Particle Swarm Optimization Based NMPC: An Application to District Heating Networks

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Abstract. Predictive control is concerned with the on-line solution of successive optimization problems. As systems are more and more complex, one of the limiting points in the application of optimal receding horizon strategy is the tractability of these optimization problems. Stochastic optimization methods appear as good candidates to overcome some of the difficulties. Indeed, these methods are not dependent on the structure of costs and constraints (linear, convex...), can escape from local minima and do not require the computation of local informations (gradient, hessian). In this paper, a Particle Swarm Optimization (PSO) is proposed to solve the receding horizon principle with an application to district heating networks. Tests of the approach are given for a network benchmark, showing that more than satisfactory results are achieved, compared with classical control laws for such systems.

Keywords: Particle swarm optimization (PSO), NMPC, Energy savings.

1 Introduction

Receding horizon based methods are efficient tools to control industrial systems based on the introduction of on-line optimisation problems in the feedback loop. The systems to control being more and more complex, the corresponding optimization problems continuously challenge the limitation of classical deterministic methods such as Successive Quadratic Programming. These optimization problems can often be solved by stochastic optimization algorithms which are able to find good suboptimal solutions to hard
optimization problems. Of course, a severe attention has to be paid to the stability of the corresponding closed loop control law. In this way of thinking, ant colony was used in previous studies to compute a receding horizon control law for the case of constrained hybrid systems [1]. In this paper, the focus is on the use of another metaheuristic optimization method, Particle Swarm Optimization (PSO) to compute a closed loop law for the control of district heating networks.

In a competitive technological, economical and environmental context, Energy Savings has emerged as a crucial point. Due to the development of cogeneration systems or heat storage tanks, the use of district heating networks appears as an interesting way to achieve high global efficiencies of energy networks. However, the modeling of these systems are concerned with partial differential equations (for the computation of thermal energy propagation) and nonlinear algebraic and implicit equations (for the computation of mass flows and pressures in the whole system). Finally, costs and constraints of the corresponding continuous optimization problems can only be computed in a simulation environment. The problem could be solved by deterministic algorithms. As no analytic expressions are available, the computation of descent directions (gradient or subgradients) imply numerous evaluations of costs and constraints functions. Further, numerous local minima do exist, and near optimal initial points have to be known to get satisfactory results. Thus, this kind of system appears to be a good benchmark for the study of stochastic optimization algorithms for the computation of closed loop control laws.

The paper is organized as follows. PSO is firstly described in section 2. District heating networks are presented and modeled in section 3 together with the use of PSO for the receding horizon based control law. Finally, conclusions and forthcoming works are drawn in section 4.

2 Particle Swarm Optimization Based NMPC

2.1 Classical PSO Algorithm

Particle swarm Optimization (PSO) was firstly introduced by Russel and Eberhart [2]. This optimization method is inspired by the social behavior of bird flocking or fish schooling. Consider the following optimization problem:

$$\min_{x \in \chi} f(x)$$ (1)

$P$ particles are moving in the search space. Each of them has its own velocity, and is able to remember where it has found its best performance. Each particle has some "friends". The following notations are used:

- $x_p^k$ (resp. $v_p^k$): position (resp. velocity) of particle $p$ at iteration $k$;
- $b_p^k = \arg \min (f(x_{p-1}^k, b_{p-1}^k))$ : best position found by particle $p$ until iteration $k$;