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Model predictive control under forecast uncertainty for optimal operation of buildings with integrated solar systems

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ABSTRACT

In this paper, we explore intelligent operation strategies, based on stochastic model predictive control (SMPC), for optimal utilization of solar energy in buildings with integrated solar systems. Our approach takes into account the uncertainty in solar irradiance forecast over a prediction horizon, using a new probabilistic time series autoregressive model, calibrated on the sky-cover forecast from a weather service provider. In the optimal control formulation, we model the effect of solar irradiance as non-Gaussian stochastic disturbance affecting the cost and constraints, and the nonconvex cost function is an expectation over the stochastic process. To solve this complex optimization problem, we introduce a new approximate dynamic programming methodology that represents the optimal cost-to-go functions using Gaussian process regression, and achieves good solution quality. In the final step, we use an emulator that couples physical system models in TRNSYS with the SMPC controller developed using Python and MATLAB to evaluate the closed-loop operation of a building-integrated system with a solar-assisted heat pump coupled with radiant floor heating. For the system and climate under consideration, the SMPC saves up to 44% of the electricity consumption for heating in a winter month, compared to a baseline well-tuned rule-based controller, and it is robust, imposing less uncertainty on thermal comfort violation.

1. Introduction

Model predictive control (MPC) can provide superior building performance by solving an optimal control problem for a prediction horizon, using a process model to predict the future evolution of the system, while incorporating the most up-to-date information on weather forecast and system states (Mayne et al., 2000; Braun, 1990; Oldewurtel et al., 2012). Compared to data-driven control approaches using machine learning techniques, such as Q-learning (Liu and Henze, 2006; Yang et al., 2015), and artificial neural networks (Benedetti et al., 2016), MPC takes advantage of prior knowledge on the system physics, and thus, requires less training data (Afram and Janabi-Sharifi, 2014).

The challenge is to incorporate in the MPC controllers key features of the system while achieving efficient solutions. For example, in buildings with integrated solar technology coupled with HVAC and thermal energy storage, the system dynamics, the production of renewable energy, and the system capacity depend on stochastic disturbances such as solar irradiance. Also, the energy conversion during the operation of these complex systems is often expressed by nonconvex functions (Candanedo and Athienitis, 2011; Li et al., 2015; Quintana and Kummert, 2015). Optimal utilization of solar energy in buildings requires efficient system design (such as integration of solar-assisted heat pumps, thermal storage devices, etc.) and intelligent control strategies with algorithms that handle stochastic disturbances and provide solutions that approximate well the global minima of nonconvex optimization problems.

For solar systems, considering the uncertainty in solar irradiance forecast enables decisions with improved risk tolerance and system performance (Petersen and Bundgaard, 2014; Oldewurtel et al., 2012). Stochastic model predictive control (SMPC) is a promising approach as it directly accounts for the uncertainty in weather forecast, and enables the use of chance constraints representing conditions that are satisfied with a predefined probability (Charnes and Cooper, 1959; Oldewurtel et al., 2012; Zhang et al., 2013; Ma et al., 2015; Tanner, 2014). However, this approach requires updated disturbance forecast information for every prediction horizon (Henze et al., 2004; Candanedo and Athienitis, 2011; Tanner, 2014). Also, forecast models need to (i) incorporate the physical nature of the disturbances; (ii) take advantage of existing information such as recent measurements and external forecast; and (iii) entail a certain level of fast computation for implementation in actual controllers (Lazos et al., 2014).

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Nomenclature

sc	sky-cover, %
I_g	global horizontal irradiance, W/m^2
I_{dir}	direct horizontal irradiance, W/m^2
I_{dif}	diffuse horizontal irradiance, W/m^2
c	sky condition, 1. Clear; 2. Partly-cloudy; 3. Overcast
t	time step index
K	prediction horizon
M	number of collocation points
N	number of solar irradiance samples
d_x	dimension of system states vector
d_u	dimension of control inputs vector
$\mathbf{x}_t$	vector of system states at time t
$\mathbf{u}_t$	vector of control inputs at time t
$\mathbf{w}_t$	vector of stochastic disturbances at time t
$\mathbf{v}_t$	vector of exogenous inputs at time t
$\mathbf{A}$	state matrix
$\mathbf{B}$	input matrix
$\mathbf{f}$	system dynamics
g	constraint function
$\mathbf{a}$	vector of autoregressive process
$\mathscr{U}(\mathbf{x})$	set of admissible control inputs
$\mathbf{X}$	set of feasible state space
$\mathbf{z}_t$	Gaussian noise at time t
$\boldsymbol{\mu}_t$	vector of policy functions at time t
$C(\cdot)$	cost-to-go function
$\mathbb{E}[\cdot]$	expectation
J	objective function
T_{enve}	average envelope temperature of the room, °C
T_{room}	room air temperature, °C
T_{floor}	average floor slab temperature, °C
T_{tank}	average tank temperature, °C
T_a	outdoor dry bulb air temperature, °C
T_{bipvt}	outlet air temperature of the BIPV/T system, °C
T_{op}	operative temperature, °C
T_{set}	setpoint temperature, °C
T_{max}	upper bound of setpoint temperature, °C
T_{min}	lower bound of setpoint temperature, °C
MPC	model predictive control
SMPC	stochastic model predictive control
ADP	approximate dynamic programming
GPR	Gaussian process regression
LHS	Latin hypercube sampling
RBC	rule-based control
PB	performance bound
BIPV/T	building-integrated photovoltaic-thermal
COP	coefficient of performance
HC	heating capacity
HVAC	heating, ventilation and air-conditioning
PV	photovoltaic
RFH	radiant floor heating
TES	thermal energy storage
UTC	unglazed transpired solar collector

1.1. Solar-assisted heat pumps

Building-integrated solar technologies allow onsite collection of solar power and heat, which can be utilized by HVAC systems (Chen et al., 2010; Kim et al., 2014). Compared to conventional heat pumps, solar-assisted heat pump (SAHP) systems with thermal storage are able to utilize solar heat and achieve higher energy efficiency (Sun et al., 2015; Bucker and Riffat, 2016; Chu and Cruickshank, 2014). There are three major types of typical configurations of SAHP: (i) In parallel systems, solar thermal/photovoltaic collectors can be connected to thermal storage devices and provide hot water in parallel with conventional heat pumps (Freeman et al., 1979; Kaygusuz and Ayhan, 1999); (ii) In direct series systems, the collectors serve as the evaporators of heat pumps, allowing the refrigerant to directly absorb solar heat and facilitate the evaporation process (Chaturvedi et al., 2014; Ji et al., 2008; Chow et al., 2010); (iii) In indirect series systems, collected heat from solar thermal collectors is supplied to closed unit heat pump evaporators (Zhang et al., 2014; Bridgeman, 2010; Sterling and Collins, 2012; Candanedo and Athienitis, 2010). Due to the ease of maintenance/installation and high efficiency, indirect series systems are suitable for cold climate applications (Chu et al., 2014). Typically, the coefficient of performance (COP) and capacity of heat pumps can be modeled with multivariate polynomial functions of the source and load side temperatures (Verhelst et al., 2012; Gayeski et al., 2012). Thus, in the case of indirect series systems, the COP and capacity depend on the solar irradiance and thermal storage tank temperature. The multivariate polynomial COP model could lead to nonconvex cost function, while the dependency of the capacity on the stochastic solar irradiance can be expressed by chance constraints on the control inputs in the control problem formulation, imposing two major challenges in developing optimal control strategies.

1.2. Statistical forecast models

Statistical forecast models have been widely used in building energy management applications. Typical weather forecast models predict the future weather based on simple historical patterns such as using the same data as the previous day, typical days of a month, etc. (Henze et al., 2004). However, such models do not capture nonlinear patterns such as the effect of cloud cover on solar irradiance (Lazos et al., 2014). On the contrary, machine learning models trained with historical weather data, incorporate nonlinear patterns in weather variations and are better suited for predicting future weather (Dong and Lam, 2014; Lanza and Cosme, 2001).

Extracting information from past profiles works well for weather parameters with relatively small variation from one hour to the next, such as temperature and relative humidity. However, observable past patterns have limited influence on highly stochastic parameters such as solar irradiance (Mathiesen and Kleissl, 2011). In these cases, weather forecast services such as those from the National Oceanic and Atmospheric Administration (NOAA) that measure various meteorological parameters to generate predictions, can serve as baselines for predictive models (Pedersen and Petersen, 2017).

Previous studies developed weather forecast models that quantify the predictive uncertainty and take into account external weather forecast information or on-site measurements. Machine learning approaches such as Gaussian process regression (Zavala et al., 2009; Bilionis et al., 2014; Shann and Seuken, 2014), artificial neural networks (Chen et al., 2011; Yadav and Chandel, 2012) and support vector machines (Chakraborty et al., 2016) have shown promising results. However, implementation of such information in actual building controllers may require more straightforward approaches based on easily measurable and accessible data. Autoregressive models (Oldewurtel et al., 2012; Zhang et al., 2013) are computationally efficient and capture the physical nature of weather parameters (Lazos et al., 2015). In this paper, we extend the autoregressive process to model the cloud variability over time while using a probabilistic model to classify the sky condition as clear, partly-cloudy, and overcast based on the hourly-updated weather forecast.