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A differential discrete particle swarm optimization approach to model predictive control of building temperature

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Abstract- A differential discrete particle swarm optimization method, aimed at designing a predictive air temperature controller for civil buildings, is presented. The predictive control allows the controller outputs to be computed in order to optimise the future behaviour for a heating/cooling plant in a building, regarding set-point tracking and control effort minimization to save energy. The controller is able to predict the building environmental conditions over a specified time interval, thus mathematical models describing the indoor building climate, as well as predicting the outside weather, are used. In this paper, the proposed design method is compared with a standard particle swarm algorithm, and preliminary experimental results are discussed.

I. Introduction

In a building, managing effectively the heating/cooling plant means to achieve an optimal trade-off between energy saving and to guarantee the comfort to people living and working in the building. This goal can be achieved by keeping the room air temperature in a comfortable range by means of a heating/cooling plant. However, these artificial modifications are accomplished by spending additional energy through a regulator. The use of model predictive control (MPC) [4] for indoor environment control has the advantage of providing the system by the ability to react before any deviations in the controlled variable take place, by avoiding delays in the system response [5]. This approach leads to an effective management of all the variables in the system and, in turn, to energy saving, such as proved experimentally in previous works [6-7].

For these reasons, a Model Predictive Controller (MPC) for temperature regulation of a building, where people can change the desired temperature of the room in order to provide the best environmental conditions turns out to be useful. MPC is an on-line constrained optimization method [4], based on an iterative receding horizon control strategy. The aim of the control is to minimize energy consumption, while keeping the state variables as close as possible to the desired one.

However, the prerogative of this class of algorithms is to employ models able to predict several variables over a specified horizon. On this basis, an optimization problem is defined in order to find the best controls satisfying the model and the cost function. Model predictive control cost functions often define a very complex, non linear, non convex search space. Therefore, heuristic approaches turn out to be suitable, such as in [3], where in a real-time application, a Particle Swarm Optimization (PSO) [1] searches for optimal control inputs over a specified prediction horizon.

In this paper, for a temperature control task with a discrete search space for possible control assignments, a novel Differential Discrete Particle Swarm Optimization (DDPSO) for MPC is proposed. In particular, the proposed approach extends the work in [2], by re-designing the *particle section* (all possible solutions in the search space) in order to represent a sequence of discrete controls. In this way, the "velocity section" turns out to be related to the probability of achieving the suitable discrete control value. The proposed approach is validated and compared with a standard PSO on an experimental case study. The experimental tests are currently ongoing, but preliminary results show an interesting performance of the proposed approach.

II. The proposed method

In this Section, an overview of MPC control is explained first, then the proposed DDPSO and the related cost function are presented.

A. MPC control

The performance of MPC relies on two main modules: a *Forward* model, predicting the next state variables $\boldsymbol{x}$ of the process on the basis of the receding horizon, and an *Inverse* model, trying to optimize a sequence of future control values $\boldsymbol{u}$ where the system output is expected to track a given reference input $\boldsymbol{tg}$ (Fig. 1).

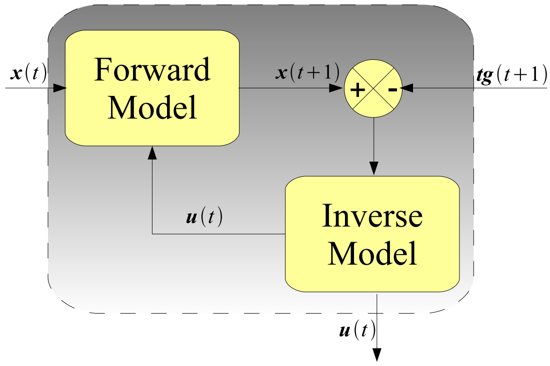

Figure 1. Model Predictive Control.

In the first phase, the *Forward* model is identified previously from process data in order to minimize prediction mismatches. The estimated model has to perform in real time, thus has to be as simple as possible and capable of describing the system dynamics in order to predict future outputs accurately. Therefore, main design effort is related to system modelling and identification. The aim of the forward model is to compute a prediction on the state variables, given controls and previous state values. Such a model can be formalized through the following equations:

$$\begin{array}{ccc} \mathbf{x}(t_1) & = & Forw(\mathbf{x}(t_1-1),..,\mathbf{x}(t_1-k),\mathbf{u}(t_1-1),...,\mathbf{u}(t_1-k)) \\ ... & ... & ... \\ \mathbf{x}(t_p=t_1+\Delta t) & = & Forw(\mathbf{x}(t_p-1),...,\mathbf{x}(t_p-k),\mathbf{u}(t_p-1),...,\mathbf{u}(t_p-k)) \end{array} \quad (1)$$

In the second phase, the control sequence is calculated by means of an *Inverse* model setting, in order to achieve the desired target vector $\boldsymbol{tg}$ with the best performance:

$$\{\mathbf{u}^{opt}(t_1),...,\mathbf{u}^{opt}(t_p)\} = Inv(\mathbf{x}(t_1),...,\mathbf{x}(t_p),\mathbf{tg}(t_1),...,\mathbf{tg}(t_p)) \quad (2)$$

This process should be fast and reliable simultaneously in order to have a control solution useful in real time, as well as to optimize a cost function E optimizing the energy consumption. Such as for cost functions defining non convex search on the space of possible solutions U, an evolutionary approach is used. In [3], for the inverse problem of an MPC system for temperature regulation, Particle Swarm Optimization is shown to be faster than standard Genetic Algorithms (GA) from one side, and to compute solutions better than Sequential Quadratic Programming (SQP). On this basis, the problem in (2) can be reformulated as

$$\{\mathbf{u}^{opt}(t_1),...,\mathbf{u}^{opt}(t_p)\} = \min_{\mathbf{u}=U} E(\mathbf{x}(t_1),...,\mathbf{x}(t_p),\mathbf{tg}(t_1),...,\mathbf{tg}(t_p)) \quad (3)$$

In case of a discrete number of controls, the Particle Swarm Optimization (PSO) approach is modified in order to a-priori discretize the space of the solutions U.

B. Differential Discrete Particle Swarm Optimization

In this Section, a PSO variant, the Differential Discrete Particle Swarm Optimization, able to search in the discrete parameter space is presented.

PSO is a population-based stochastic optimization technique [1] inspired by the social behaviour of bird flocking. The system is initialized with random solutions ("particles") with an assigned random "velocity" v_i, and then "flown" through the parameter space. Each *i-th* particle (i.e. a potential solution) "flies" within its search space, conditioned by values of its *personal best position pb* (i.e., the best position found by the particle so far, and having the highest scoring according to a fitness function), and the *global best position G* (i.e. the best position found by all other particles). As a result, each particle searches around a region defined by its personal and all its neighbours best positions.

In the temperature control task, the position space is the discrete space of possible control assignments, thus in the proposed approach, the particle section has to be redesigned suitably to represent a sequence of discrete controls. The "velocity section" (Fig 2) is related to the probability of having a suitable discrete control value. By extending the binary discrete PSO in [2], an unchanged equation for the "velocity section" update is proposed, though differences occur in the "position section" (Fig. 2). Given a population P and a set of discrete controls $U = \{u_1,\ldots,u_s\}$, the steps of the proposed DDPSO are shown in Fig. 2.

At step k

for each element i of P

pick a random $u^{proposed} \in U$

(a) compute "velocity section"

$$v_i^{proposed} = v_i(k) + c_i^1(pb_i - u_i^{proposed}) + c_i^2(G - u_i^{proposed})$$

$$v_i^{previous} = v_i(k) + c_i^1(pb_i - u_i(k)) + c_i^2(G - u_i(k))$$

(b) compute "position section" vector

$$ratio = v_i^{proposed} / v_i^{previous}$$

$$u_i(k+1) = \begin{cases} u_i^{previous} & \text{if } rnd < \sigma(ratio) \\ u_i^{proposed} & \text{otherwise} \end{cases}$$

Figure 2: the proposed DDPSO procedure. It mainly consists in two section: (a) "velocity section" and (b) "position section"

The process is tuned by the acceleration constants $c^1 = w_1 R_1$ and $c^2 = w_2 R_2$, where R_1 and R_2 are random variables in [0,1], and w_1 and w_2 represent the weighting of the stochastic acceleration terms pulling each particle towards *Global* and *personal* best solutions. The step involving the random *rnd* value represents the stochastic choice of the control driven by the "velocity section". The overall process optimization is guided by a cost function, minimizing the energy consumption of the control system.

C. The Cost Function

A general form of the cost function is generally given by two terms, one controlling the distance from the reference weighted by a parameter λ_1, and the other one trying to minimize the control effort in order to achieve the desired target, weighted by a second parameter λ_2:

$$E(\mathbf{u}) = \lambda_1 \sum_{i=1}^{s} (\mathbf{tg}(t_i) - \mathbf{x}(t_i))^2 + \lambda_2 \sum_{i=1}^{s} \Delta u(i) \tag{4}$$

Tuning both of these two terms drives the solutions to balance the accuracy of the desired target and, in this case, the energy consumption of our control architecture. The proposed cost function is redefined in order to achieve the controls, suitably satisfying the Room Temperature Control, able to perform the Energy consumption.

$$E(\mathbf{u}) = \lambda_1 \sum_{i=1}^{s} (\mathbf{tg}(t_i) - \mathbf{x}(t_i))^2 + \lambda_2 \sum_{i=1}^{s} \left|u(t_i)\right|^2 \tag{5}$$

III. Experimental results

A preliminary experimental case study of the proposed DDPSO approach for MPC control has been performed in a room of a building provided by the company Ballast srl, in Naples (Italy), under the framework of the EU-funded research project MONDIEVOB [9].

A. Experimental setup

The test room has a floor area of about 40 m^2. Its climate is controlled through several sensors. The outdoor temperature (T_{ext}) and indoor temperature (T_{in}) are measured by means of PT100 sensors, while the sun radiation (R_o) by a TSL 252R (Texas Instruments) sensor. The sensor signals are acquired by a National Instruments data acquisition board NI-USB 6211 and processed on a laptop PC by NI LabView 8.1 software. The environmental quantities were acquired for 7 consecutive days in the period between 20-27 October, 2009. The sampling period was 1 min for each quantity.

B. Model Identification

After the acquisition phase, data are processed, by means of Matlab Identification Toolbox® software (R2008a version) in order to find a multiple-input single-output (MISO) model of the room under test. The mathematical model best fitting the acquired data is the following Auto Regressive with eXogenous input (ARX) model:

$$T_{in}(k)=\frac{\begin{bmatrix}B_{Text} & B_{R_0} & B_u\end{bmatrix}}{1+1.285q^{-1}-0.005q^{-2}-0.005q^{-3}-0.187q^{-4}-0.020q^{-5}-0.029q^{-6}-0.004q^{-7}-0.045q^{-8}}\begin{bmatrix}T_{ext}\\ R_0\\ u\end{bmatrix} \quad (6)$$

where:

$$\begin{aligned}B_{Text} &= 0.001\,q^{-6}\\ B_{R_0} &= 0.002\,q^{-17}-0.015\,q^{-18}-0.109\,q^{-19}\\ B_u &= -0.094\,q^{-2}+0.096\,q^{-3}\end{aligned} \quad (7)$$

and u={0.1, 0.2, ..., 1} is the *control input* for the heating plant. T_{ext} and R_o are inputs and T_{in} is the output to be controlled.

MPC requires suitable models to predict the outside climate during the prediction horizon, thus the auto-regressive model proposed in [8] has been used to predict outside temperature and solar radiation for a time horizon of 60 minutes.

C. Preliminary results

The proposed DDPSO was compared with the standard PSO by carrying out 20 runs of both algorithms configured such as reported in Table 1.

DDPSO		PSO	
W_1	2	W_1	2
W_2	2	W_2	2
Number of particles	*24*	*Number of particles*	*24*

Table 1: Settings for the comparison tests between PSO and the proposed approach.

The cost function (5) has a prediction horizon of 60 minutes with λ_1 = 1 and λ_2 = 0.6.

Further performance indexes are taken in account in order to compare the two approaches,. In particular, the set-point accuracy is:

$$SP_e=\sum_{i=1}^{s}(\mathbf{tg}(t_i)-\mathbf{u}(t_i))^2 \quad (8)$$

and the energy consumption

$$E_v = \sum_{i=1}^{s} \left| u(t_i) \right|^2 \tag{9}$$

For each of the 20 runs, 500 iterations have been performed for both approaches.
In Tab. 2, the achieved results are shown, while in Fig. 3, the mean values of E in (5) over the 500 iterations for both the algorithms are reported.

	DDPSO	**PSO**
E (mean value)	12.93	336.90
SP_e (mean value)	0.73	26.92
E_v (mean value)	12,49	310.75
σ_E	0.35	19.37
σ_{EV}	0.41	15.68
σ_{SP_e}	0.36	11.67

Table 2: Experimental mean and standard deviation on 20 runs results for the proposed DDPSO and the standard PSO.

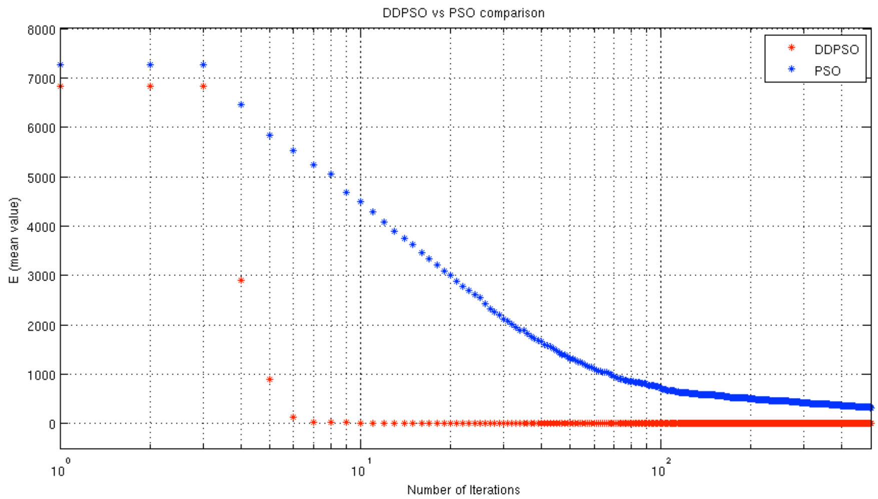

Figure 3: Comparison between the proposed DDPSO and a standard PSO.

The proposed approach achieves better solutions in a number of iterations less than the standard PSO. This result is particularly useful for MPC control in real-time applications, where a good solution has to be achieved in a bounded time.

Conclusions

In the present paper, a differential discrete particle swarm optimization method (DDPSO) is presented, aiming at designing a model predictive control for air temperature controller in a civil building. The proposed design method is compared with a standard particle swarm algorithm. Preliminary experimental results with encouraging performance of the proposed DDPSO compared with the standard PSO suggest future application to real-time purposes.

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