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Cost-optimal model predictive scheduling of freezers

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ABSTRACT

A cost-optimal model predictive scheduling algorithm is presented that operates in a day-ahead market. The underlying optimizer is a heuristic branch and bound algorithm that finds the constrained optimal scheduling of a freezer with respect to hourly changing energy price. The method is also able to iteratively re-estimate the heat capacity of the freezer.

Simulation experiments were performed on a freezer model identified from measurement data. Results show that the proposed algorithm successfully decreased the cost of operation, however the computational complexity increases when the price is growing.

The proposed method can be generalized for home appliances of different kind.

1. Introduction

One of the major technical challenges nowadays is the efficient management of energy production and consumption. Facing the constrained energy resources and energy production capacity together with the rapidly increasing and dynamically changing energy consumption, electrical energy providers and line operators, and also the electrical appliances themselves are providing more and more smart solutions with economical, technical and environmental goals, that facilitates the development of smart grid technologies and solutions both on the demand and on the supplier sides.

The approaches from the supplier side include the methods of optimized pricing (Joe-Wong, Sen, Ha, & Chiang, 2012) that aim at balancing the electrical grid subject to variations in the supply (e.g. caused by the changing availability of renewable energy sources), and also in the demand. As a result of optimized pricing, hourly changing electrical energy prices are available for the day-ahead electricity market (see e.g. Spot (2010)), that is continuously expanding, and the amount of energy being traded through them is increasing. The authors of Tianhu, Jumpei, and Yumiko (2017) analyzed the effect and potential contribution capability of microgrid to electric power system demand–supply adjustment in hour-ahead electricity market through Price-Based demand response and they concluded that the overall operation efficiency and flexibility both improved. In the work (Kim, Oh, & Ahn, 2015) a new framework has been proposed considering decentralized energy coordination and generation that can be utilized in energy dispatch or energy flow scheduling.

The demand side tools and techniques of energy management are also developing rapidly. This area includes the optimal operation of certain electrical appliances with controllable on/off switching taking into account the dynamically changing electrical energy prices and the operating constraints. An optimal day-ahead microgrid scheduling method for an office building considering weather scenarios is developed in Shimomachi et al. (2014), while an optimal residential load control method with price prediction is reported in the paper (Mohsenian-Rad & Leon-Garcia, 2010). Household appliances can also be a subject of optimal operation or scheduling, see e.g. the paper (Du & Lu, 2011). A method is proposed in Báez-González, del Real, Carlini, and Bordons (2016) to minimize the energy cost associated to olive oil production in a day-ahead market.

The optimal energy demand management tasks with changing electrical energy prices most often lead to model based optimization problems for which efficient solution methods are available in the literature. In Sou, Weimer, Sandberg, and Johansson (2011) a mixed integer linear programming based approach is used for the optimal scheduling of domestic appliances in a smart environment. The use of cooperative particle swarm optimization and similar soft computing methods was reported in Pedrasa, Spooner, and MacGill (2010) to energy consumption optimization in smart home applications. An

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optimal scheduling algorithm has been given in Setlhaolo and Xia (2014) where the optimal scheduling of different household appliances has been formulated as a nonlinear integer programming problem and solved by genetic algorithm. An adaptive scheme has been proposed for temperature control in household freezers with low-end sensing and actuation equipment in Leva, Piroddi, Felice, Boer, and Paganini (2010).

On the other hand, model predictive control (MPC) is a powerful and popular method for solving multivariable optimal control problems in energy related control and scheduling applications, too (see e.g. Ma, Qin, and Salsbury (2014) and Rodrigues, Godina, Pouresmaeil, Ferreira, and Catalão (2017)). The online estimation of the model parameters (e.g. in a varying temperature situation) enables the controller to adjust the used model to the actual system, e.g. in the work (Pedersen, Schwensen, Biegel, Green, & Stoustrup, 2017), where the demand response potential of a refrigerator system being used in a supermarket has been proposed together with an estimator of the actual food temperature. The authors of Elliott and Rasmussen (2013) propose a decentralized MPC architecture for a multi evaporator-air conditioning system that is decentralized and modular, in order to avoid competing controllers and the practical difficulty of implementing a centralized controller. Model predictive control can also be used in the charging control of electrical vehicles in a Smart Grid as presented in Di Giorgio, Liberati, and Canale (2014). The model predictive approach, however, requires to have a reliable dynamical model of the controlled dynamical system. The authors of the work (Sossan et al., 2016) propose a gray-box modeling approach for household refrigerators as a basis of a demand side management application. In Schné, Jaskó, and Simon (2014), the authors provide a dynamical model of a household refrigerator together with a parameter identification.

The general aim of this work is to propose a theoretically sound yet computationally effective method for cost optimal adaptive scheduling of cooling/heating appliances. Because of the computationally exhaustive nature of the standard MPT toolbox (Herceg, Kvasnica, Jones, & Morari, 2013) available for this purpose (see in Bálint and Magyar (2016)), heuristic elements were needed to develop a computationally feasible method (Bálint, Magyar, & Hangos, 2017). In addition, the need for an adaptive version of the method has also arisen to follow the change in the load of the cooling/heating appliances (Bálint, Hangos, & Magyar, 2017). Based on the earlier attempts (Bálint, Hangos et al., 2017), this paper proposes an effective method for cost optimal adaptive scheduling of cooling appliances together with a simple way of estimating the model parameters needed for the scheduling.

The paper is organized as follows. The problem is defined in Section 2 together with the dynamical model of the freezer. The scheduling problem is formulated as a model predictive control problem in Section 3, two proposed heuristic algorithms are also presented here. The case study of a simple freezer is given in Section 4, which is followed by the discussion of the results in Section 5. Finally, the most important concluding remarks and some future research directions are given in Section 6.

2. Problem statement

The problem of cost-optimal scheduling of freezers possesses important specialties that can be effectively utilized in the proposed heuristic solution. These specialties are present both in the dynamic models of the freezers and in the special control aim driven by the time-dependent electricity prices.

2.1. Dynamic model of freezers for scheduling

In the simplest case, a freezer can be regarded as a container that is cooled by a cooling liquid circuit driven by an electrical motor. The schematic picture of the main elements of this simple freezer is shown in Fig. 1.

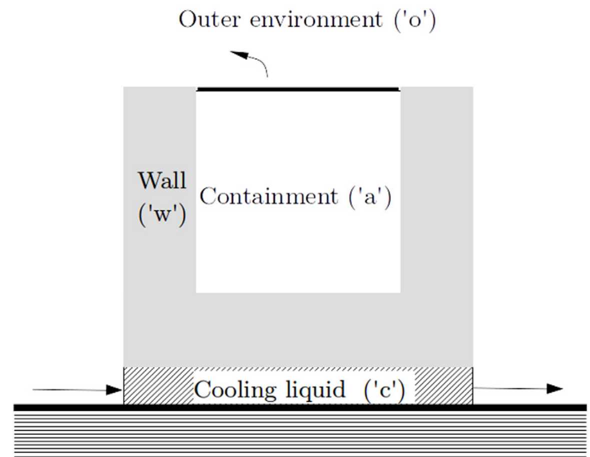

Fig. 1. The schematic picture of the freezer.

Table 1
Model variables and parameters.

Meaning	Symbol	Classification	Unit
Containment air temperature	T_a	State variable	°C
Wall temperature	T_w	State variable	°C
Binary switch status	S	Input variable	–
Outer air temperature	T_o	Parameter	°C
Cooling liquid temperature	T_c	Parameter	°C
Minimal inner air temperature	$T_{a,min}$	Parameter	°C
Maximal inner air temperature	$T_{a,max}$	Parameter	°C
Minimal wall temperature	$T_{w,min}$	Parameter	°C
Maximal wall temperature	$T_{w,max}$	Parameter	°C
Air-wall heat transfer coeff.	K_w	Parameter	$\frac{kW}{°C}$
Air-env. heat transfer coeff.	K_o	Parameter	$\frac{kW}{°C}$
Wall-env. heat transfer coeff.	K_x	Parameter	$\frac{kW}{°C}$
Wall-cool. liq. heat transfer coeff.	K_c	Parameter	$\frac{kW}{°C}$
Heat capacity of the containment	C_a	Parameter	$\frac{kJ}{°C}$
Heat capacity of wall	C_w	Parameter	$\frac{kJ}{°C}$

The containment is characterized by its air temperature T_a. It is heated by the outer environment through the door of the freezer, and cooled by the wall with temperature T_w. A liquid cooling system with liquid temperature T_c provides cooling when the cooling binary switch S is on, while there is no cooling of the wall when it is switched off ($S = 0$). The side wall is also heated by the outer environment.

The variables and parameters of the freezer model are collected in Table 1.

The engineering model. The simplest possible dynamic model that describes the dynamics of the above described freezer can be constructed from the energy balances for the containment air and that of the wall in the following form (see Hangos and Cameron (2001))

$$C_a \frac{dT_a}{dt} = K_w(T_w - T_a) + K_o(T_o - T_a) \tag{1}$$

$$C_w \frac{dT_w}{dt} = K_w(T_a - T_w) + K_x(T_o - T_w) + S \cdot K_c(T_c - T_w) \tag{2}$$

with the variables and parameters collected in Table 1.

The first terms in the right-hand side of the equations correspond to the heat transfer between the containment air and the wall, the second transfer terms correspond to the transfer between the outer environment and the containment air or the wall, respectively, and the last term in the second equation describes the effect of the cooling liquid. *The parameters of the model are assumed to be constant.*