductive heat losses to the surrounding ground. (Fig. 5.16 also reveals that the isotherms sometimes are not exactly perpendicular to the axis of symmetry and/or the top layer: however, this is due to an inaccuracy in the plotting routines.)
It was already mentioned that in the discharging period the outer rings were used only in the beginning. This also supports the conclusion that one of the aims of the dynamic optimal control strategy is to reduce the conductive heat losses of the long-term storage, by discharging the outer rings of the storage first.

Configuration B with collectors, short-term and long-term storage

A similar approach is used for configuration B, without a heat pump (Fig. 5.17). In this case the collector heat loss coefficient is chosen 2 W/m²/K and the collector area is 2500 m², as already mentioned in Section 3.3.2. The initial temperature distribution in the ground is assumed to be identical to that of configuration C.

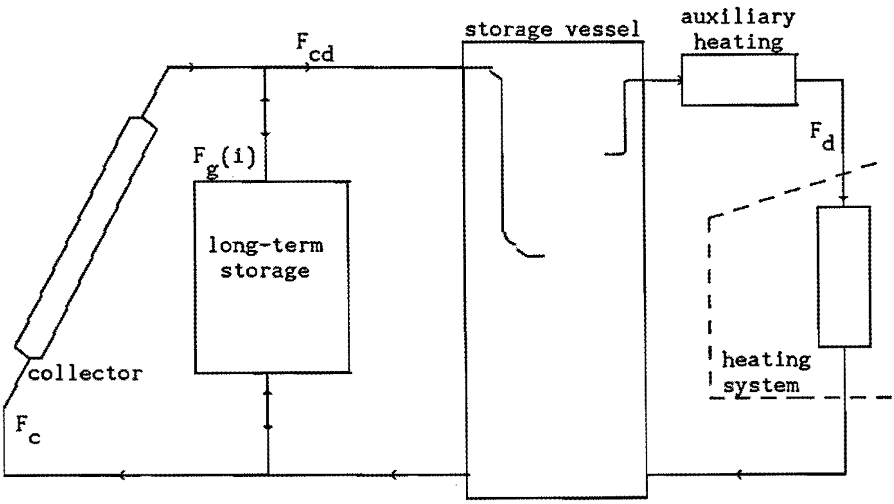


Fig. 5.17: Configuration B, with collectors, short-term and long-term storage.

Table 5.2 gives the energy consumption and storage characteristics.

Table 5.2: Results with hierarchical optimisation. System with collectors, short-term and long-term storage.

IQd	443.4	ETAdau	0.213		
				IQg0	559.5
IQgsau	117.9			IQg1	699.6
IQgshp	0.0			IQig	335.9
IQpump	22.8			IQog	182.7
IQtot	140.7			IQggr	-22.4
				IQggz	-8.5
IQcol	490.0	ETAcol	0.896		
dim[IQ...] = 10@10 J.					

Compared to the results of configuration C (Table 5.1), the total energy consumption in this case is considerably lower, owing to the large contribution of the collectors, which is not surprising when considering the differences in collector area and heat loss coefficient. The amount of heat injected in the long-term storage is considerably greater, but only a relatively small part (55 %) is extracted in winter.
The heat loss to the surrounding ground is about 9 %, the rest of the injected heat (36 %) remains within the storage volume. In this case the periodic stationary situation is not yet reached at all, and it is to be expected that this periodic situation will be associated with a relatively high temperature level in the storage, as compared to the initial temperature distribution. Although this has a negative effect on the collector efficiency, the contribution of the auxiliary heating will be reduced.
The optimisation results in Table 5.2 reflect the situation of a "start-up" year rather than the periodic optimal situation.

Fig. 5.18 gives the flows in the long-term storage, the heat flows and temperatures of the characteristic days.
The contribution of the auxiliary heating is mainly concentrated in January and February. The minima in Qgsau at the end of the discharging period correspond to the maxima in Teq. This effect was also reported in configuration C, and it reflects the direct use of collector heat; the temperature level to be extracted from the storage is too low or is associated with higher pumping costs.

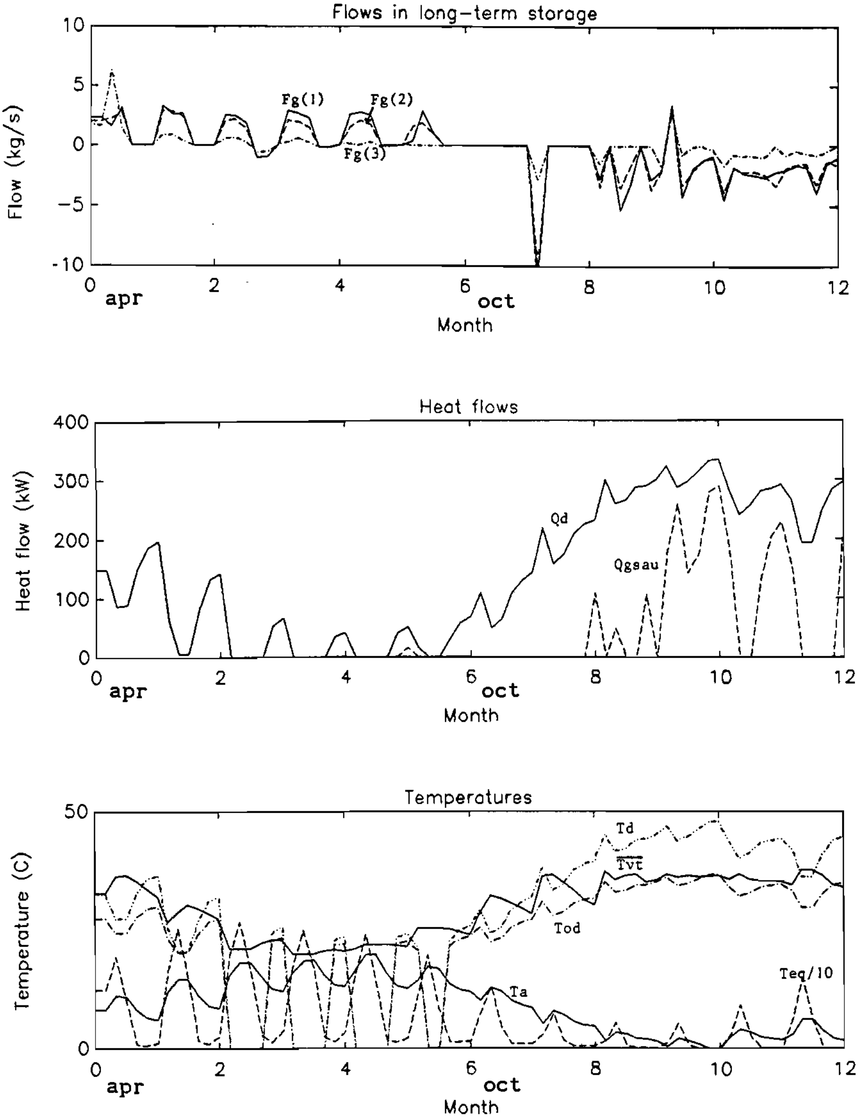


Fig. 5.18: Long-term storage flows, heat flows and temperatures for characteristic days under dynamic optimal control. Configuration B.

The flow rates in the long-term storage during the charging period show a pattern comparable to that of configuration C.
In the discharging period the picture is rather different: The storage is used until the end of the optimisation period, and the two inner sectors have the same flow rate, whereas the outer sector has a small flow rate.

Fig. 5.19 gives the temperature distributions in the long-term storage volume.

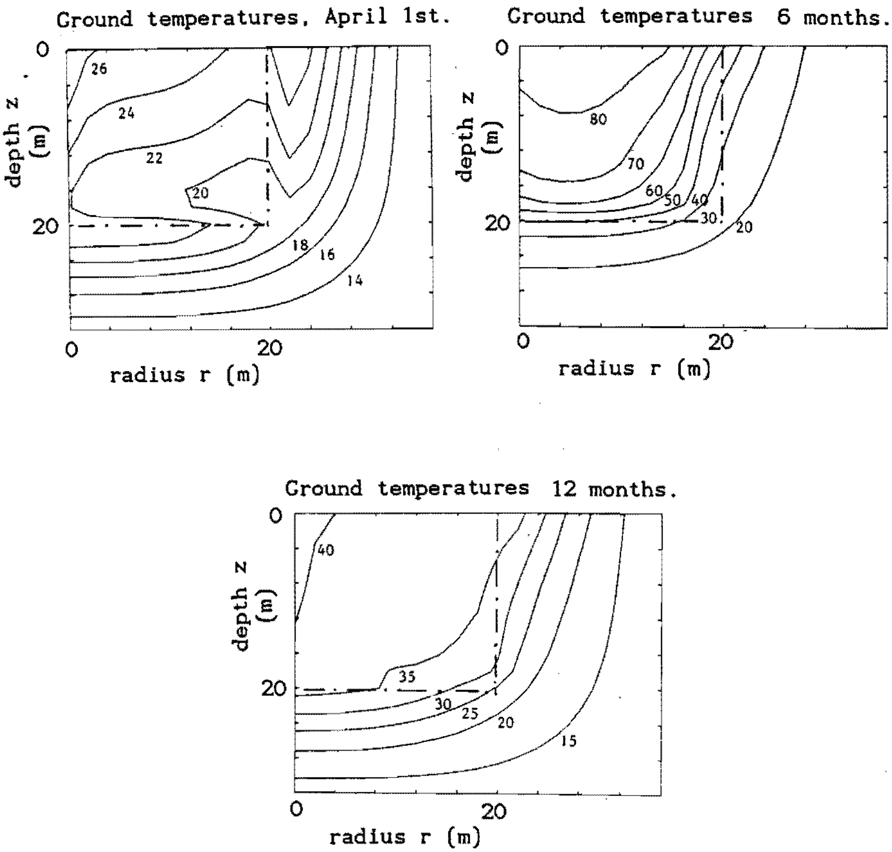


Fig. 5.19: Temperature distribution in the storage volume after 0, 6 and 12 months.

The large collector area, with a small heat loss coefficient, results in relatively high temperature levels after 6 months. These high temperatures are necessary to meet the heat demand without a heat pump, but it was already indicated that at the end of the discharging period the collectors can deliver heat at a higher temperature than the storage. As a result, the temperature of the storage after the first year under dynamic optimal control is still relatively high, which confirms that the periodic stationary situation has not yet been reached, as already reported.

The dynamic optimal control results in a rather spherical temperature distribution at the end of the charging periods, and the "heat islands" do not show up at the end of the discharging period, indicating that this strategy has efficiently exploited the thermal stratification in the ground.

Combining Fig. 5.18 and Fig. 5.19, the need for auxiliary heating in the second half of the winter period can be explained: The temperatures in the long-term storage are too low to meet the required temperature, which is in the order of 40 to 45 °C. Increasing the storage flow rate would result in a larger extracted heat flow, but the temperature difference between extracted temperature and demand temperature would also increase, and result in more auxiliary heating. Decreasing the storage flow rate positively affects the extracted temperature, but negatively affects the extracted heat flow.

The dynamic optimal control results for both configuration B and C show characteristic structures. In Section 5.8.3 a comparison will be made with previous results, and some consequences of dynamic optimisation for a better design of the long-term storage are investigated.

5.6 Sensitivity to variations in the disturbances

5.6.1 Introduction

In the results presented thus far an exact knowledge of the future disturbance patterns was presumed. In the previous chapters we already mentioned the need to take deviations from these patterns into consideration (cf. the new design procedure in Section 4.6.3).
In this section the effect of these deviations is investigated for a specific configuration. This serves as a stepping-stone to Section 5.7, in which the results of adaptation methods will be discussed.

5.6.2 The effect of random noise

In this section the effects of random variations in the assumed disturbance pattern on the optimal control strategy and the criterion function value are discussed. To distinguish between the disturbances and the variations in these disturbances, I refer to these variations with the general term "noise". The effects of noise can be formulated in terms of:

a - The change in optimal control strategy and criterion value if dynamic optimisation is applied to the system with noise.
b - The change in criterion value if the optimal control of the system without noise is applied to the system with noise.

To study these effects, let us consider configuration A, which was also used in the Sections 5.2 to 5.4. The optimal control strategy over a 24-hour period is calculated for the characteristic days of January, April, July and October. The initial conditions of the short-term storage are fixed (cf. Section 5.1). The weather patterns, provided with different levels of Gaussian noise, are defined as:

$$Ta' = Ta\ (1+\frac{gn}{100}\ \sigma_{Ta}\ rn) \tag{5.1}$$

$$Qs' = Qs\ (1+\frac{gn}{100}\ \sigma_{Qs}\ rn) \tag{5.2}$$

where gn denotes the Gaussian noise percentage, and rn is a random number between -1 and 1.

Fig. 5.20 gives the percentual difference between the criterion value under optimal control obtained with and without noise for different noise levels (case a), whereas Fig. 5.21 gives the differences in heat demand. Quantities with an accent (') refer to the situation with noise. Fig. 5.20 and 5.21 also show the effects over a "year", obtained by accumulating the results of the four characteristic days. Detailed numerical information can be found in Appendix A.

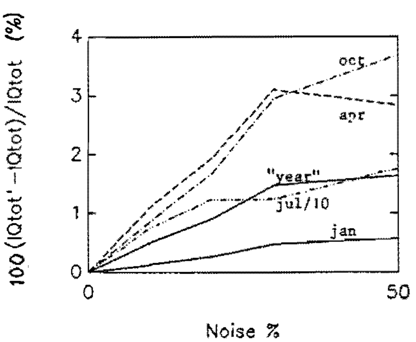


Fig. 5.20: Criterion function value.

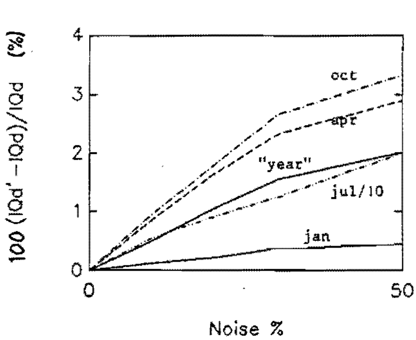


Fig. 5.21: Heat demand.

The percentual differences of the optimal criterion value and heat demand with and without Gaussian noise as a function of the noise level (case a).

The effects of Gaussian noise on both heat demand and criterion function are generally in the same order of magnitude (for noise levels from 10 to 50 %: up to 20 % for July (the results of July are divided by 10 in the graph), up to 4 % for the other months, and about 2 % for the "year"), or, in other words, random fluctuations in the disturbance pattern will result in another optimal control strategy but the performance of this strategy will not differ much from the original situation without noise. Thus the optimum in the criterion function is a "flat" optimum with regard to the disturbance parameters Qs and Ta.
The relatively large percentual changes of both heat demand and criterion value as a function of the noise level for the characteristic day of July can be explained from the high standard deviation in the insolation level characterising this day, which accounts for large differences between Qs and Qs', and from the fact that the heat demand in July is comparatively small, which means that the relative influence of a change in Ta is large. An analogous explanation holds for the small percentual changes in January.

In Fig. 5.22 the percentual change in criterion function value (given by dIQtot/IQtot) is given for different noise levels if the dynamic optimal strategy without noise is applied (case b). Appendix A gives more detailed numerical information concerning the differences in energy flows and efficiencies.

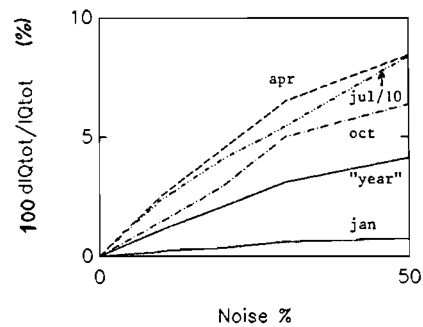


Fig. 5.22: Percentual change in criterion function value if the optimal control without noise is applied to a situation with noise, as a function of the noise level (case b).

The effects of noise are more pronounced as compared to case a. Except for January, the percentual change in criterion value is significantly larger than the change in heat demand, which was already given in Fig. 5.21. In October and April, a noise level of 50 % leads to an increase in energy consumption of up to 10 %, with an increase in heat demand of about 3 %. The effects are most pronounced in July where, owing to the reason already mentioned above, applying the original control strategy results in an energy consumption increase of 80 %, with an

increase in heat demand of only 20 %. However, the absolute changes in energy consumption are of the same order of magnitude as the changes in the other characteristic days.
For the January-day the effects are small, because the dynamic optimal control for this day makes maximal use of the heat pump in every time-step (see Section 5.3), which is limited by the constraints imposed on Nc, for any situation with noise.
The effect of the presence of the heat pump also holds, to a lesser extent, for October and April where the changes in criterion function value were significant, but small: fluctuations in weather patterns are only partly transferred to the condenser output.
Finally, the noise-effects over a "year" amount to 4 %, which is a small but significant increase in energy consumption (compare, for example, Sections 5.2 to 5.4 with regard to the differences in IQtot(year) under different types of control).

Further insight into the effects of noise can be obtained by looking at the differences in dynamic optimal control strategy with and without noise (case a). A representative example is given in Fig. 5.23, which shows for the April-day the weather patterns and associated dynamic optimal flow rates without noise and with 50 % noise.

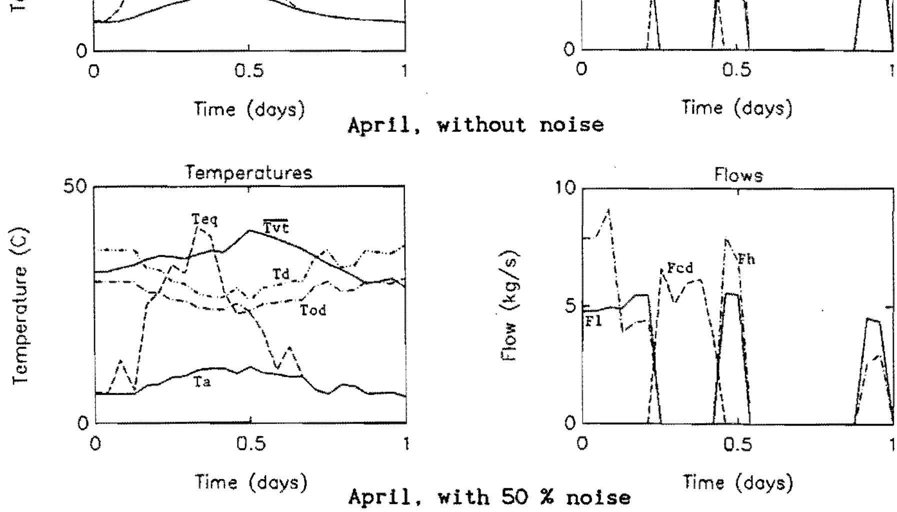


Fig. 5.23: Difference in disturbance pattern and associated optimal flow rates for the characteristic day of April.

Owing to the relatively large fluctuations in Qs during one day, the variations in Teq are much larger than in Ta.
The differences in control variables are rather small, and the operational modes are the same in both cases. This also holds for the other control variables (Nc, fr) and for the other characteristic days, except in July, where the only operational mode applied (direct use of collector heat) is shifted in time, in accordance with the fluctuations in Qs.
Another conclusion from Fig. 5.23 is that the behaviour of the average short-term storage temperature is almost identical in both cases, and this also supports the idea of a "reference trajectory" which was already discussed in Sections 5.3 and 5.4.2.

From the investigations concerning case a and b, it is concluded that for the type of system considered here the dynamic optimal control is robust in a sense that stochastic fluctuations hardly affect the optimal criterion function value and the best way of controlling the system. The effects of weather patterns with noise are perceptible, but small for noise levels up to 50 % .The extent to which the optimum is affected depends on the type of characteristic day used, and the associated operational modes that are predominantly active.
It should be noted that the change in optimal control for different noise levels usually comes down to a tuning of the control variables within an operational mode, and only in rare cases to chosing a different operational mode. This is an important finding with regard to the application of adaptation techniques, as will be discussed in Section 5.7.

5.6.3 The effect of a change in a single time-step

Another approach to the evaluation of the sensitivity with respect to the weather pattern is the calculation of the first derivatives of the criterion function to the disturbances $\underline{z}(1:N)$:

$$\frac{\partial F}{\partial \underline{z}(1:N)} = [\ \partial F/\partial Ta(1:N) \quad \partial F/\partial Qs(1:N)\ ]^T \qquad (5.3)$$

The differences between this approach and that in the previous section are that these derivatives:
- do not give an indication of how the control strategy changes in the optimal case, but:
- can easily be calculated directly in the optimisation process;
- give an indication of the deterministic time-dependency of the influence of $\underline{z}(1:N)$ on F;
- can be used to determine whether a deviation from the assumed pattern has a significant influence on the performance.

Fig. 5.24 gives these derivatives for two totally different control strategies having approximately the same performance. The control strategy "with a heat pump" shows heat pump operation during the greater part of the day. The strategy "without heat pump" only employs the collector, and results in approximately the same energy consumption because of the increased auxiliary heating.

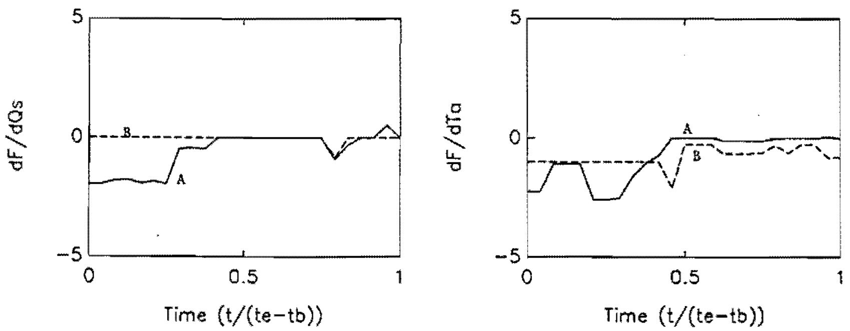


Fig. 5.24: The (scaled) derivatives of the criterion function with respect to the disturbances for two different dynamic optimal control strategies having approximately the same performance.
The time-axis indicates the time-step in which the derivative is calculated.
A : strategy using a heat pump
B : strategy without a heat pump

The control strategy using the heat pump is more sensitive to deviations in Qs and, to a lesser extent, in Ta than the strategy without a heat pump. This may seem in contrast with the results of the previous section, where it was argued that the heat pump had a smoothing effect on the influence of variations in Qs and Ta. However, in this particular situation the heat pump is in operation during the first quarter of the day, whereas in the strategy without a heat pump the collector is employed in the middle of the day. This, combined with a large heat demand at the beginning of the day, accounts for the results in Fig. 5.24: in the strategy with heat pump the effects of a change in weather variables in the first part of the day are dominant .

The derivatives give an answer to the question which strategy is to be preferred from the point of view of robustness, if the performance is roughly equal. In fact, this forms an additional criterion, which is not taken into account quantitatively. The appearance of such additional criteria was already discussed in Section 2.4.9.

The derivatives also indicate whether a change in Qs or Ta in a particular time-step has a significant influence on the performance of the system, thereby possibly indicating a need to "tune" (or adapt !) the control strategy if an actual deviation is not negligible.

Together with the approach of Section 5.6.2, these derivatives provide the tools for the sensitivity analysis which is part of the proposed design procedure, as described in Section 4.6.3.

5.7 Adaptive control

5.7.1 Introduction

Section 2.5 previewed some possible alternatives to apply adaptive control to the systems considered. These alternatives can be summarised as follows:

A - guiding the system back to a desired state trajectory (model reference adaptive control)

B - on every adaptation step: calculating the dynamic optimal control over a moving horizon, the initial conditions being the actual states of the system

C - like B, but combined with terminal state constraints (cf. Section 5.4)

For illustrative purposes I confine myself here to a treatment of configuration A, but with a collector heat loss coefficient of 5 $W/m^2/K$. The set of control variables is identical to that used in Sections 5.2 to 5.4, but with the switch-on fraction fr fixed at 1. The disturbance pattern is based on the characteristic weather data of April, being one of the most interesting weather patterns because of the different operational modes, as illustrated in the previous sections.

Section 5.7.2 discusses adaptation alternative A. Section 5.7.3 covers the other adaptation methods, which are based on dynamic optimisation.

5.7.2 Model reference adaptive control

In order to apply this method a number of choices have to be made. It is necessary to determine the adaptation interval, i.e. the period of time between two adaptation steps. Within this adaptation interval, the number of time-steps and the weighting factors in the criterion function (Eq. 2.40) have to be chosen.

The optimisation time-step remains one hour. The adaptation interval is also one hour, and the adaptation time-step is chosen to be 10 minutes, which means that the desired trajectory has to be approached in 6 steps. To allow for a gradual movement towards the desired trajectory. I take exponentially growing weighting factors in the criterion. The problem can now be regarded as a dynamic optimisation problem with a one-hour optimisation period of 6 time-steps.

To illustrate the effects of this type of adaptation, a representative example is discussed in which the weather pattern of the reference trajectory is the characteristic April-day, also used in the previous sections. Fig. 5.25 shows the reference state trajectory and the associated optimal control over a 24-hour period. The time-axis contains the (24*6=) 144 adaptation steps.

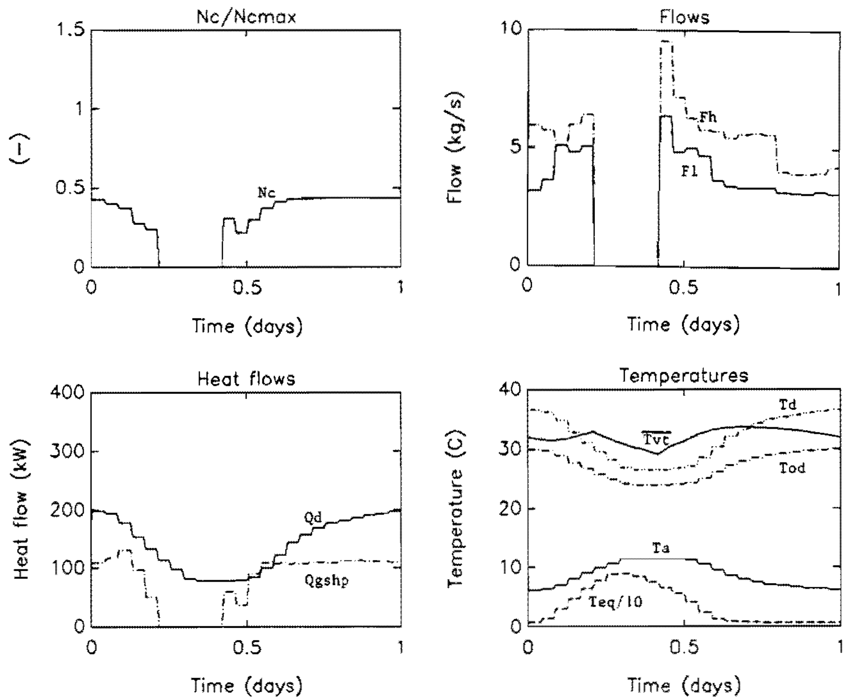
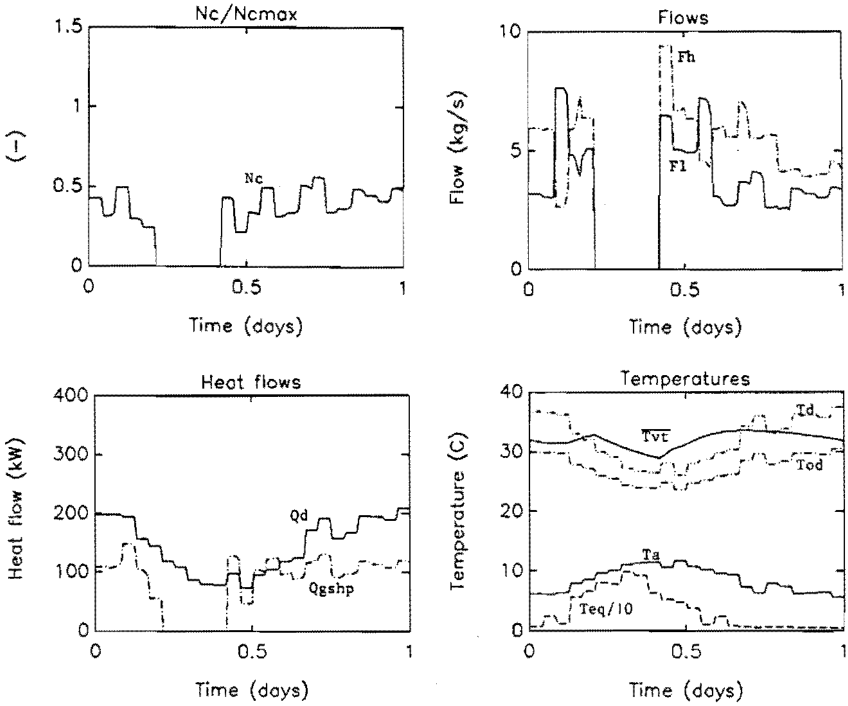


Fig. 5.25: Reference trajectory and optimal control for the characteristic day of April.

The reference trajectory is indicated by the curve of the average short-term storage temperature in Fig. 5.25 (note the difference with the dynamic optimal control strategy of April in Section 5.3, owing to the smaller collector heat loss coefficient and the switch-on fraction being fixed at 1).

The disturbed pattern is obtained by taking the weather data of the April-day, superimposed with 30 % Gaussian noise as defined in Eq. 5.1 and 5.2. Fig. 5.26 gives the results of the adapted dynamic optimal control. Detailed numerical information is given in Appendix A.



<u>Fig. 5.26:</u> Model reference adaptive control applied to the characteristic weather pattern of April with 30 % Gaussian noise, and with the reference trajectory of Fig. 5.25.

The heat demand is increased with 3 %, because of the noise. Maintaining the reference trajectory leads to an increase in energy consumption of 6 %. This can be compared with Section 5.6.2, where, under slightly different circumstances (switch-on fraction fr not fixed to 1, higher collector heat loss coefficient), the energy consumption under dynamic optimal control with 30 % noise showed a 3 % increase.

From these investigations I conclude that it is possible to maintain a desired trajectory under deviations from the disturbance pattern. The effect on the control variables is comparatively small: No switches of operational mode, but only modifications in the momentary values of the control variables are required to get a satisfactory match of the

desired trajectory. This is an important finding from a practical point of view: frequent switching of operational modes is generally not a desirable situation.
The most important question, however, is: Is this type of adaptation preferable/useful/desirable ? As could be expected on an intuitive basis, maintaining the original state trajectory certainly does not lead to the lowest energy consumption: a change in weather pattern leads to a change in the dynamic optimal state trajectory, which implies that other trajectories are always inferior. The fact that in this case no exact weather forecasts were used, as in dynamic optimal control, is of minor importance, as will be shown in Section 5.7.3.
The main drawback of this type of adaptation is its inability to respond to structural deviations in the weather pattern, and therefore its use is limited to those situations where the desired state trajectory is a "required" state trajectory, for example in process heating applications.

5.7.3 Adaptive control based on dynamic optimisation

For this type of adaptation method the optimisation horizon and the adaptation interval have to be chosen
Theoretically, the best optimisation horizon might be infinite, but, apart from the computational consequences, that would have other drawbacks: First, an accurate prediction of the disturbances has to be made over an infinite horizon, and in Chapter 4 it was already argued that this is not possible. Moreover, the only control variables of practical interest are the variables until the next adaptation.

An approach often proposed is a one-step-ahead prediction, combined with a calculation of the optimal control during that step (cf. Section 4.9). For the systems considered this would come down to momentary optimisation, and in Section 5.2 it was argued that (apart from a computational artefact in a specific case) this results in significantly worse control strategies.
Thus, the optimisation horizon is a trade-off between the desire for an infinite horizon, and the possibility to obtain reliable predictions. In the following, results are presented for optimisation horizons of 24 and 48 hours.

The adaptation interval depends on the frequency of the update of weather forecasts. In the results described here the update interval is assumed to be one hour.

Accurate weather forecasts

To get a better insight in the results, the situation in which the weather predictions are accurate is discussed first. The following three cases are compared:

B1 - the dynamic optimal control strategy over a seven-day horizon;
B2 - a succession of dynamic optimal control strategies based on 24-hour predictions, updated every hour;
B3 - like B2, but with 48-hour predictions.
The weather pattern is given by a seven-day stretch taken from the reference weather data of April.
In Table 5.3 the energy consumption and storage content data are given.

Table 5.3: Optimisation results for cases B1, B2 and B3.

	dynamic optimal control over a 7-day period	adaptation with 24-hour forecasts	adaptation with 48-hour forecasts
IQd [MJ]	58607	58607	58607
IQgsau	882	1333	884
IQgshp	14111	17254	15559
IQpump	2881	2781	2654
IQtot	17866	21358	19090
IQcol	50902	48630	50471
IQe	59757	74410	77069
IQhp	22879	26373	22561
IQv0	8400	8400	8400
IQv1	12265	12487	12170
ETAdau [-]	0.012	0.018	0.012
ETAcol	0.852	0.654	0.655
COP	1.621	1.528	1.514

With accurate forecasts, case B1 results in the best control strategy over the whole interval, the energy consumption being 17.9 GJ.. But it is interesting to notice that with a 48-hour prediction horizon the energy consumption increases with not more than 7%. The 24-hour horizon leads to significantly worse results. Table 5.3 reveals the source of these differences in more detail: Compared to case B1, Cases B2 and B3 lead to a reduction in the efficiencies of collector and heat pump (ETAcol and COP), but only case B2 shows an increase in auxiliary heating. This indicates that the price to be paid for a reduction in prediction horizon consists of a reduction in component efficiencies first, followed by an increase in auxiliary heating.

Fig. 5.27 to 5.29 give the control strategy, the heat flows and the most important temperatures for these cases.

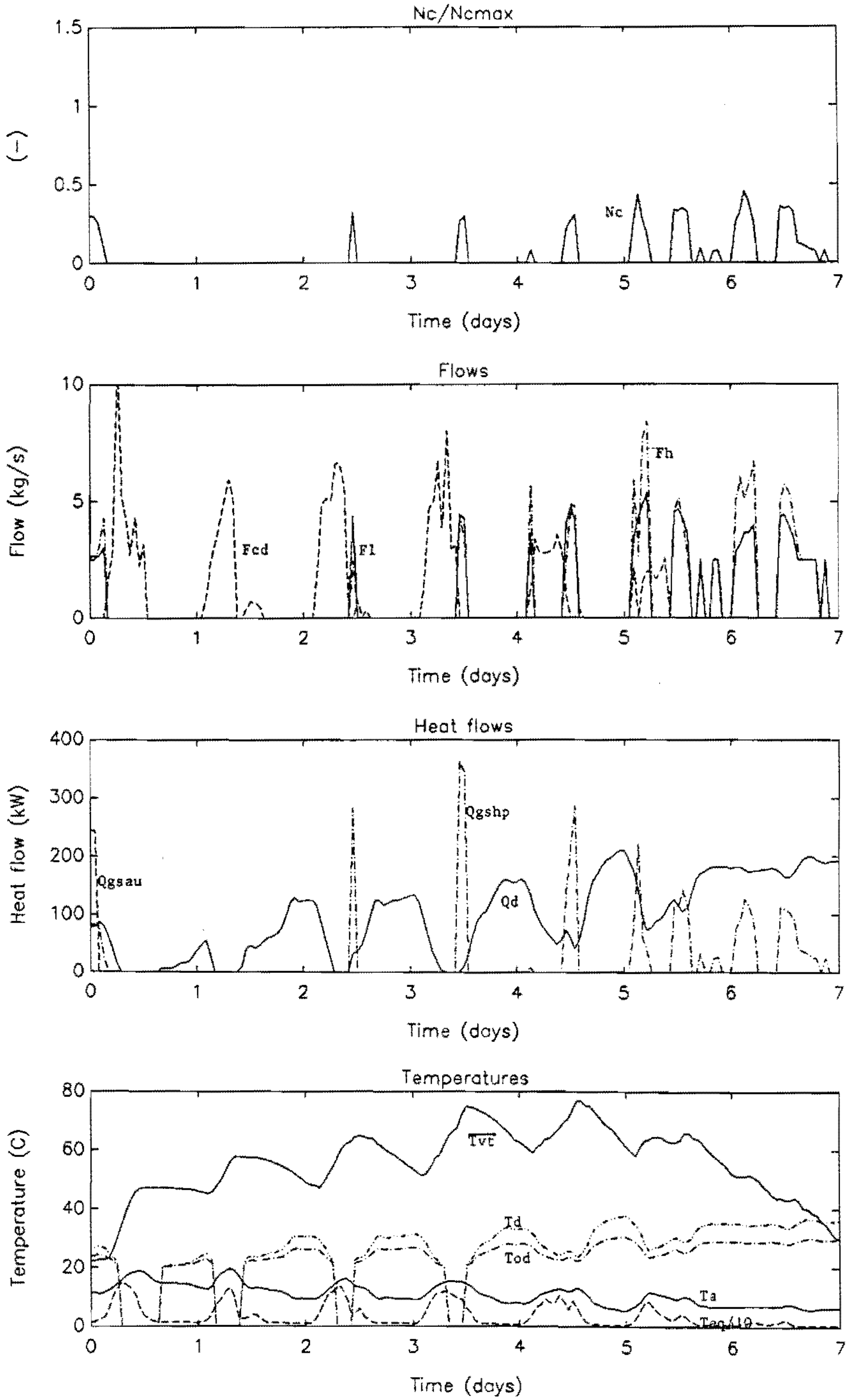


Fig. 5.27: The dynamic optimal control strategy over a seven-day horizon.

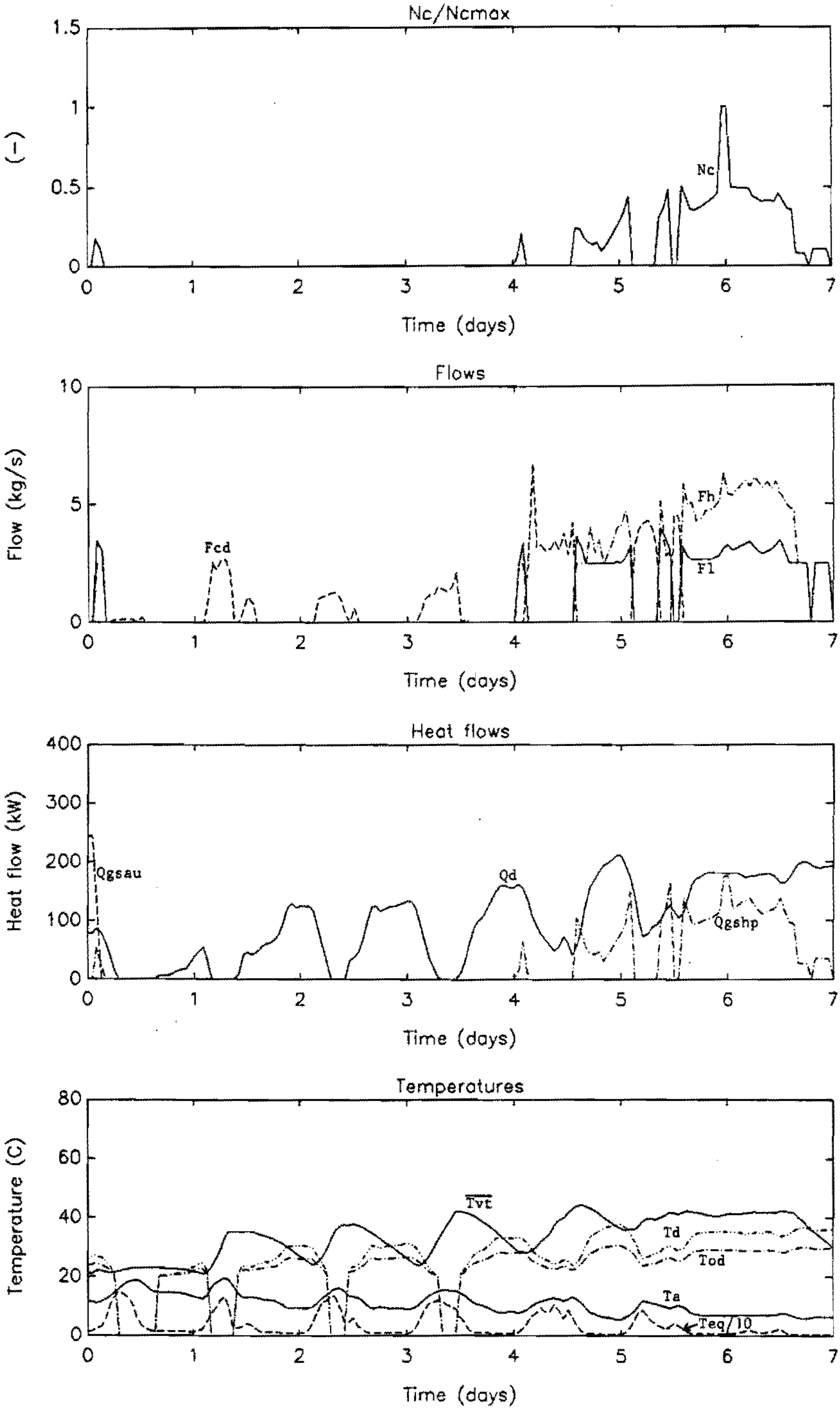


Fig. 5.28: Adaptive dynamic optimisation over a 24-hour horizon.

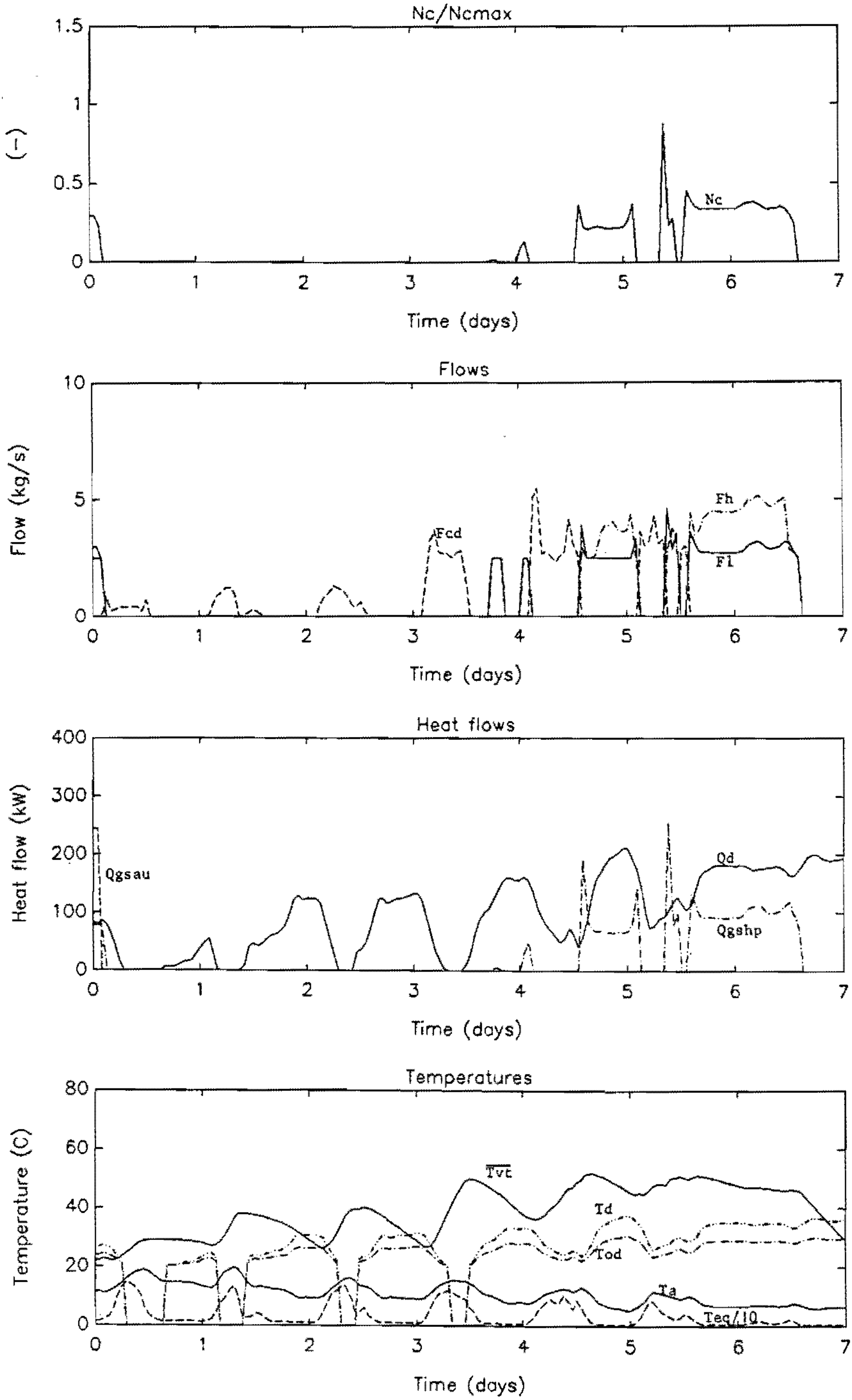


Fig. 5.29: Adaptive dynamic optimisation over a 48-hour horizon.

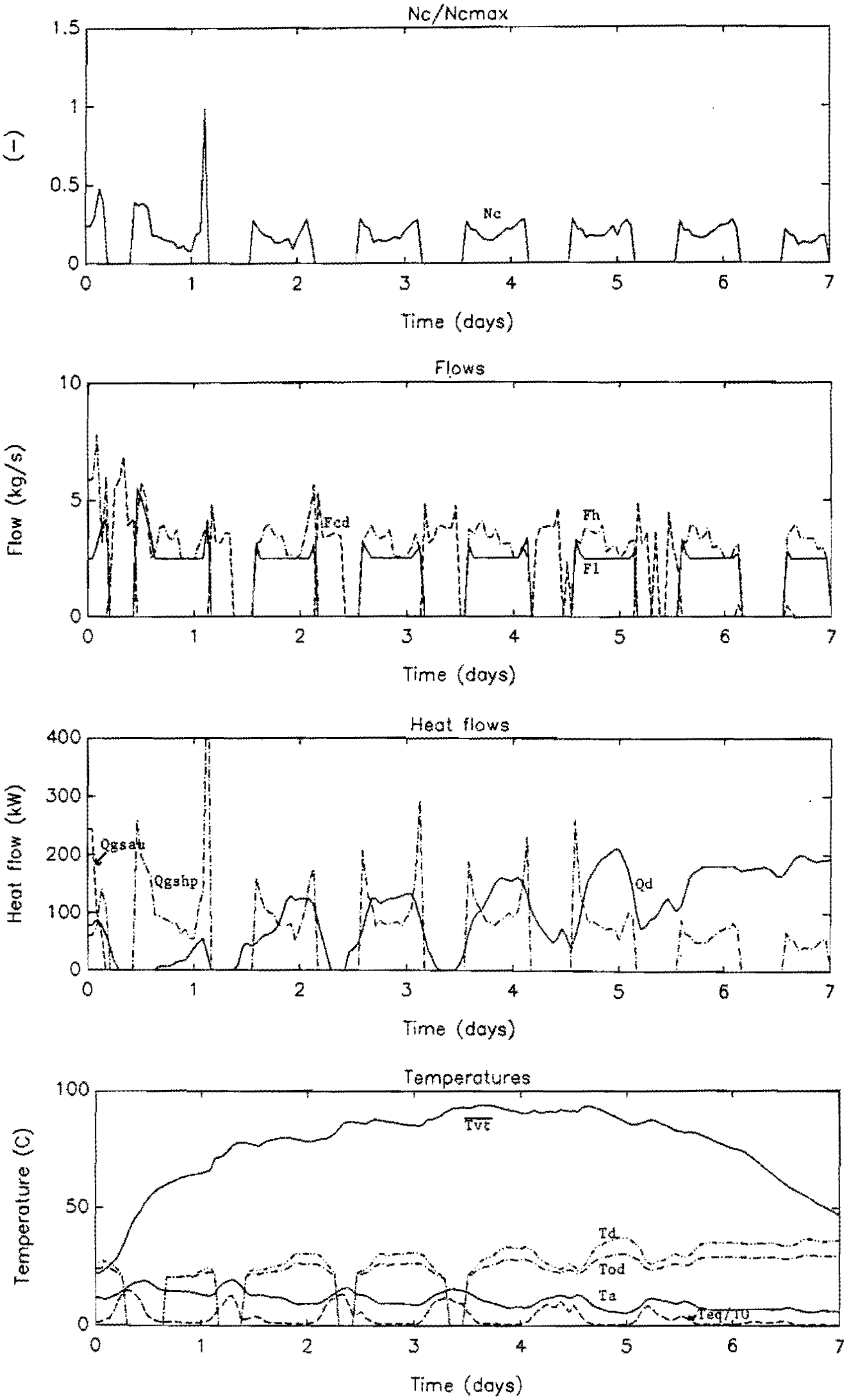
The most important features of the dynamic optimal control of case B1 (Fig. 5.27) are the direct use of collector heat in the first four days, which results in high storage temperatures, followed by a combined operation of collector and heat pump. In case B2 and B3 (Fig. 5.28 and 5.29) the control strategy in the (relatively warm) first part of the period is also to use the collector exclusively. Focusing on the short-term storage temperatures in Fig. 5.28 it can be observed that, owing to the limited prediction horizon, the storage temperatures are kept too low, which results in worse conditions for operating the heat pump at the end of the optimisation period. This effect is smaller in the case of the 48-hour prediction horizon, because of a better anticipation to the cold weather at the end of the period. However, in order to avoid auxiliary heating in the second half of the period, it is necessary to operate the heat pump more frequently than in case B1, and at a lower average efficiency, which was already reported in Table 5.3.

Fig. 5.27 can be compared with Fig. 5.12, the differences however being the collector heat loss coefficient and the use of the switch-on fraction fr as a control variable. Although the control strategies are rather different, the behaviour of the average short-term storage temperature shows a striking resemblance, again supporting the idea of a reference state trajectory.

From these results it is concluded that the dynamic optimal control of this system over a relatively long period is well approximated by successive optimisations over a horizon of, say, 48 hours. This can also be explained by the end-costs effect: the longer the optimisation period, the smaller the effect of the terminal state of the system on the criterion value .(Note that, owing to the one-hour update of the control strategy, only the first step of a control strategy is actually applied, and the effect of thermal "exhaustion" of the short-term storage, which was mentioned in Section 5.3, does not occur. The end-costs effect also accounts for the conclusion that the best optimisation horizon need not be infinite).

Inaccurate weather forecasts

The following figures give the control variables, the heat flows and the most important temperatures for situations with inaccurate weather forecasts. The predicted weather pattern is a succession of seven identical average April-days (which is, in fact, seven times the weather pattern of Fig. 5.25 of Section 5.7.2), the actual weather is the seven-day stretch of April, which was also used in obtaining the results with accurate forecasts. The differences between prediction and reality are comparatively large in this case. More results obtained with this approach are discussed in [BLO88].
In Fig. 5.30 the dynamic optimal control for a period of seven identical April days is applied to a period with "realistic" weather. Fig. 5.31 gives the results for a 48-hour prediction horizon, the predicted weather being equal to the weather pattern of the succession of seven identical April days.
More numerical results on energies and efficiencies are given in Appendix A.



<u>Fig. 5.30:</u> Application of the optimal control over a seven-day prediction horizon to realistic weather.

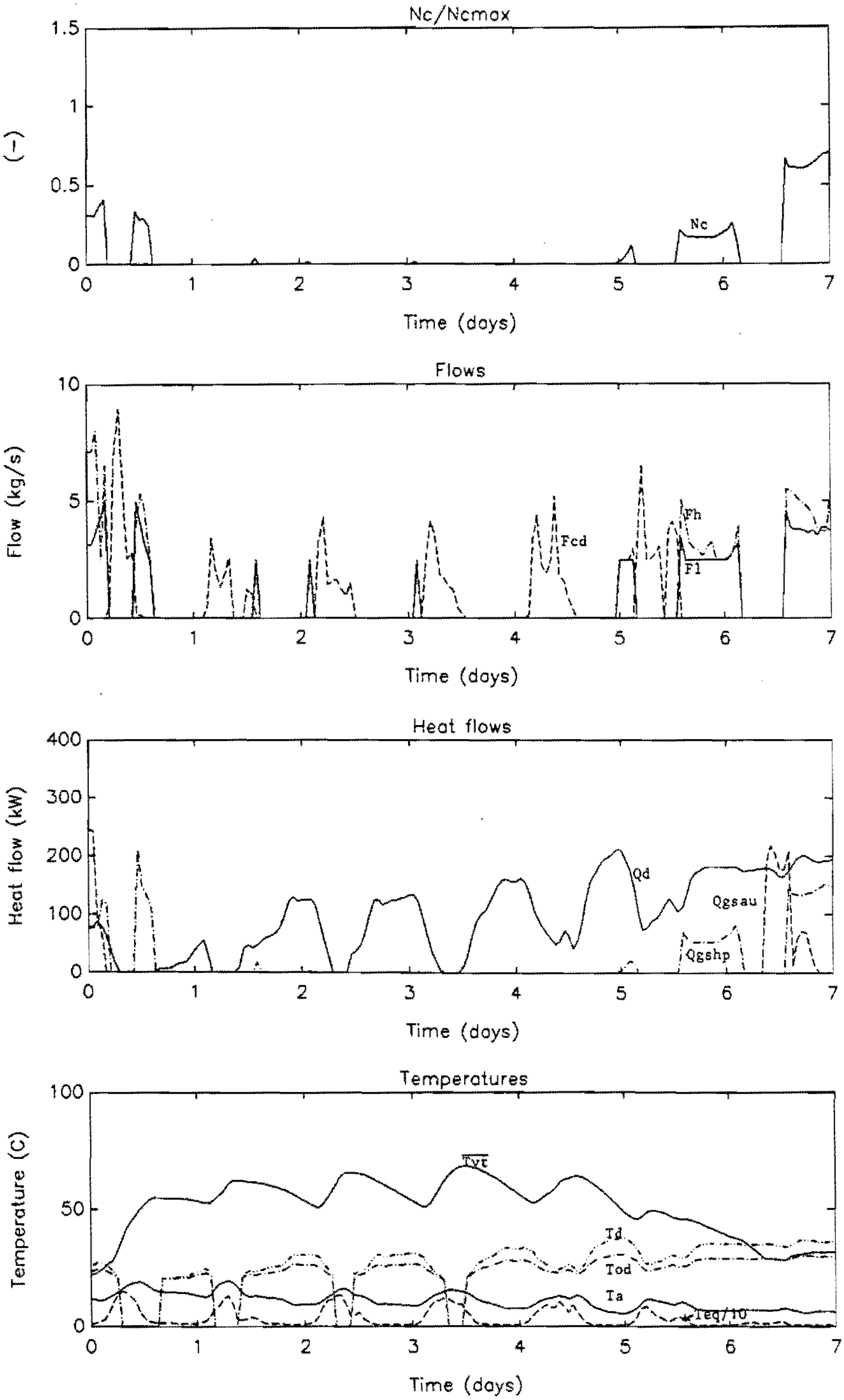


Fig. 5.31: Application of dynamic adaptive control over a 48-hour horizon to realistic weather.

The dynamic optimal control strategy shown in Fig. 5.30 reflects the periodic behaviour of the weather pattern for which this strategy was calculated. Applying this strategy to the actual weather pattern leads to a high average temperature of the short-term storage, as can be seen in the figure. Although there is no need for auxiliary heating in this case, the performance under this control strategy is very poor, the total energy consumption being 41.8 GJ, as compared to 17.9 GJ. obtained with accurate weather forecasts (Table 5.3). The conditions for robustness (cf. Section 5.6) are certainly not met in this case.
Adaptation with a 48-hour prediction horizon (Fig. 5.31) shows a considerably better performance, with an energy consumption of 21.7 GJ, which is only by 20 % inferior to case B1 of Table 5.3. The average storage temperature shows a behaviour which comes fairly close to the dynamic optimal curve in Fig. 5.27, although at the end of the period still some auxiliary heating is needed.
The results of a 24-hour prediction horizon are not depicted, but the total energy consumption in that case is 25.4 GJ.

Although the weather predictions over 24 or 48 hour periods are highly inaccurate (maintaining the original predictions, as is done in this case, nearly represents a worst case analysis, because based on the actual weather data better predictions could be obtained), adaptive control based on dynamic optimisation results in significantly better performance, because the actual initial state conditions are taken into account.

From these results an accurate estimate of the optimal horizon cannot be made. However, it is felt that, keeping in mind the unavailability of satisfactorily accurate weather forecasts over more than 48 hours, and the end-costs effect discussed before, a choice of 48 hours for this class of systems is sufficient.

As mentioned in Section 5.7.1, the adaptation method B might be refined by imposing terminal state constraints. For this refinement the effect of the terminal state constraints on the first steps of the optimal control strategy should be investigated. If this influence is negligible, it may be concluded that the optimisation horizon can be chosen smaller (and thus the resulting control will be more robust, because it is based on more accurate predictions).
However, an elaborate treatment of this refinement was not found possible within the scope of this thesis.

From the results in this section it can be concluded that adaptation with the aid of dynamic optimisation is useful for an on-line tuning of the control strategy, even if the weather predictions (necessary for calcuting the dynamic optimal control) are rather inaccurate.

5.8 Near-optimal control and design considerations

5.8.1 Introduction

Up till now, the main goal in this chapter was to provide an insight in the control aspects, and to establish a better basis for design, based on dynamic optimisation. Now the resulting optimal controls are exploited to develop practicable near-optimal control strategies for which insights obtained from the optimisation results are used, together with experiences from previous research in the System and Control Technology Group.
As pointed out before, it is not possible to cover the large number of conceivable configurations and system layouts by a limited number of control rules. Therefore the discussion is focused on two representative space-heating systems:
- a heat pump system with collectors and short-term storage (Configuration A).
- a collector system with long-term storage (Configuration B).

5.8.2 A heat pump system with collectors and short-term storage

Results from previous research (cf. Section 4.7)

Slenders and Van Stiphout [SLE84, STI83] studied a system configuration comparable to A, but with different sizes. They presented dynamic optimisation results under the following restrictive conditions:
- the return temperature from the space heating system is constant
- on the supply side of the system, water is extracted at the bottom of the storage
- the weather and demand patterns are sinusoidal

They compared a conventional control strategy in which Nc has a constant value if the heat pump is in operation, Fl is at a maximum value and Fh equals the demand flow Fd, with dynamic optimal control.
The dynamic optimal control strategy reduced the total energy consumption by 16 %. It seems rather surprising that this was achieved by a decreasing energy consumption of the heat pump, combined with an increase of the use of auxiliary energy. This illustrates an important phenomenon: minimising the total energy consumption leads to better results than are obtained by maximising the contribution of the (high efficiency) heat pump, or minimising the consumption of the (low efficiency) auxiliary heater. Or, in other words, an <u>improperly</u> chosen criterion (for some examples: see Section 4.2.3 and 4.7) will <u>necessarily</u> lead to an inferior performance.
Quite remarkably, the output temperature of the heat pump was below the actual demand temperature, even though it could have produced that temperature simply by operating at a somewhat higher rotation speed. But that would have entailed future repercussions.

The operational mode enabled by Fch (see Section 3.3.1), was used if the collector output temperature was not yet quite high enough for direct storage without the heat pump.

From these results some general characteristics were derived:
First, the operational modes were selected, corresponding to a decreasing value of Teq, in the following order :
- heat pump off, collector flow bypasses heat pump
- both heat pump and bypass (Fcd) on
- heat pump on, no bypass

Secondly, as mentioned above, in the case of heat pump operation the condenser output temperature Toh was a few degrees below the demand temperature Td in all situations.
Both characteristics, i.e. the selection of the operational mode and the tuning of the heat pump operating conditions in order to obtain a Toh somewhat below Td, are of a momentary nature, and could be implemented in an existing system with fairly simple means. It may seem strange that these rules do not relate to the energy content of the storage. The explanation is that all optimisations had an energetically "empty" storage as a starting condition, i.e. the storage temperature was considered to equal the heating system return temperature at the start of the optimisation interval. As a result, the temperature of the water extracted from the bottom of the storage was strongly influenced by the constant return temperature which, in this case, was the lowest temperature in the system. This stabilising effect caused the momentary nature of the controls.

Results in this work

From the results of Sections 5.3 and 5.4, the following conclusions can be drawn:
- The storage vessel is operated at a relatively high temperature level in periods of cold weather, in which the space heating system will also return a relatively high temperature. As a result, the stabilising effect mentioned above does not occur here, and the associated rules of thumb are not applicable.
- The contribution of the auxiliary heater is always minimal, which is in contrast with the experiences of Slenders and Van Stiphout mentioned above.
- A direct use of collector heat can only be found in summer, and the collector fluid flow rate follows the pattern of Teq.
- If the heat pump can produce more heat than required for that day, the output power is limited by reducing the operating hours (via the switch-on fraction fr) rather than by capacity reduction by Nc. This not only illustrates the usefulness of the extra degree of freedom given by fr, but also indicates that in general strong fluctuations in Nc, other than between zero and an "optimal" value, do not occur.

Chapter 4 mentioned the use of another control variable for this system: the height of extraction from the short-term storage at the supply side. Introduction of this control variable was in fact suggested by the results of Slenders and Van Stiphout, where the simultaneous use of heat pump and auxiliary heating gave me the impression of a "missing degree of freedom" in the system. However, experiments with this control variable in configuration A revealed that in almost all cases the dynamic optimal place of extraction was the (coldest) bottom layer of the storage. Therefore this control variable has not been used any further. But this indicates an important result of dynamic optimisation: close inspection of the optimal control strategies sometimes leads to detecting a "bottleneck" or a missing degree of freedom in the system, and thus to possible consequences with regard to the design. Therefore the important step of reflecting upon the interpretation of the optimal control was included explicitly in the proposed design method (see Section 4.6.3).

A near-optimal control strategy

Section 4.5 presented two ways to obtain near-optimal, practicable strategies. In this section a near-optimal control is discussed, in which the momentary relation between measurable states in the system is dominant, but which has one parameter depending on the time of the year.

The strategy is based on a desired trajectory of the average short-term storage temperature, obtained in Section 5.3 and 5.4.
Section 5.4 showed that configuration A is capable of achieving a broad range of states of the storage without the need for exceptional modes of operation. Section 5.7.2 showed that with adaptation a desired trajectory can be tracked fairly easily. This provides a basis for a near-optimal control based on a desired trajectory. It was argued in Section 5.7.2 that adaptation to a desired trajectory is only in very rare cases a useful method. However, the approach here differs from Section 5.7.2 because the influence of the actual weather pattern on the desired trajectory is, to a certain extent, taken into consideration, as explained below.

This near-optimal strategy may be summarized as follows:
- The control variables Nc, Fl, Fh, Fcd can either have a chosen, constant value (Nc = 1000, Fl, Fh and Fcd = 5 kg/s) or are zero.
- The switch-on fraction fr is the result of a momentary optimisation procedure, the criterion being the difference between the desired and the actual values of the average storage temperature.
- The control variable Fch is always zero, in agreement with the results of the previous sections.

The desired storage temperature has the following pattern:

- from 6.00 a.m. until 18.00 p.m., this temperature increases linearly with time: In January from 40 to 45 °C
  In April from 31 to 43 °C
  In July from 21 to 23 °C
  In October from 30 to 35 °C

  the given limits are directly related to the demand pattern, and require only a rough estimate of Ta;
- from 18.00 p.m. to 6.00 a.m., the desired storage temperature equals (Td+Tod)/2. This is a momentary quantity (no estimation needed).

- Based on the outlet temperature of the storage, Tov, and on the actual value of Teq, an operational mode is selected:
  if Tov $\leq$ Teq-5 : only the collector is operated.
  if Tov > Teq-5 : the heat pump is operated together with the collector.

Fig. 5.32 presents the resulting energy consumption and the differences in stored heat for the reference weather patterns. In Fig. 5.33 the near-optimal control for April is shown. Detailed numerical results are given in Appendix A.

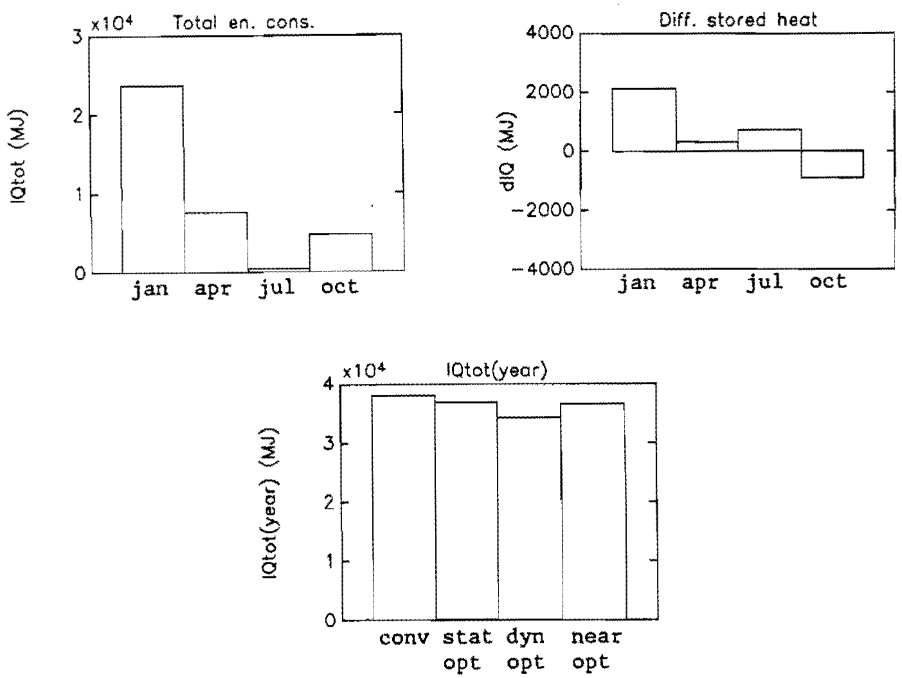


Fig. 5.32: Energy consumption and difference in stored heat for near-optimal control strategies.
IQtot(year) = 36.56 GJ.

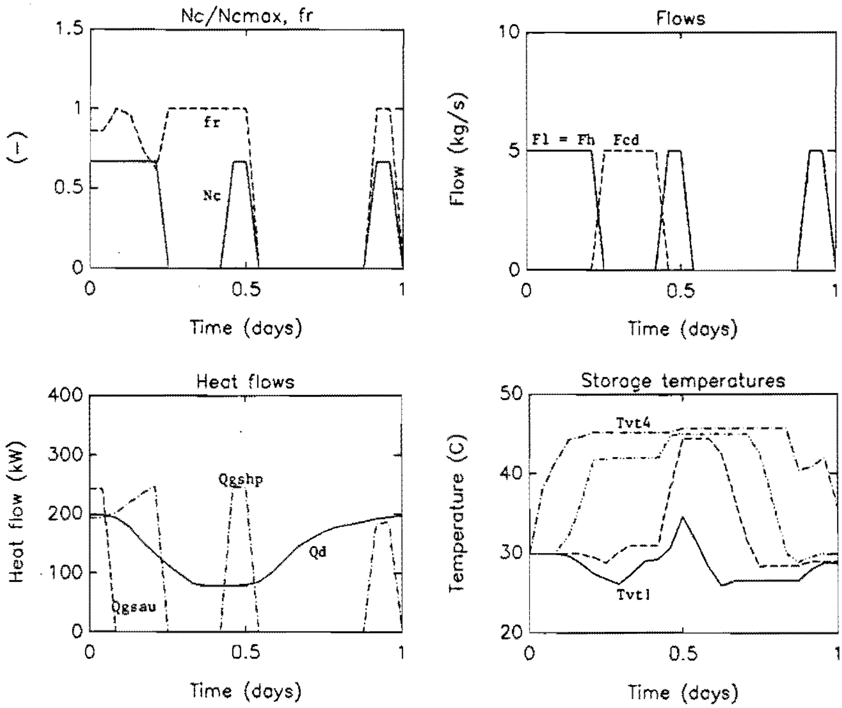


Fig. 5.33: The near-optimal control strategy for the April weather pattern.

Although the performance of the near-optimal strategy is necessarily inferior to the dynamic optimal strategies, the results are quite good when compared to a conventional strategy. Again it must be stressed that this near-optimal strategy is directly applicable, and expected to be more robust. The increases in energy consumption when compared to dynamic optimal control range from 4 % (January, July) to 20 % (October). If the results of the four characteristic days are combined so as to a represent a yearly result (Fig. 5.32: IQtot(year)), this increase is 6.7 %. The reduction in performance compared to a conventional control strategy ranges from -10 % (April, October) to -0.5 % (January), and combined to a yearly result, this reduction is -4 %.
The results in Fig. 5.33 can be compared with those of Section 5.3. Under this near-optimal strategy, practically the same operational modes are applied as under the dynamic optimal strategy.

5.8.3 A collector system with long-term storage

Results from previous research

The configuration studied by Rijk, Van der Linden and Van Hemert [RIJ85, LIN83, HEM83] was a system with solar collectors and a cylindrical ground storage, providing space heating to 100 houses, which has been realised in Groningen, in The Netherlands. They used dynamic optimisation, for a one-year period with relatively large time-steps, the control variables being the fluid flows per coaxial ring of pipes. The optimisation interval was 1 year, starting on April 1st.
Although their calculations were performed under different assumptions, their results reflected the same tendencies, some general features being:

- In the beginning, heat injection was concentrated in the inner rings.
  By the end of summer the outer rings also received some heat, to lay a protective "shield" around the hot centre of the storage, thus reducing the heat loss to the surrounding ground.
- In the extraction period heat was withdrawn from the outer rings first (otherwise this heat would disappear to the surrounding ground). By the end of the extraction period, the flow rates in every ring were at a maximum, to recover as much from the remaining heat as possible.

The energy consumption of the auxiliary heater was reduced by 28 % [RIJ85], compared to a control strategy with all fluid flows having the same value throughout the year, owing to a better build-up and exploitation of the thermal stratification in the ground.
Rijk discussed an on/off near-optimal control strategy derived from dynamic optimal control. The simple, near-optimal control strategy was found to have a 20 % smaller energy consumption than the conventional strategy of exploiting seasonal heat storage in the ground.

Results in this work; Long-term storage design considerations

The results discussed in Section 5.5, for both configurations, support the above conclusions. Both dynamic optimal control strategies are aimed at a reduction of the heat losses to the surrounding ground.
In Section 5.5 the configuration with a heat pump showed a rather complicated control behaviour, owing to the importance of the temperature level of the heat extracted from the long-term storage. It was not found possible to establish a direct relationship between the control strategy and the temperature distribution in the ground on the one hand, and the short-term storage temperatures and the heat demand on the other. But it is felt that, with a more detailed analysis and smaller time-steps, a relation may be found comparable to the near-optimal strategy for configuration A.

Final conclusions with regard to the best control strategy can not be drawn at this point. However, the conclusion of Van Meurs [MEU85], stating that a distributed control strategy for seasonal storage with vertical pipes will not result in a significant increase of the performance, is certainly not supported here.

The results in this and other, previous work suggest that the design of a long-term storage with vertical pipes in the ground can be improved. Some possibilities are discussed here briefly.

From a thermodynamic point of view a spherical storage volume is to be preferred if the heat losses are to be minimised. Although in the configuration studied here the storage volume is cylindrical-shaped, the optimal control results show a spherical temperature distribution after the charging period, which suggests that the configuration of pipes in the ground might be chosen in a better way. An improvement suggested in the literature is to inject pipes from one point at the surface under different angles, resulting in a star-shaped distribution of pipes in the storage volume. However, research on this type of configuration [DEL85] showed that it provides a very effective way of <u>disturbing</u> a spherical temperature distribution in the ground, because the pipes are placed perpendicular to the isotherms in the ground. Therefore I concluded that this configuration is not suitable for seasonal storage.

Another possible improvement is to inject pipes of different length at various places in the storage. In this way the system has more degrees of freedom: if the storage volume just below the surface is comparatively hot, but the volume at greater depths is cold, the configuration with pipes of the same length is not able to extract the heat in the top of the storage without heating up the bottom of the storage. This would be avoided if pipes of different length were used.

A third improvement is to change the uniform distribution of the pipes over the surface of the storage to a distribution with an emphasis on the center of the storage. The number of pipes per surface-unit at the perimeter of the storage can be chosen relatively small, which was also indicated by the optimal control strategies of Section 5.5. where the outer rings were of relatively minor importance. This can be combined with the placement of a ring of pipes at a relatively larger radius, for a reduction of heat losses from the center of the storage.

The improvements suggested here have not been studied further within the context of this thesis. But an important conclusion from all this is that dynamic optimisation provides another, instructive way of looking at the layout of a system, resulting in the detection of possible bottlenecks and improvements, as indicated in Section 4.6.3.

5.9 Simultaneous optimisation of control and design variables

5.9.1 Introduction

The previous sections already indicated the use of dynamic optimisation for an evaluation of a system configuration.
Finally, in this section the focus is on one of the most important steps in the proposed design procedure (Section 4.6.3), the simultaneous optimisation of design and control variables, reflecting the integrated design approach I have suggested in Sections 2.1.4 and 4.6.3.

The optimisation procedure is applied to configuration A, with a heat pump, collector and short-term storage. Section 5.9.2 discusses the assumptions with regard to optimisation period and criterion function. Section 5.9.3 gives the results for this configuration.

5.9.2 Application of the method for design optimisation

The determination of the characteristic disturbance patterns is the first step in the application of the method. For the configuration studied in this section the characteristic patterns can be represented by 24-hour "averages" in parts of the year, together with a number of "stretches", according to Section 5.4.4. If a long-term storage was employed, the characteristic patterns would be essentially the same, as mentioned in Section 5.5.
For the purpose of illustration the results are discussed for the optimisation over a year represented by four 24-hour periods, the characteristic days of January, April, July and October, under the assumption that these periods are representative for the operational conditions throughout the year. A future refinement in this procedure might be the introduction of a number of "stretches", as mentioned before.
The design parameters to be optimised together with the control variables are:

- the heat pump size: HP (in terms of, judicially chosen, units referring to the heat exchanger areas of condenser and evaporator and the swept volume of the piston compressor: Aco = HP*6 m^2, Aev = HP*10 m^2 Vc = HP*0.0001 m^3, for a selected working fluid).
- the mass of the short-term storage medium: Mv.
- the effective collector area: Ac.
- the collector heat loss coefficient: Uc.

The control variables are the fluid flows, the rotation speed of the heat pump compressor and the fraction of the time-step that the supply circuit is in operation.
The starting points for the design parameters are: HP = 60 , Mv = 100000 kg , Ac = 1000 m^2, Uc = 5 $W/m^2/K$.

The upper and lower boundaries for the design variables are here:

$20 \leq HP \leq 90$
$40000 \leq Mv \leq 150000$
$500 \leq Ac \leq 1500$
$2 \leq Uc \leq 16$

The control variables are chosen initially so as to start with their dynamic optimal, or conventional values associated with this design. The initial states of the short-term storage are identical to the ones selected in Section 5.1. The optimisation is combined with terminal state constraints, which are chosen identical to the initial states. The criterion parameters are chosen to be in this example:

pay back period	= 15 years
interest rate	= 6 %
specific costs heat pump	= Dfl. 2500.-/HP
specific costs storage	= Dfl. 500.-/m^3
specific costs collector	= Dfl. 750.-/Uc/m^2
price of natural gas	= Dfl. 0.40/m^3
fixed costs of system	= 5 % of total specific costs

Some of these specific costs are rather "optimistic". This, of course, affects the resulting optimal sizings, but has no influence on the conclusions with regard to the effects of incorporating system control in the design.
For each characteristic pattern, the dynamic optimal values for design and control parameters are determined using the simultaneous procedure described in Section 4.6.2.

5.9.3 Results

In this section the results of the simultaneous design and control optimisation procedure are presented for two cases:

- optimisation of design parameters combined with dynamic optimal control.
- design optimisation combined with conventional control, as discussed in Section 5.2.

Table 5.4 gives the optimal sizing parameters for both situations, together with the energy consumption over the four characteristic days.

Table 5.4: Optimal sizing parameters with dynamic optimal and conventional control.

		conventional control	dynamic optimal control
HP	[-]	24	20
Ac	[m^2]	606	500
Uc	[$W/m^2/K$]	16	16
Mv	[kg]	40000	40000
IQtot(year)	[GJ]	43.24	43.21

From these results I conclude that the criterion parameters force the system to be as small as possible, while maintaining a certain level of energy saving. With conventional control, the collector area and the heat pump must be significantly larger than with dynamic optimal control, to maintain this level. This means that during the greatest part of the year the heat pump is constantly operated at full speed, a result which is in accordance with Section 4.8.
The total energy consumption is almost equal in both cases, the difference in criterion function value is purely a result of the different sizing parameters.
Fig. 5.34 and 5.35 give the control strategies and the states of the system for both situations, and the weather data of April. For more detailed information: see Appendix A.

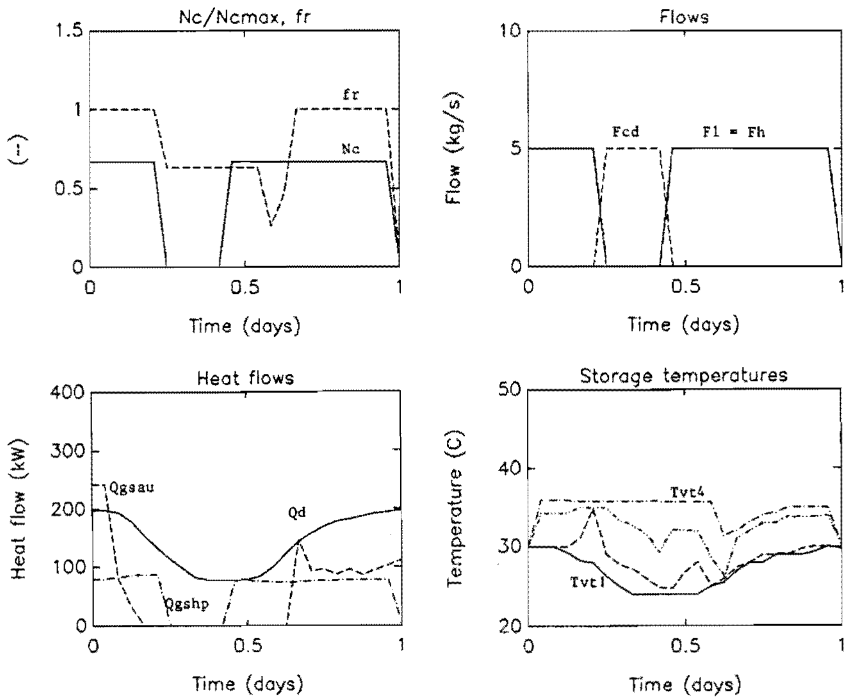
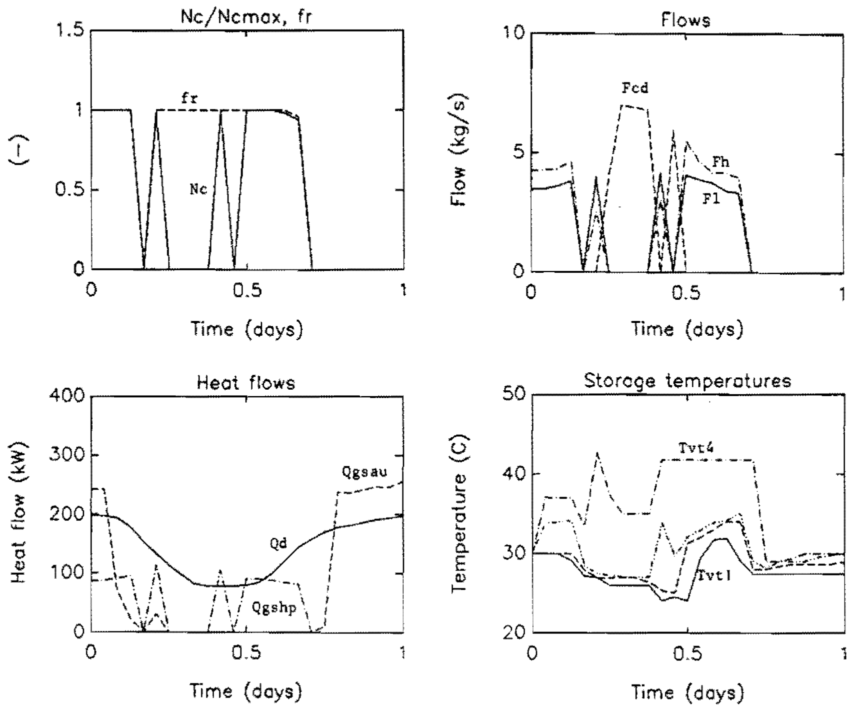


Fig. 5.34: Results of the design method for a heat pump system with a collector and short-term storage, with a conventional control strategy. Weather data of April.



<u>Fig. 5.35:</u> Results of the design method for a heat pump system with a collector and short-term storage, with a dynamic optimal control strategy. Weather data of April.

Comparing the results in Fig. 5.34 and 5.35 with the dynamic optimal control results of Section 5.3, it can be concluded that, although the sizing of the system is quite different, the operational modes applied are roughly the same. The need for auxiliary heating at the end of the day is a result of the terminal state constraints, the latter forcing the storage temperatures to decrease below the level of the demand temperature.

Results have also been obtained for situations with higher specific costs, leading to the conclusion that the optimal sizing parameters depend strongly on the assumptions about the criterion parameters. But in practical design situations these criterion parameters are usually known fairly accurately.

It is concluded that with this simultaneous optimisation procedure a better basis for the optimal choice of design parameters is provided. The trade-off between control and design effects leads to a better system control, and, above all, to a more economic design.

5.10 Computational aspects

In this section two problems occurring in the optimisation process are treated in more detail. These problems can mainly be reduced to the nature of the systems considered in this study.

Local minima

The possibility of local minima was already dealt with in Section 2.4.9. In non-linear systems like the ones discussed here, with different operational modes per time-step, generally a large number of "true" local minima exists. By a "true" local minimum I mean a minimum that truely exists, and not an artefact caused by optimisation routine that has apparently gotten stuck.
A situation which often results in a local minimum can be found in a configuration with a heat pump: a certain amount of heat is needed for future use, and this can be realised in several ways, by modulating the rotation speed of the heat pump in subsequent time-steps. A contour plot of the criterion function as a function of Nc in two subsequent time-steps will generally reveal that at least two local minima exist. The differences in criterion value in these cases are usually rather small, but the local minima are certainly "true": A transition of one local optimum to the other is not possible without a temporary increase in functional.
Another example of local extrema was already given in Section 5.6.3, which treated a situation with two totally different control strategies with nearly the same criterion value. This example also illustrates the effect of different starting control strategies, as mentioned in Section 2.4.9., in which the necessity of a number of restarts of the optimisation process was discussed.
So the problem of local minima is a structural problem, which is incorporated in the nature of the systems. However, it is felt that it also indicates a sort of "missing degree of freedom" in the system.

Rapid fluctuations in the optimal control strategy

A problem related to the local minima and the missing degrees of freedom is the occurrence of rapid changes in control variables in subsequent time-steps. Examples of such "turbulent" strategies can be found throughout the previous sections, and generally these strategies are not desirable.
These controls could be avoided if an extra term was added to the criterion function putting a penalty on large fluctuations in the control variables of subsequent time-steps. But this would also exclude simple on/off control strategies, and from the previous results it is clear that these on/off points are quite important.
The adhoc strategy applied to turbulent controls is peak-shaving: the control strategy is smoothed if the peaks cannot be explained physically. Although peak-shaving is a step which involves a lot of arbitrary choices, it often leads to a better control strategy, in our experience.

6 Conclusions

6.1 Introduction

In this thesis the aim was to study the design and control of thermal energy systems from the point of view of the optimisation method as well as the applications. In this chapter the general conclusions of this research are summarised, together with some recommendations for possible future lines of research.

6.2 Conclusions with regard to the optimisation approach

For the systems discussed in this thesis the chosen iterative numerical dynamic optimisation procedure is to be preferred: It does not require an explicit analytical knowledge of the system equations (although the availability of these equations can give an opportunity to use analytical gradients), and it can easily be adapted to other system configurations.

The optimisation method described in this thesis can handle a variety of dynamic optimisation problems for non-linear systems with a large number of control and state variables, provided the constraints upon the controls are linear functions of these controls.

The possibility of convergence to a local optimum, and the presence of a non-smooth process behaviour and performance criterion, introduce the need to monitor and control the optimisation process constantly, in order to arrive at the desired solution in an acceptable CPU-time. A black-box approach was found less suitable for these problems.

The positive effect on convergence of the optimisation process, of certain options suggested in the literature (cf. Section 2.3), could not be confirmed, and even must be doubted, in the application to the kind of systems dealt with in this thesis. For example: the active set strategy, applied to the handling of constraints, may sometimes show a much slower convergence than the incomplete projection strategy, described in Section 2.4.3.

The method developed may employ analytical as well as numerical derivatives of the criterion function with respect to the control variables. For dynamic optimisation with a relatively large number of state variables, the analytical calculation of this gradient will take a considerable amount of computer memory, particularly if this is done using the conventional, backward-time, recursive relationships. In Section 2.4.2 a forward-time calculation procedure of the gradient is described, which combines a saving in computer memory use and CPU-time with a better interpretability.

The numerical determination of the gradient was found to be particularly advantageous, because it provides an easier possibility of scanning the shape of the criterion function, e.g. the occurrence of sharp "valleys" that slow convergence. In the optimisation procedure developed in this thesis, this information is used to adapt the search direction in order to avoid the optimisation process from getting "stuck". In my experience "playing" with the search direction in this and similar ways is far more beneficial to the convergence rate than options like the active set strategy, however useful that may be.

The method described in this thesis has, of course, limitations. For example, it is not yet possible to impose nonlinear constraints upon the control variables.
Besides, for simple linear-quadratic problems other (second-order) methods are to be preferred.

A programme package has been developed for dynamic optimisation of discretised nonlinear large-scale systems with different operational modes. The package is implemented in standard Fortran77, and runs on various types of computers, including PC's.

6.3 Conclusions with regard to the design and control of thermal energy systems

Dynamic optimisation provides a better basis for the design and control of thermal energy systems.
The dynamic optimisation approach leads to a better system design, on the one hand because bottle-necks are revealed and system dimensions can be optimised in the same procedure, on the other hand because the results suggest more cost-effective layouts and configurations.
It establishes a significantly better system performance, owing to a better exploitation of the various components of a given system, as well as to a better anticipation of daily or seasonal changes in heat demand patterns.

A new design method for thermal energy systems is presented. The predominant characteristic of this method is that optimally controlled, instead of conventionally controlled, design alternatives are compared.

An important step in the design method is the translation of dynamic optimal control strategies to practicable strategies, which can be done along several ways, a number of which are dealt with in this thesis (cf. Sections 4.5 and 5.8.2).

To evaluate the practical applicability of the dynamic optimal control strategy, a sensitivity analysis is needed. For the configuration highlighted in this thesis the optimal control proved to be robust to random Gaussian fluctuations of about 50 % in the disturbance pattern.

If short-term fluctuations from the assumed disturbance pattern are important, the approach can either be adaptation, or attempting to detect a correlation between measurable states in the system and the optimal control.

Several variants of adaptation have been discussed. From the point of view of performance the adaptation with the aid of dynamic optimisation is to be preferred. Important parameters are the adaptation horizon, and the terminal constraints, if any. From the results presented in this thesis a reasonable estimate of a suitable horizon is 48 hours, but it must be stressed that this depends on the configuration, the disturbance variables and the way they act upon the system.

The approach of correlating measurable states and optimal control has also been investigated. It has been found possible to derive a near-optimal control strategy, based on dynamic optimal control, for a heat pump system with collectors and short-term storage. That strategy is based upon the tracking of the optimal trajectory of the storage temperatures.

An important, and often ignored, aspect of dynamic optimisation is its ability to detect deficiencies, invalid assumptions etc. in the calculation models of the components and the criterion function. The reason for this is that dynamic optimisation tries to get the "best" out of any component, which results in extreme ways of exploiting the possibilities provided by the models and the criterion.

In order to monitor the optimisation process, and for an interpretation of the results, "white" models (as opposed to black-box models) are preferable.

A programme package was developed for simulation of thermal energy systems, and integrated with the optimisation package mentioned above into the SYNTES-programme package (SYNthesis of Thermal Energy Systems).

6.4 Recommendations

With regard to applying dynamic optimisation to thermal energy systems, the introduction of more accurate models, in which secondary effects are not ignored, and models for more types of components, would enhance the applicability of the approach.

The design method described in this thesis should be compared with other design procedures, preferably by application to a realistic project.

The current state of affairs in The Netherlands with regard to seasonal storage is that aquifer storage is of primary interest. The design method developed in this thesis should also be applied to this type of storage.

With regard to the optimisation method it can be recommended to introduce a better treatment of state constraints. This may improve convergence and eliminates the need for restrictive assumptions and/or penalty functions.

The prospect of dealing with systems operating in different operational modes by means of the mathematical technique of mixed real-integer programming merits further research.

With regard to the use of dynamic optimisation as a design tool for other purposes, it is pointed out that the approach is not restricted to a number of specific configurations nor to the domain of thermal energy systems. The applicability of dynamic optimisation to other processes should be investigated in a systematic way (cf. Section 4.6.3).

Foreseeable future developments

In thermal energy systems design, it will be of more importance to follow the "think twice before you start to build" principle (cf. Section 2.1.4), especially in energy conservation applications. Owing to the current political climate for energy conservation, this principle will be of more importance in the immediate future. One simply cannot afford to build an improperly designed demonstration project.

The industrial tendencies towards more batch-wise production imply a growing need for a treatment of control and design aspects comparable to the one presented in this thesis.

The tendencies in software and hardware for computation point towards faster and more dedicated processors for certain calculations and parallellisation of the algorithms. With more computational power, more helpful tools for "interactive" optimisation, and better graphics capabilities, calculation of the optimal control will be a step of minor importance, and translation to practicable controls may become a step of major importance.

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Appendix A: Numerical results

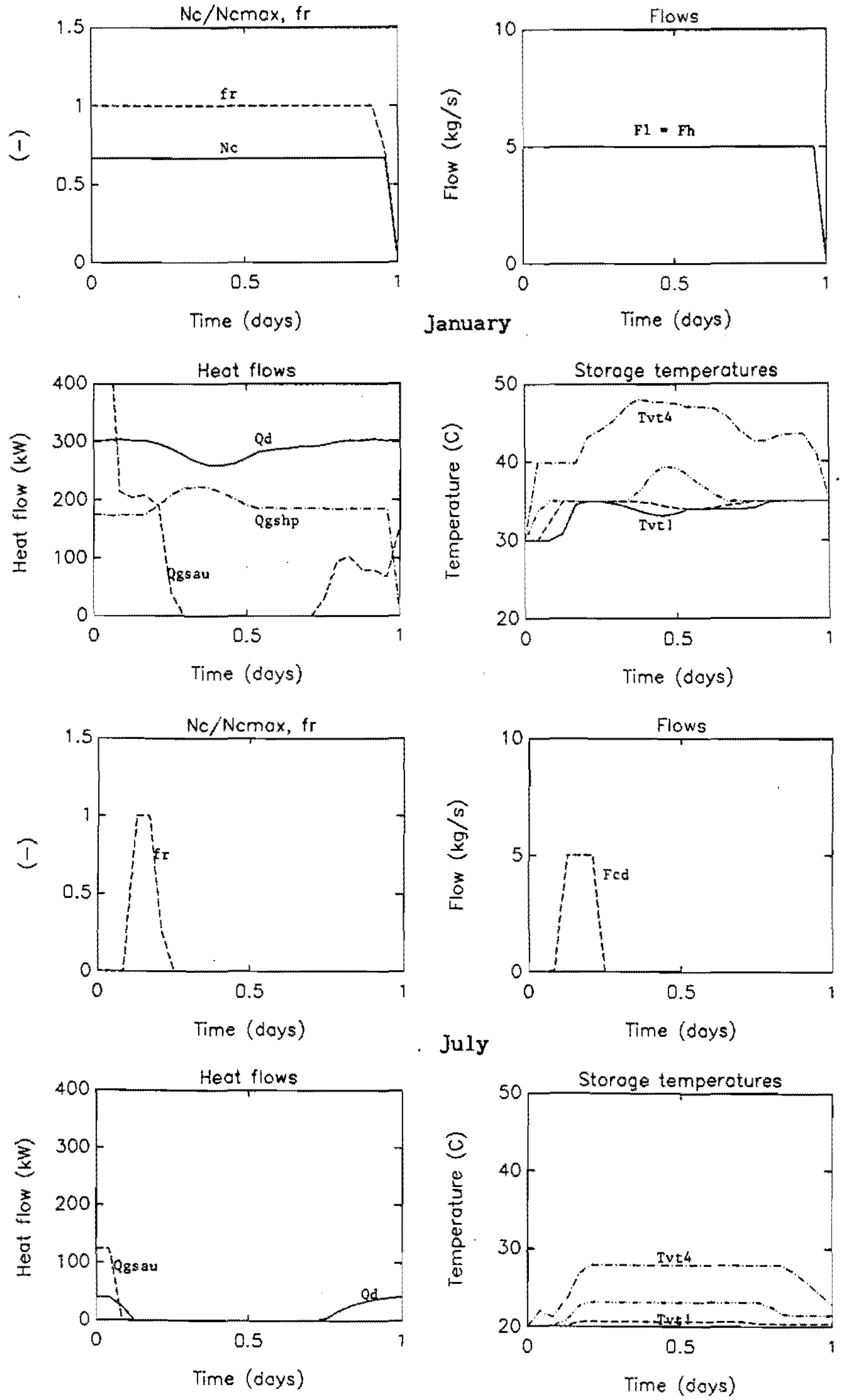
In this Appendix the numerical results of the optimisation runs are given. ETAdau refers to the fraction of the heat demand which is delivered by the auxiliary heater. ETAcol refers to the collector efficiency, defined as the quotient of the collected heat IQcol and the maximum heat to be withdrawn (given the momentary values of Tic and Teq), given by IQe. COP is the heat pump coefficient of performance.
All energies are given in MJ, except for the results of hierarchical optimisation, where the unit is 10@10J.
The total energy consumption is based on the "smoothed" criterion (cf. Sec. 2.4.9) and can differ slightly from the sum of its components IQgsau, IQgshp and IQpump.
For results obtained for the four characteristic days also the "year"-ly totals of the most important quantities are given. The graphs of conventional, static and momentary optimal control, for the days not shown in Fig. 5.3 of Section 5.2 are given in Figs. A.1.a to A.1.e.

Conventional control (Section 5.2)

	jan	apr	jul	oct	year
IQd [MJ]	24991	12127	960	8407	46487
IQgsau	7336	875	455	225	8891
IQgshp	15639	7156	0	4717	27512
IQpump	827	426	74	291	
IQtot	23770	8455	524	5231	37981
IQcol	9192	5967	1084	3763	20008
IQe	12863	8350	1517	5265	27997
IQhp	21234	10841	0	7395	39471
IQvt0	12600	12600	8400	12600	
IQvt1	14712	12650	8888	11767	
Etadau [-]	0.235	0.058	0.379	0.021	0.153
Etacol	0.715	0.715	0.715	0.715	0.715
COP	1.358	1.515	0.000	1.568	1.435

Static optimal control (Section 5.2)

	jan	apr	jul	oct	year
IQd [MJ]	24991	12127	960	8407	46487
IQgsau	4708	1413	455	256	6833
IQgshp	18599	6274	0	3544	28418
IQpump	640	428	77	361	
IQtot	23932	8109	527	4156	36725
IQcol	9976	6472	870	4336	21655
IQe	18743	12161	8371	8147	47423
IQhp	24297	11304	0	7065	42667
IQvt0	12600	12600	8400	12600	
IQvt1	15672	12907	8674	11462	
Etadau [-]	0.151	0.093	0.379	0.024	0.117
Etacol	0.532	0.532	0.104	0.532	0.457
COP	1.306	1.802	0.000	1.993	1.501



<u>Fig. A.1a:</u> Conventional control, January and July.

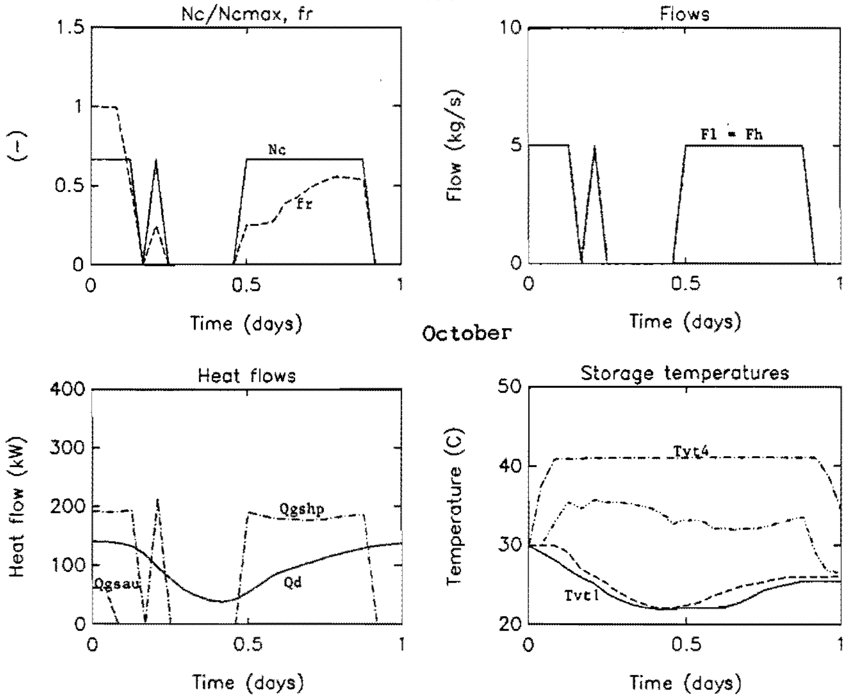


Fig. A.1b: Conventional control, October.

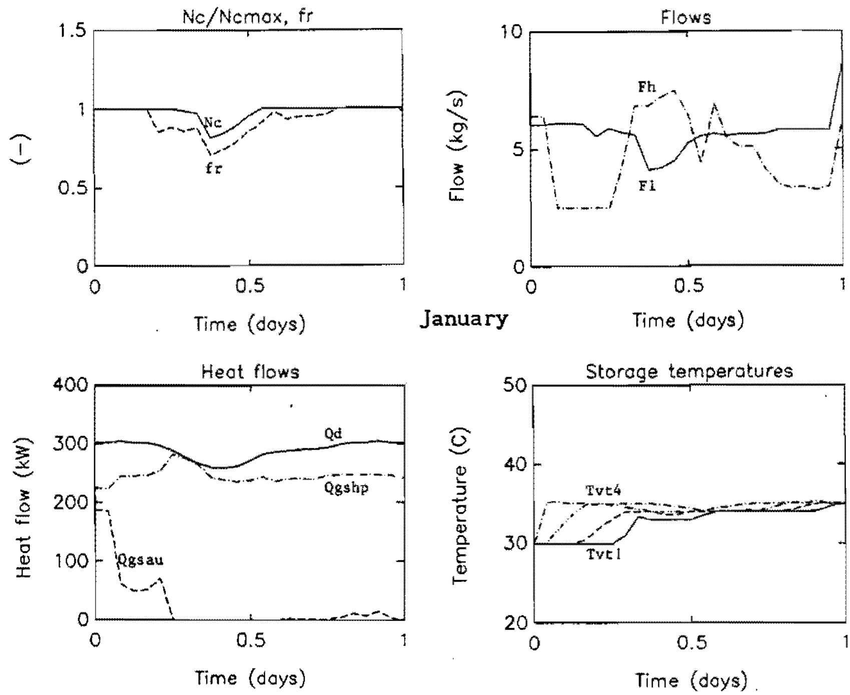


Fig. A.1c: Momentary optimal control, January.

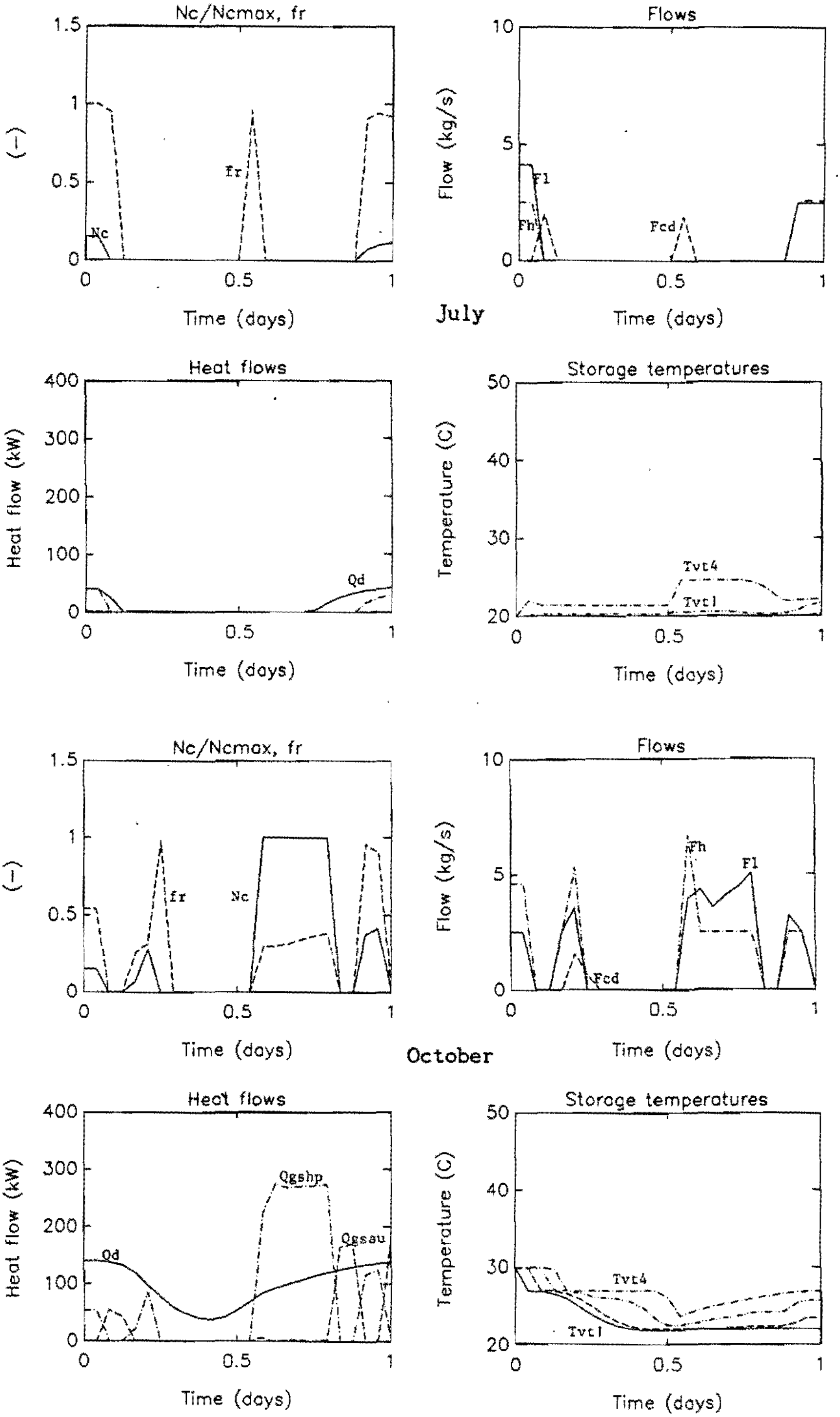
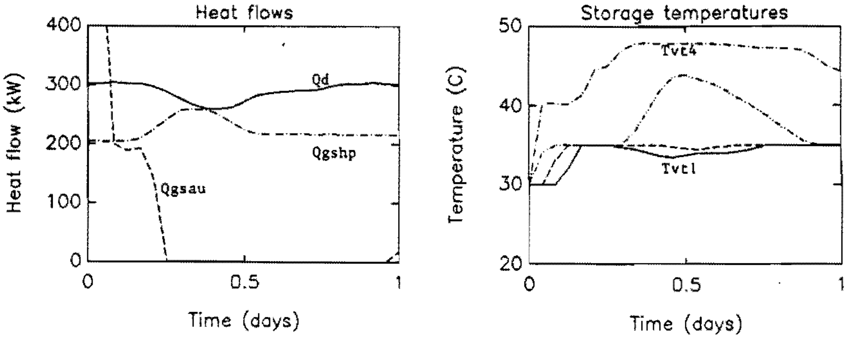
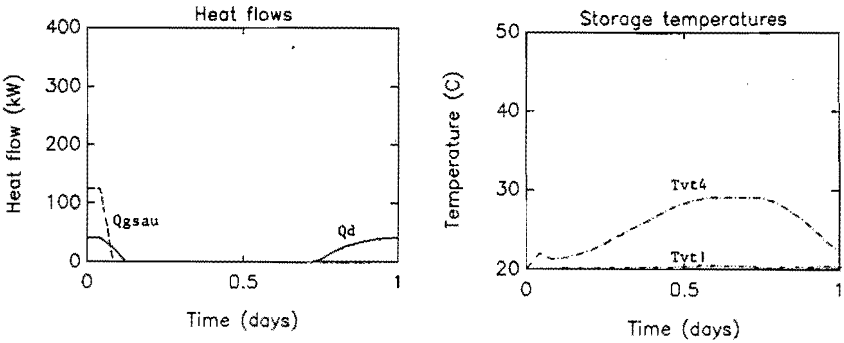


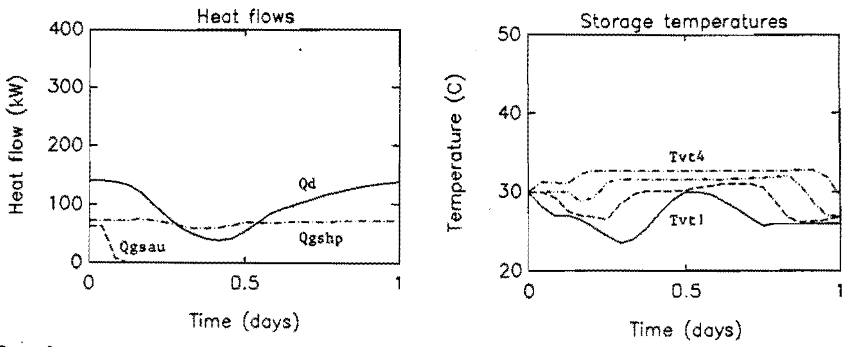
Fig. A.1d: Momentary optimal control, July and October.



January Nc = 1446, fr = 0.88, Fl = 6.00, Fh = 6.31, 1 ≤ n ≤ 24



July fr = 0.42, Fcd = 0.52, 2 ≤ n ≤ 15



October Nc = 1404, fr = 0.99, Fl = 5.86, Fh = 3.82, Fcd = 3.82
6 ≤ n ≤ 9

Fig. A.1e: Static optimal control, January, July and October.

Momentary optimal control (Section 5.2)

	jan	apr	jul	oct	year
IQd [MJ]	24991	12127	960	8407	46487
IQgsau	1743	3693	18	2255	7710
IQgshp	16440	5374	383	2916	25113
IQpump	760	417	112	220	
IQtot	18944	9484	515	5392	34335
IQcol	8629	3761	1075	2038	
IQhp	21289	8095	959	4339	34684
IQvt0	12600	12600	8400	12600	
IQvt1	14712	11335	8828	10294	
Etadau [-]	0.056	0.244	0.015	0.215	0.133
COP	1.295	1.506	2.506	1.488	1.381

Dynamic optimal control (Section 5.3)

	jan	apr	jul	oct	year
IQd [MJ]	24991	12127	960	8407	46487
IQgsau	3860	877	455	226	5419
IQgshp	17965	5736	0	3322	27023
IQpump	962	474	33	346	
IQtot	22772	7084	483	3891	34231
IQcol	10207	6690	866	4107	21871
IQe	13810	9485	6000	6649	35946
IQhp	24040	9114	0	6485	39640
IQvt0	12600	12600	8400	12600	
IQvt1	14736	12281	8671	11039	
Etadau [-]	0.124	0.058	0.379	0.022	0.093
Etacol	0.739	0.705	0.144	0.618	0.608
COP	1.338	1.589	0.000	1.952	1.467

Static optimal control with periodic state constraints (Section 5.4)

	jan	apr	jul	oct	year
IQd [MJ]	24991	12127	960	8407	46487
IQgsau	52	48	0	1490	1591
IQgshp	19138	6181	0	3647	28966
IQpump	718	696	57	361	
IQtot	19905	6924	57	5483	32372
IQcol	10214	7328	1000	4407	22950
IQe	19190	10306	6245	8280	44022
IQhp	24950	12088	0	7215	44254
IQvt0	16255	13638	8925	11379	
IQvt1	16255	13638	8965	11379	
Etadau [-]	0.002	0.003	0.000	0.142	0.027
Etacol	0.532	0.711	0.160	0.532	0.521
COP	1.304	1.956	0.000	1.978	1.527

<u>Dynamic optimal control with periodic state constraints</u> (Section 5.4)

	jan	apr	jul	oct	year
IQd [MJ]	24991	12127	960	8407	46487
IQgsau	2	0	0	688	691
IQgshp	18850	6220	0	4079	29149
IQpump	1004	725	34	384	
IQtot	19855	6945	34	5144	31979
IQcol	10474	7338	1605	4715	24134
IQe	14109	10628	6010	7605	38354
IQhp	24989	10155	0	7708	42853
IQvt0	15821	14447	11347	11319	
IQvt1	15821	14447	11992	11319	
Etadau [-]	0.000	0.000	0.000	0.066	0.012
Etacol	0.742	0.690	0.267	0.620	0.629
COP	1.326	1.633	0.000	1.890	1.470

<u>Dynamic optimal control with terminal state constraints</u> (Section 5.4)

April, 24 hrs, $\underline{x}(N) = \underline{x}d$, represented by $\overline{Tvt}$

$\overline{Tvt}$	25	30	35	40	45	50
IQd [MJ]	12127	12127	12127	12127	12127	12127
IQgsau	7834	875	875	875	875	875
IQgshp	2030	5951	7616	9511	11393	13289
IQpump	261	482	533	539	675	570
IQtot	10100	7306	9021	10923	12943	14731
IQcol	2411	6834	7638	8292	8953	9574
IQe	3768	9592	10505	11852	13054	14703
IQhp	2903	9406	11518	13621	15644	19807
IQvt0	12600	12600	12600	12600	12600	12600
IQvt1	10714	12590	14674	16789	18880	20979
Etadau [-]	0.517	0.058	0.058	0.058	0.057	0.058
Etacol	0.640	0.712	0.727	0.700	0.686	0.651
COP	1.430	1.581	1.512	1.432	1.373	1.490

<u>Dynamic optimal control for two stretches</u> (Section 5.4)

	stretch 1 (Fig. 5.12)	stretch 2 (Fig. 5.13)
IQd [MJ]	58607	118470
IQgsau	5	15528
IQgshp	36753	67927
IQpump	2584	3679
IQtot	39340	87084
IQcol	29868	53788
IQe	48010	78440
IQhp	56228	101170
ETAdau [-]	0.000	0.105
ETAcol	0.622	0.686
COP	1.530	1.489

Hierarchical optimisation (Section 5.5)

	system with collectors, heat pump and seas. stor.	system with collectors and seasonal storage
IQd [10@10 J]	443.4	443.4
IQgsau	65.1	117.9
IQgshp	185.8	0.0
IQpump	20.0	22.8
IQtot	270.9	140.7
IQcol	245.7	490.0
IQe	326.4	546.7
IQhp	300.4	0.0
IQv0	5.712	5.712
IQv1	5.627	5.700
ETAdau [-]	0.117	0.213
ETAcol	0.753	0.896
COP	1.617	0.000
IQig [10@10 J]	135.1	335.9
IQog	89.1	182.7
IQg0	559.5	559.5
IQg1	589.0	699.6
IQggr	-21.1	-22.4
IQggz	-7.9	-8.5

Dynamic optimal control with Gaussian noise (Section 5.6)

		jan			apr	
Noise %	20	30	50	20	30	50
IQd [MJ]	25047	25087	25103	12327	12407	12479
IQgsau	3843	3883	3884	878	885	878
IQgshp	18038	18048	18068	5871	5955	5930
IQpump	964	964	965	476	469	481
IQtot	22832	22882	22902	7221	7304	7285

		jul			oct	
Noise %	20	30	50	20	30	50
IQd [MJ]	1048	1080	1152	8559	8631	8687
IQgsau	505	506	530	225	228	229
IQgshp	0	0	0	3387	3435	3463
IQpump	43	43	43	347	346	347
IQtot	543	543	568	3956	4005	4034

Dynamic optimal control without noise applied to disturbance patterns with Gaussian noise (Section 5.6)

		jan			apr	
Noise %	20	30	50	20	30	50
IQd [MJ]	25047	25087	25103	12327	12407	12479
IQgsau	3938	3989	4016	1260	1422	1586
IQgshp	17975	17977	17979	5678	5658	5629
IQpump	962	962	962	474	474	474
IQtot	22860	22914	22943	7402	7544	7679

Noise %	jul 20	30	50	oct 20	30	50
IQd [MJ]	1048	1080	1152	8559	8631	8687
IQgsau	646	714	856	328	402	444
IQgshp	0	0	0	3336	3341	3352
IQpump	42	42	42	346	346	346
IQtot	681	746	888	4005	4085	4138

Model reference adaptive control (Section 5.7)

	reference trajectory	30 % Gaussian noise on weather data
IQd [MJ]	12127	12407
IQgsau	0	0
IQgshp	6823	7215
IQpump	715	738
IQtot	7538	7953
IQcol	6863	6841
IQe	7918	7917
IQhp	12117	12397
IQv0	13403	13403
IQv1	13393	13392
ETAdau [-]	0.000	0.000
ETAcol	0.867	0.864
COP	1.776	1.718

Adaptive control with the aid of dynamic optimisation, exact weather forecasts (Section 5.7)

	dynamic optimal control over a 7-day period	adaptation with 24-hour forecasts	adaptation with 48-hour forecasts
IQd [MJ]	58607	58607	58607
IQgsau	882	1333	884
IQgshp	14111	17254	15559
IQpump	2881	2781	2654
IQtot	17866	21358	19090
IQcol	50902	48630	50471
IQe	59757	74410	77069
IQhp	22879	26373	22561
IQv0	8400	8400	8400
IQv1	12265	12487	12170
ETAdau [-]	0.012	0.018	0.012
ETAcol	0.852	0.654	0.655
COP	1.621	1.528	1.514

Adaptive control with the aid of dynamic optimisation, inexact weather forecasts (Section 5.7)

	dynamic opt. control over a 7-day period	adaptation based on 48-hour forecasts
IQd [MJ]	58607	58607
IQgsau	1465	6601
IQgshp	37233	12430
IQpump	3113	2718
IQtot	41804	21712
IQcol	39952	48670
IQe	47680	63807
IQhp	46636	19460
IQv0	8400	8400
IQv1	19590	13319
ETAdau [-]	0.020	0.090
ETAcol	0.838	0.763
COP	1.253	1.566

Near-optimal control based on dynamic optimal control (Section 5.8)

	jan	apr	jul	oct	year
IQd [MJ]	24991	12127	960	8407	46487
IQgsau	7005	875	455	225	8560
IQgshp	15839	6327	0	4250	26418
IQpump	838	443	49	294	
IQtot	23650	7642	498	4767	36560
IQcol	9303	6881	1327	4054	21572
IQe	13017	9628	1857	5672	30177
IQhp	21499	9778	0	6816	38094
IQvt0	12600	12600	8400	12600	
IQvt1	14712	12925	9131	11699	
Etadau [-]	0.224	0.058	0.379	0.021	0.147
Etacol	0.715	0.715	0.715	0.715	0.715
COP	1.357	1.545	0.000	1.604	1.442

Design optimisation with conventional control (Section 5.9)

	jan	apr	jul	oct	year
IQd [MJ]	24991	12127	960	8407	46487
IQgsau	20225	4569	726	241	25762
IQgshp	6723	4450	0	4281	15456
IQpump	838	638	98	553	
IQtot	27727	9627	814	5071	43241
IQcol	4485	5033	669	4365	14553
IQe	5599	6283	835	5449	18167
IQhp	9663	7670	0	7662	24996
IQvt0	5040	5040	3360	5040	
IQvt1	5892	5028	3649	4487	
Etadau [-]	0.647	0.301	0.605	0.023	0.443
Etacol	0.801	0.801	0.801	0.801	0.801
COP	1.437	1.724	0.000	1.790	1.617

Design optimisation with dynamic optimal control (Section 5.9)

	jan	apr	jul	oct	year
IQd [MJ]	24991	12127	960	8407	46487
IQgsau	19614	6634	455	232	26936
IQgshp	7296	3318	0	4234	14849
IQpump	588	463	38	435	
IQtot	27439	10388	488	4894	43210
IQcol	4533	4109	1312	4408	14363
IQe	5970	5112	1929	6090	19102
IQhp	10151	5627	0	7668	23447
IQvt0	5040	5040	3360	5040	
IQvt1	5892	4884	4076	4486	
Etadau [-]	0.628	0.438	0.379	0.022	0.464
Etacol	0.759	0.804	0.680	0.724	0.752
COP	1.391	1.696	0.000	1.811	1.579

Stellingen behorend bij het proefschrift van A.C.E.P. van Delft

1 Bij het ontwerp van (warmte-)technische processen dienen, om een zo goed mogelijk eindresultaat te verkrijgen, de besturingsaspecten reeds vanaf het begin van het ontwerpproces op een systematische manier in de beschouwingen betrokken te worden (dit proefschrift).

2 De tendens in de procesindustrie van continue naar (semi-)ladingsgewijze productie brengt met zich mee dat er meer aandacht nodig is voor onderzoek naar de besturing van niet-stationaire processen. De in dit proefschrift geschetste aanpak voor het optimaal ontwerpen en bedrijven van warmtetechnische processen is ook toepasbaar op de veel bredere klasse van niet-stationaire, niet-lineaire processen zoals ze in de procesindustrie steeds meer voorkomen (dit proefschrift).

3 Bij dynamische optimalisering van warmtetechnische processen is het noodzakelijk realistische criteria te hanteren. De fysica (niet-lineair systeemgedrag, niet-kwadratische criteria), en niet de wens er een mathematisch elegante probleemstelling (lineair systeemgedrag, kwadratische criteria) van te maken, dient centraal te staan. De resultaten van o.a. Orbach (1979) en Winn (1979) hebben in dit verband dan ook maar een betrekkelijke waarde (A. Orbach: Optimal control of distributed parameter systems for solar thermal applications, Ph.D. Thesis, Drexel University, 1979, C.B. Winn and D.E. Hull: Optimal controllers of the second kind, Solar Energy 29(1979) en dit proefschrift).

4 De ontwikkelingen in computerapparatuur en -programmatuur zorgen ervoor dat bij dynamische optimalisering het vinden van de optimale oplossing een probleem van steeds kleinere importantie wordt, terwijl het vertalen van die oplossing naar voor de praktijk hanteerbare besturingsconcepten steeds belangrijker wordt.

5 De opmerkingen van Van Meurs (1985) betreffende de geringe positieve effecten van het afzonderlijke aansturen van het debiet door de pijpen van een cylindervormige bodemwarmtewisselaar zijn niet voldoende onderbouwd, en worden zeker niet bevestigd door de resultaten in dit proefschrift (G.A.M. van Meurs: Seasonal heat storage in the soil, proefschrift Technische Universiteit Delft, 1985, en dit proefschrift).

6 Voor het welslagen van toekomstige demonstratieprojecten in de energiebesparingssfeer is het absoluut noodzakelijk dat over zowel besturing als ontwerp van de te bouwen installatie grondig vóórgedacht wordt.

7 Het verdient aanbeveling ministers van onderwijs en wetenschappen voor het leven te benoemen, teneinde er zo goed mogelijk van verzekerd te zijn dat deze ministers nog gedurende hun ambtsperiode met de gevolgen van hun beleid geconfronteerd worden. In dit verband is het, gezien de invulling van het beleid op het ministerie van onderwijs en wetenschappen, onterecht het kabinet Lubbers te kwalificeren als een no-nonsense kabinet.

8 Van ideologieën komt alleen maar ellende.

9 Gezien de snelle veranderingen in de PC-wereld is het geven van onderricht in het gebruik van Personal Computers op een middelbare school zinloos.

10 Representatieve steekproeven die ordes van grootte kleiner zijn dan de populatie, bijvoorbeeld ter verkrijging van verkiezingsprognoses, bestaan niet. Het enquêteren van een groep mensen stelt immers eisen aan de bereidheid tot medewerking en de bereikbaarheid van de ondervraagden. Om deze reden zijn bijvoorbeeld gehuwde of samenwonende tweeverdieners altijd ondervertegenwoordigd in de steekproef.

11 Uit oogpunt van gelijkberechtiging van man en vrouw verdient in de genealogie het vervaardigen van een kwartierstaat de voorkeur boven het opzetten van een stamboom op basis van een geslachtsnaam.

12 Het komt de wetenschappelijke kwaliteit van proefschriften ten goede als bij het schrijven daarvan niet rekening gehouden wordt met de "standaard domme lezer", maar met de "deskundige en op zijn minst zijdelings geïnteresseerde vakgenoot".

Curriculum vitae

Alex van Delft is geboren op 20 oktober 1960 in Drunen. Daar doorliep hij de basisschool. Van 1973 tot 1979 bezocht hij het Dr. Moller-college te Waalwijk, waar hij het diploma Gymnasium β behaalde. In september 1979 begon hij met een studie Technische Natuurkunde aan de Technische Universiteit Eindhoven. Het ingenieursdiploma werd in februari 1985 behaald, met als afstudeerhoogleraar Prof. ir. O. Rademaker van de Vakgroep Systeem- en Regeltechniek. Van maart 1985 tot maart 1989 verrichtte hij onderzoek in dezelfde vakgroep op het terrein van dynamische optimalisering van warmtetechnische systemen. Vanaf april 1989 is hij in dienst van DSM Kunststoffen b.v. te Geleen als stafmedewerker procesbesturing.

Stellingen behorend bij het proefschrift van A.C.E.P. van Delft

1 Bij het ontwerp van (warmte-)technische processen dienen, om een zo goed mogelijk eindresultaat te verkrijgen, de besturingsaspecten reeds vanaf het begin van het ontwerpproces op een systematische manier in de beschouwingen betrokken te worden (dit proefschrift).

2 De tendens in de procesindustrie van continue naar (semi-)ladingsgewijze productie brengt met zich mee dat er meer aandacht nodig is voor onderzoek naar de besturing van niet-stationaire processen. De in dit proefschrift geschetste aanpak voor het optimaal ontwerpen en bedrijven van warmtetechnische processen is ook toepasbaar op de veel bredere klasse van niet-stationaire, niet-lineaire processen zoals ze in de procesindustrie steeds meer voorkomen (dit proefschrift).

3 Bij dynamische optimalisering van warmtetechnische processen is het noodzakelijk realistische criteria te hanteren. De fysica (niet-lineair systeemgedrag, niet-kwadratische criteria), en niet de wens er een mathematisch elegante probleemstelling (lineair systeemgedrag, kwadratische criteria) van te maken, dient centraal te staan. De resultaten van o.a. Orbach (1979) en Winn (1979) hebben in dit verband dan ook maar een betrekkelijke waarde (A. Orbach: Optimal control of distributed parameter systems for solar thermal applications, Ph.D. Thesis, Drexel University, 1979, C.B. Winn and D.E. Hull: Optimal controllers of the second kind, Solar Energy 29(1979) en dit proefschrift).

4 De ontwikkelingen in computerapparatuur en -programmatuur zorgen ervoor dat bij dynamische optimalisering het vinden van de optimale oplossing een probleem van steeds kleinere importantie wordt, terwijl het vertalen van die oplossing naar voor de praktijk hanteerbare besturingsconcepten steeds belangrijker wordt.

5 De opmerkingen van Van Meurs (1985) betreffende de geringe positieve effecten van het afzonderlijke aansturen van het debiet door de pijpen van een cylindervormige bodemwarmtewisselaar zijn niet voldoende onderbouwd, en worden zeker niet bevestigd door de resultaten in dit proefschrift (G.A.M. van Meurs: Seasonal heat storage in the soil, proefschrift Technische Universiteit Delft, 1985, en dit proefschrift).

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