



Formulation of a model predictive control algorithm to enhance the performance of a latent heat solar thermal system



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ABSTRACT

Model predictive control has proved to be a promising control strategy for improving the operational performance of multi-source thermal energy generation systems with the aim of maximising the exploitation of on-site renewable resources. This paper presents the formulation and implementation of a model predictive control strategy for the management of a latent heat thermal energy storage unit coupled with a solar thermal collector and a backup electric heater. The system uses an innovative Phase Change Material slurry for both the heat transfer fluid and storage media. The formulation of a model predictive controller of such a closed-loop solar system is particularly desirable but also challenging mainly due to the nonlinearity of the heat exchange and thermal storage processes involved. A solution for the model predictive control problem to regulate a system with intrinsic nonlinearities is introduced using a mixed logic-dynamical approach. The model predictive control regulation is tested and compared with a baseline rule-based controller considering both ideal and estimated disturbance predictions. Results demonstrate the capability of the predictive controller in anticipating future disturbances and in optimising the utilisation of the more efficient energy sources. When compared to the rule-based controller, the model predictive control algorithm leads to reductions of the system primary energy demand ranging from 19.2% to 31.8% as a function of the variation of a soft constraint on meeting demand constraints. The work contributes to new knowledge on how model predictive control algorithms can be implemented to maximise the benefits of integrating thermal energy storages that employ latent heat of fusion with solar thermal technologies.

1. Introduction

The pursuit of higher levels of thermal comfort has led to a dramatic increase in the use of energy in buildings in recent times. It has been estimated that buildings are responsible for up to 40% of global energy needs [1]. Thus, there is a pressing need to explore suitable technologies and innovative strategies with the aim to enhance the energy efficiency of buildings. Building energy consumption may be minimised through a range of measures, including efficient envelope and Heating, Ventilation and Air Conditioning (HVAC) system technologies. In order to achieve low or zero carbon buildings [2], the remaining building energy demand, once energy efficiency measures have been implemented, can be met by renewable energy sources. Solar technologies are the leading renewable energy solution suitable for addressing this challenge at a building scale. However, the exploitation of solar energy is often limited by its stochastic variation over time, and by the mismatch between its availability and the energy demand of buildings and

consumers [3]. The implementation of advanced and model-based regulation strategies, such as Model Predictive Control (MPC), are seen as potential solutions for reducing this mismatch and consequently enhancing the exploitation of renewable energy sources.

1.1. Principles of Model Predictive Control and applications in regulating energy flows in buildings

MPC is a well-established method for optimised constrained control in industrial processes, and recently, it has received increasing attention in the field of building control. Prior to the past decade, practical implementation of MPC in building automation systems was rare, largely because of high computational demands in massive optimisation problems. However, MPC has become increasingly attractive due to the increase in computational power of building automation systems, and increasing availability of real-time monitored building data [4].

MPC can exploit both predictions of future disturbances (e.g.

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Nomenclature

A	state matrix
B_u	manipulated input matrix
B_v	measured disturbances matrix
C	output matrix
c_p	specific heat capacity [kJ/kg °C]
D_u, D_v	direct transmission matrices
e	slacking variable for the violation of the soft constraint [kWh _{el} /°C]
F_R	collector heat removal factor [–]
G_T	solar radiation incident per unit of surface area [kW/m ²]
h	specific enthalpy [kJ/kg]
m	mass [kg]
Q	weighting matrix on the states
\dot{Q}_{dp}	heating power associated with the heat transfer fluid [kW _{th}]
\dot{Q}_{he}	heating power delivered by the auxiliary heater [kW _{th}]
\dot{Q}_{hx}	heating power required by the secondary heat exchanger [kW _{th}]
$\dot{Q}_{he,max}$	maximum power deliverable by the auxiliary heater [kW _{el}]
\dot{Q}_{loss}	storage heat losses [kW _{th}]
\dot{Q}_g	heating power delivered by the solar thermal collector [kW _{th}]
\dot{Q}_{need}	space heating demand [kW _{th}]
R	weighting matrix on the manipulated input
S	surface area [m ²]
t	time [h]
T	temperature [°C]
$T_{st,max}, T_{st,min}$	storage unit maximum and minimum temperature bounds [°C]
u	manipulated input vector
U	overall heat transfer coefficient [W/m ² °C]
v	measured disturbances vector
V	volume [m ³]
\dot{W}_{he}	electric power required by the auxiliary heater [kW _{el}]
x	system states vector
y	system output vector

Greek symbols

δ	pump operation (on/off)
ρ	density [kg/m ³]
$(\tau\alpha)_e$	transmittance-absorptance product of the solar collector [–]

Logic operators

\sim	logic operator “not”
$\&$	logic operator “and”

Subscripts

$10, 60, 90$	pump speeds
a	ambient air
$coll$	solar thermal collector
in	inlet of the solar thermal collector
inf,PCM	lower phase change limit for the Phase Change Material
p	prediction horizon
PCM	Phase Change Material slurry
r	reference value (or set-point)
st	thermal energy storage unit
sup,PCM	upper phase change limit for the Phase Change Material

Acronyms and abbreviations

COP	Coefficient of Performance
EWY	Example Weather Year
HVAC	Heating, Ventilation and Air Conditioning
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
MLD	Mixed Logical Dynamical
MPC	Model Predictive Control
PCM	Phase Change Material
RBC	Rule Base Controller
SF	Solar Factor

internal gains, weather, etc.) and operational requirements (e.g. thermal comfort bands and maximum allowable energy demand), to anticipate the energy needs of the building and optimise its thermal behaviour from defined control goals. Constraints are included directly in the optimisation problem, which is solved at each time-step [4]. In general, an optimisation-based control strategy aims to find the optimal trade-off between conflicting objectives (e.g. reducing the operational building energy costs while ensuring satisfactory thermal comfort conditions for building users).

The scientific literature offers a number of studies on the application of MPC for energy management of buildings. Afram and Janabi-Sharifi [5] described a framework for MPC implementation and Hilliard et al. [6] outlined trends and opportunities for MPC implementation in commercial buildings. Killian and Kozek [7] provided an extended survey of the current and future potential applications for MPC building thermal regulation, and some of the authors of the present paper have presented a review of MPC algorithms for building thermal energy management [4]. These works have covered the successful implementation of MPC algorithms in various thermal and energy management strategies for buildings or building elements. MPC algorithms have been studied for demand side management strategies in micro-grids [8] and residential buildings connected with renewable energy sources [9]. MPC algorithms have also been used for optimising the thermal management of complex buildings [10], regulating domestic

appliances [11], enhancing the performance of photovoltaic systems [12] or heat exchangers [13], and stand-alone energy supply systems [14]. Further opportunities have been identified in peak load shifting for systems used to deliver space heating or cooling [15] using MPC. In [16] and [17], for example, the potential for thermally activated building structures to be fully exploited using MPC is described. In [18], a robust MPC problem was formulated to optimally regulate a building conditioned with a variable air volume air handling unit. MPC has also been effectively applied to active energy storage systems [19], as well as for the optimal management of on-site renewable energy sources [20].

Good examples of the practical implementation of MPC algorithms in buildings include ten households in Brugg [21], the 3E Headquarters in Brussels [22], a commercial Building in Allschwil [23], a building of the Czech Technical University in Prague [17], the UC Merced Campus [24], the Engineers Construction Engineering Research Laboratory (CERL) in Champaign [25], and the airport of Adelaide [26]. These examples cover several building typologies and are located in various climates. They demonstrate that MPC can effectively reduce energy consumption of HVAC systems and facilitate the integration of buildings into more flexible energy grids. The main drawback that has limited the widespread implementation of MPC controllers in building automation systems has been the bottleneck represented by the need to have a reliable mathematical model of the building [27].

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