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An ant colony optimization-based fuzzy predictive control approach for nonlinear processes

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ABSTRACT

In this paper, a new approach for designing an adaptive fuzzy model predictive control (AFMPC) based on the ant colony optimization (ACO) is proposed. On-line adaptive fuzzy identification is introduced to identify the system parameters. These parameters are used to calculate the objective function based on a predictive approach and structure of RST control. Then the optimization problem is solved based on an ACO algorithm, used at the optimization process in AFMPC to determine optimal controller parameters of RST control. The utility of the proposed controller is demonstrated by applying it to two nonlinear processes, where the proposed approach provides better performances compared with proportional integral-ant colony optimization controller and adaptive fuzzy model predictive controller.

1. Introduction

Model predictive control (MPC) is a mature control technique with multiple applications in the process industry [3,8,13,20]. The philosophy of MPC control algorithm is based on the on-line use of an explicit process model, to predict the manipulated variables and thus the future control actions are optimized throughout a finite horizon. Many MPC approaches essentially assume that the plant can be described by a linear model, which is a deviation from real life situations where most industrial plants exhibit inherently non-linear dynamics. But many industrial processes have strong nonlinearities and predictive control is applied in order to provide satisfactory control results, many researchers have later focused their attention on developing a new family of MPC algorithms, called nonlinear model predictive control (NMPC) methodologies [8]. However, the fuzzy models of the Takagi–Sugeno (T–S) type proved to be suitable for nonlinear control [1,10,12,28,29,31,32], estimation [11,12] and particularly in nonlinear MPC [9,34], because of their ability to give an accurate approximation of the complex nonlinear systems. This can be done by combining the data with the prior knowledge [21,28,29]. The adaptive fuzzy logic systems (AFLS) is employed to determine the controller structure as well as the free parameters of the adaptive fuzzy logic systems [4,5,25,34]. However, the solution of the optimal predictive control requires the inverse of the prediction matrices at each sampling step, which is difficult to achieve in real time. And the second important problem in nonlinear predictive control is to solve the optimization problem. The conventional iterative optimization methods are very sensitive to the initialization of the algorithm and usually lead to unacceptable solutions due to the con-

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Nomenclature

n_a	degree of $A(z^{-1})$
n_b	degree of $B(z^{-1})$
N_1	minimum prediction time domain
N_2	maximum prediction time domain
N_u	control time domain
J	objective function
MCE	mean cost function
IAE	absolute value of error
τ_{ij}	concentration of pheromone
d_{ij}	desirability of edge (i,j)
γ	constant rate
α	preference weight of pheromone trail
β	preference weight of the first heuristic parameter
τ_0	initial concentration
$\delta\tau_{ij}$	increment of pheromone deposited
q_0	the selection parameter in ant colony transition rule
$\Omega_k(i)$	the set of nodes yet to be visited by ant k
q	process flow-rate (l/min)
v	reaction volume (l)
k_0	reaction rate constant (min^{-1})
E/R	activation energy (K)
T_0	feed temperature (K)
T_{c0}	inlet coolant temp (K)
ΔH	heat of reaction (cal/mol)
C_p, C_{pc}	specific heats (cal/g/K)
ρ, ρ_c	liquid densities (g/l)
h_a	heat transfer coefficient (cal/min/K)
C_{a0}	inlet feed concentration (mol/l)
$Q(t)$	feed rate
$i(t)$	supply current of the pump
$H(t)$	water level in the tank
$Q_s(t)$	output flow
a	section of the output channel
A	section of the tank
H_s	water level in the output channel
NOA	number of ants
$iter_{max}$	maximum number of ACO iteration
PST	plant simulation time

vergence to local optima [33]; hence, the intelligent evolutionary algorithms are more suitable for the optimization in AFMPC [14,23,27], such as genetic algorithm (GA), ant colony optimization (ACO), and particle swarm optimization (PSO) have attracted a lot of attention [9,15,30]. These methods are stochastic optimization techniques attempting to achieve better solutions by application of knowledge from previous iterations and are able to overcome complex non-linear optimization tasks like non-convex problems, and non-continuous objective functions.

Owing to the advantages of the ACO, this optimization method is considered in this paper. Indeed, it has been successfully applied to various real-world optimization problems such as online routing in telecommunication networks problem, multi-depot vehicle routing problem, railroad-blocking problem, and the mobile agent routing problem [36–38]. However, there are still some weaknesses of the ACO in practice [19], namely the search usually gets trapped in local optimal solution and it also requires a lot of computational time to obtain the optimal solution.

To avoid these weaknesses, this paper proposes an improved Ant colony optimization hybridized with an adaptive fuzzy model predictive approach, called ACO-Based AFMPC. The major advantage of using the ACO technique over other methods is to minimize the random effect in the choice of algorithm parameters. The solution of this optimization problem is utilized to determine optimal controller parameters. The proposed method applies, firstly; a technique for the modeling of nonlinear control processes by using fuzzy modeling approach based on the T–S fuzzy model. Each model, hence developed, can be called a rule-based fuzzy implication (FI), where the consequent part, the recursive least square (RLS) approach is used to identify the subsystems parameters, which allows us to calculate the predictive control. The second step can be done by transforming the control law to a RST polynomial form [6], which should be employed by the ACO optimization algorithm.