# Predictive Control Design of Gas Turbine Using Multi-Objective Optimization Approach

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## Abstract

In this research, an intelligent multi-objective nonlinear model predictive control (NMPC) scheme is proposed for its application in the 'on-line' optimization of dynamical gas turbine model. The scheme proposed belongs to the sub-optimal NMPC strategies where near-optimal, instead of global optimal, control solutions are obtained at each control sampling time. The complexity of NMPC implementation for highly nonlinear and multi-objective control problems is very high due to its non-quadratic and non-convex multi-objective optimization nature. Therefore, this problem needs to be solved at each sampling time. For this purpose, the model predictive control strategy is utilized in this paper as an effective control design framework in order to realize the desired multi-objective optimization. Multi-objective particle swarm optimization (MOPSO) method is applied to optimize the nonlinear model predictive control (NMPC).

## Keywords
Gas turbine, predictive control, multi-objective optimization, particle swarm optimization

## 1. Introduction

Gas turbine has been extensively applied in different industries. Gas turbine provides mechanical power for transportation, power generation, and manufacturing plants. It is one of the most critical parts of world industry. It has been shown in the literature that the world average annual gas turbine market is approximately 20B Euros, in which, aviation industry, electric production, power drives, and marine gas turbines accounts for 68%, 27%, 3%, and 2%, respectively (Langston, 2005).

As it is presented in Figure 1, a turbine in a gas turbine expands pressurized gas, and basically convers pressure ratio to rotational speed. Afterwards, the shaft power is obtained and drives a compressor, which in its turn provides the pressure ratio needed for the turbine. If the installations are without losses of any kind, the turbine will be able to drive itself, but of course no more than that. In practice, the losses have to be overcome, which is the main reason that energy has to be added one way or another. This is accomplished by the incorporation of a combustion chamber, which heats the pressurized gas coming out of the compressor before it enters the turbine.

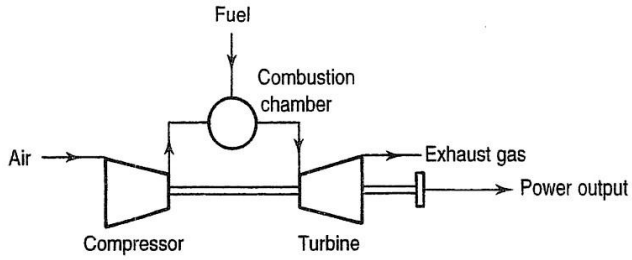


Figure1. The simple gas turbine cycle diagram

If more energy is added than what is necessary to overcome losses, the gas turbine can drive some external load, e.g., a generator. In the system under our consideration, this external load is assumed to be impossible. Instead, the installation we investigate, which is a scale model of a gas turbine, primarily serves as a test-stand for research into dynamic behavior of compressors and turbines and their interaction-not as a power plant.

This laboratory installation uses air for working fluid and natural gas for fuel. Next to surge and choke, gas turbine operation is limited by the turbine inlet temperature not being allowed to exceed a certain maximum, beyond which the stress exerted on the turbine rotor-blades becomes undesirably high. Apart from these output constraints, limits on actuator operation form input constraints. For instance, valves cannot open beyond fully opened or, apparently, close beyond fully closed.

As a complicated system, development and testing of gas turbine engines requires time and cost. After development phases, implementing control systems and health monitoring systems to maintain a safe operation for gas turbine engines requires additional cost which challenges industries to optimize.

The Greitzer compression system model (Greitzer, 1976) is a non-linear model which describes surge in axial compression systems. This model has been extensively used in the literature and most of the practical cases to surge the control design. Hansen et al. (1981) showed that it is also applicable to centrifugal compressors. The model of Greitzer and Moore (1986) dominates the recent study on rotating stall and surge control, since it is a low order non-linear model which can describe the development of both rotating stall and surge and the coupling between these instabilities.

Gu et al. (1999) provided a comprehensive literature review on major developments in the field of modeling and control of the rotating stall and surge for axial flow compressors. According to this survey, rotating stall and surge control are effective in low speed compressor machines. However, rotating stall and surge control in high-speed compressors are has been investigated in the literature with reasonable and significant successes.

In the survey on rotating stall and surge by Jager (1995), it has been also concluded that control of rotating stall for high speed axial machines is ineffective and not used in research laboratories and has no practical value. The active control of surge, also for high speed machines, has been proven as an effective technology and seems to be an approach that can be applied profitably in industrial practice (Jager, 1995).

According to the overview of Findeisen et al. (2002), model predictive control for linear constrained systems has been successfully applied as a useful control solution for many practical applications. It is expected that the use of non-linear models in the predictive control framework, which leads to a non-linear model predictive control, results in improvement in the control performance. These initial approaches cannot provide satisfactory results when applied to plants with complex dynamics, which are either highly nonlinear or are not fully understood (Karray et al., 2002). Therefore, in order to consider the nonlinearities of the plants, the nonlinear adaptive control and the nonlinear model predictive control (NMPC) schemes have been considered and widely developed since the 1990s (Feng and Lozano, 1999; Qin and Lozano, 1998).

In the multi-objective NMPC, a highly complex nonlinear and multi-objective optimization problem has to be solved at each controller sampling time in order to calculate the best control actions for the plant. It is very difficult to calculate the global optimum for this kind of problem analytically and, if possible, it would be computationally intractable. On the other hand, the interest and application of some intelligent computational techniques such as Neural Networks (Haykin, 2008), Genetic Algorithms (Goldberg, 2001) and Fuzzy Inference Systems (Klir & Yuan, 1995) (all intrinsically nonlinear), is growing in the field of process control. Coelho et al. (2010) with the help of these stochastic and heuristic computational techniques could approach the multi-objective NMPC problem obtaining near-global optimum control solutions. However, some computational restrictions related to their cost and their memory use should be taken into account.

There are several operational constraints, i.e., some undesirable effects, involved in gas turbine generation. The compressor is considered as one of the most critical part of the gas turbine and its performance represents the

characteristics of the gas turbine. In most of the practical applications of gas turbine, there are several objectives to be investigated. For example, surge avoidance can be considered as one of the main objectives. In addition to the surge avoidance, maintaining constant shaft rotational speed can be considered as other important objective to prevent shaft fatigue. Utilizing multi-objective optimization provides a candidate scheme in which solution can satisfy the gas turbine major requirements.
In our previous research (Salahshoor and Jafarian, 2013), we used multi-objective particle swarm optimization (MOPSO) to find the perfect operating points of regenerative intercooled gas turbine cycle. In this research, we apply the multi-objective optimization approach to find the optimal values for the manipulated variables including gas turbine system valves at each sample time during its operation. We investigate two scenarios, 1) set point tracking and 2) noise disturbance rejection. The application of MOPSO in the mentioned scenarios is evaluated.

## 2. Gas turbine modeling

### 2.1. The compressor model

First, a model of the compressor and plenum is created. This model is similar to the Greitzer model proposed in 1976. The Greitzer model is a lumped parameter model and the compressor itself is modeled as an actuator disc. Figure 2 depicts this setup.

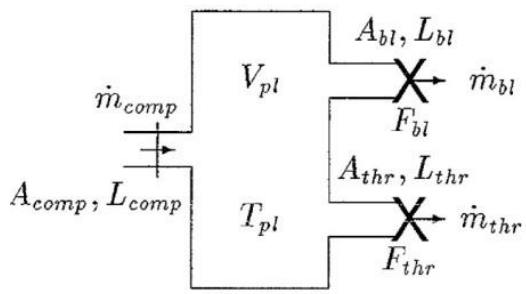


Figure 2. The basic compressor model

### 2.2. Extensions to the basic compressor model

When rotating stall is investigated, a quasi-steady approximation of the compressor response will not be adequate, since there is a definite time lag between the onset of the instability and the establishment of the fully developed rotating stall pattern. In this case, a simple first order transient response is adopted to simulate this time lag in compressor response. This can be presented in dimensionless form as following equations:

$$\tau \frac{dC}{dt} = C_{ss} - C \tag{1}$$

$$\tau = \frac{\Pi R N}{L_{comp} B} \tag{2}$$

It should be noted that for a given compressor $R$, $N$, and $L_{comp}$ are constant and $\tilde{\tau}$ is proportional to $1/B$. Furthermore, the model can be augmented with differential equations for rotational speed $N$ and plenum temperature $T_{pl}$. Especially, the first extension seems very useful since our aim is to model a gas turbine, which is hardly characterized by a constant rotational speed. Only the use of a constant speed (electrical) motor will result in such a behavior. Including rotational speed yields the following (dimension-full) equations:

$$IN \frac{dN}{dt} = P_{in} - W_p \tag{3}$$

where $I$ is inertia, Pin the in-going power, and $Wp$ is the power requested by the compressor. To model the turbine, its characteristic are used which are presented as follow:

$$T_{cc} = \frac{C_{pcomp}}{C_{pT}} T_{pl} + \frac{Power}{\dot{m}_{thr} C_{pT}} \tag{4}$$

$$T_{tbin} = T_{cc} \tag{5}$$

$$p_{tbin} = p_{pl} - \Delta p \tag{6}$$

$$\frac{d\dot{m}_{tb}}{dt} = \frac{A_{thr}}{L_{thr}} [p_{tbin} - P_{sstb}] \tag{7}$$

$$\dot{m}_{tb} = f_{turbine}(p_{tbin}, p_{tbout}, T_{tbin}) \tag{8}$$

where $Psstb$ is the steady state turbine inlet pressure needed for a certain turbine mass-flow, and fturbine the inverse of $Psstb$. Our proposed model for the complete gas turbine installation is provided as follows. We have chosen to use static equations for all mass-flows. Furthermore, yet another plenum-this time between compressor and buffer tank-is added, to reflect the fact that in reality the blow-off is positioned near the compressor and not at the buffer tank. Apart from this, it enables an overall pressure drop to be modeled apart from the throttle valve pressure drop. This setup is depicted in Figure 3.

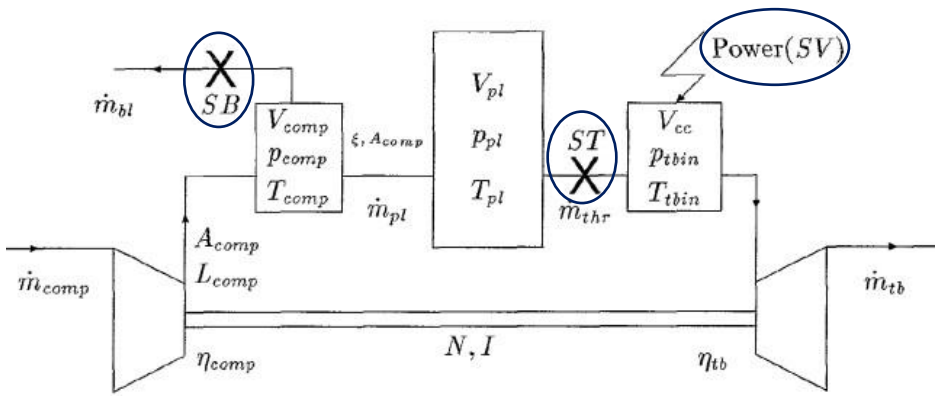


Figure 3. The final gas turbine model setup

## 3. Multi-objective nonlinear model predictive control (NMPC)

Model predictive control (MPC) algorithms are control algorithms based on solving an online optimization problem. The optimization algorithm minimizes some objective function which reflects the desired control performance subject to the model of the system and possibly constraints on inputs, states, and outputs. The solution of the optimization problem is a set of controls into the future which will be optimal with respect to the specified objective functions, as well as the constraints on the prediction horizon. Suppose the nonlinear model of the system is according to the following form:

$$\mathrm{x}_{\mathrm{k}+1} = \mathrm{f}(\mathrm{x}_{\mathrm{k}}, \mathrm{u}_{\mathrm{k}}) \tag{9}$$

$$z_k = g(x_k, u_k) \tag{10}$$

$$x_0 = x(t_0) \tag{11}$$

where $x_k \in R^{Nx}$, $u_k \in R^{Nu}$, $z_k \in R^{Nz}$. $x_k$ is defined as the state vector; $u_k$ is the controlled inputs, including: 1) the blow-off valve (SB in Figure 3), 2) the throttle valve (ST in Figure 3), and 3) the fuel valve (SV in Figure 3)); and $z_k$ is the controlled outputs. There are also constraints on the inputs and outputs given by some upper and lower bounds, defined as: $u_{min}$, $u_{max}$, $z_{min}$, $z_{max}$. It is also the objective function $J$, consists of energy, which we want to optimize. It is also possible to specify input and output constraints by more complicated functions, but for the sake of simplicity, we stick to simple box constraints. The objective function $J$ along with these bounds specifies the desired control performance. The most commonly used objective function for the model predictive control is the following quadratic function (Vroemen, 2002):

$$J = \frac{1}{2}\sum_{k=0}^{N-1}[z_k^T Q z_k + u_K^T R u_k] + \frac{1}{2}x_k^T P x_k \tag{12}$$

where: $Q = Q^T \geq 0$; $R = R^T \geq 0$; and $P = P^T \geq 0$.
The NMPC optimization problem that must be solved at each sampling instant can be formulated as:

$$\min J$$

Subject to:

$$\begin{gathered} x_{k+1} = f(x_k\,, u_k) \\ x_0 = x(t_0) \\ u_{min} \leq u_k \leq u_{max} \\ z_{min} \leq z_k \leq uz_{max} \end{gathered} \tag{13}$$

### 3.1. Multi-objective Optimization

For optimization, where only one objective is optimized, global optima are defined as the best candidate solutions that lead to the optimal value of the objective function (Hassani and Jafarian, 2016). However, when dealing with multi objective optimization problms (MOOPs), various objectives are normally in conflict with one another, i.e., improvement in one objective leads to a worse solution for at least one other objective. These solutions are referred to as non-dominated solutions and the set of such solutions is called the non-dominated set or Pareto-optimal set (POS) (Li et al., 2016; Mobin et al., 2015).
The corresponding objective vectors in the objective space that lead to the non-dominated solutions is referred to as the POF or Pareto-front (Figure 4).

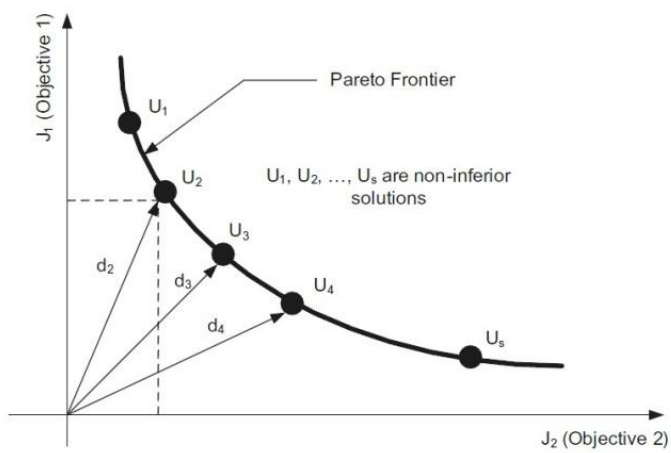


Figure 4. Example of a Pareto Optimal set

### 3.2. Multi-objective Particle Swarm Optimization (MOPSO)

The MOPSO algorithm was introduced by Coello and Lechuga (2002) as one of the first PSO algorithms extended for multi-objective optimization. Before the MOPSO algorithm can be implemented, the swarm is initialized. Then the particles' velocities are calculated. In addition to the PSO initialization, the particles are evaluated and the positions of the particles that are non-dominated are stored in the archive. Furthermore, the search space that has been explored so far is divided into hypercubes and all particles are placed in a hypercube based on the particle's position in the objective space.
A detailed description of MOPSO is provided by Tavana et al. (2016). The steps of the MOPSO are listed in Table 1 (Salahshoor and Jafarian, 2013).

Table 1. MOPSO algorithm

```
Create and initialize a swarm
    While stopping condition has not been reached
        For each particle in the swarm, do:
            Calculate new velocity
            Calculate new position
            Manage boundary constraint violations
        Update archive
        Update the particle's allocation to hypercubes
        For each particle in the swarm, do:
        Update pbest
```

## 4. Simulations and results

We start with specifying inputs and outputs for the gas turbine installation. Inputs include: 1) the blow-off valve (SB), 2) the throttle valve (ST), and 3) the fuel valve (SV). Considering more inputs is unnecessary for our control purposes, since we do not seek to control start-up and shut-down of the gas turbine. These procedures should still be carried out by hand. Any inputs less than this is hardly preferable, which we will explain by describing the valves' functions. As it is mentioned, the most important reason for choosing MPC as a control strategy is the possibility of explicitly incorporating constraints on inputs and outputs in the optimization algorithm.
First of all, valves should be constrained not to operate beyond fully opened and fully closed (saturations). This can be easily realized in MPC, whereas other control strategies which do not offer a solution as straightforward as this. It should be noted that the maximum moving rates should be specified, since real-life actuators cannot simply move with arbitrarily high speed. In MPC, this is realized by specifying the maximum move size per the sample period. For instance, the throttle valve ST requires 120 second to move from fully-open to fully-close. Actuators speed constraints are shown in Table 2.

Table 2. Decision variables constraints

| Decision variables | Constraints | Conditions |
|---|---|---|
| The blow-off valve (SB) | Low constraint | 0.0 (fully closed) |
| | High constraint | 1.0 (fully open) |
| | Change rate | 1/72 (unit per second) |
| The throttle valve (ST) | Low constraint | 0.01 (almost closed) |
| | High constraint | 1.0 (fully open) |
| | Change rate | 1/120 (unit per second) |
| The fuel valve (SV) | Low constraint | 0.01 (almost closed) |
| | High constraint | 1.0 (fully open) |
| | Change rate | 1/48 (unit per second) |

Furthermore, some outputs may not exceed certain (physical) limits. In our case, the turbine inlet temperature is not allowed to (continuously) exceed the bound of 950ºC. Beyond this temperature, the stress exerted on the turbine blades becomes unacceptably large.
The second output constraint stems from the need to avoid surge. For this purpose we defined a dummy output, called $DEVSurge$, which measures the distance from the surge-line (in terms of mass-flow). Keeping this distance greater than zero then is the same as staying out of the zone left of the surge-line, which is exactly what we want. In principle, such a dummy variable could also be used to detect the choke. In practice, choke is not really a problem, not being an instability behavior like surge.
As we mentioned before, the MPC sampling period cannot be chosen arbitrarily large, since it is also used as discretization sample time. This is the reason we chose the first two sampling intervals to be equal to 0.1s. From MATLAB simulations, it was concluded that such a sample time still allowed for reasonably accurate modeling, while it caused no considerable computing-time related problems.
The prediction horizon p was determined as a compromise between minimizing computational efforts and predicting slow system dynamics properly. We decided to choose $p = 11$, in order to reduce execution time. The turbine inlet

temperature does respond inversely to changes in $SV$, but we only seek to keep this output beneath its maximum. Next, we chose the control horizon $m = 5$, in accordance with the recommendation to choose it somewhere between 1/6 and 1/3 of the prediction horizon.

Multi-objective NMPC is used for controlling both shaft speed and gas turbine total efficiency. In other words, we deal with a multi-objective type of control problem. The objective/cost function was defined as a summation of absolute difference between set points and operating points for each control variables in time steps. A multi-objective optimization method, named multi-objective particle swarm optimization (MOPSO), is utilized for this purpose. Results are shown in Figure 5 for both clear and noisy (disturbed) measured outputs.

(a)

(b)

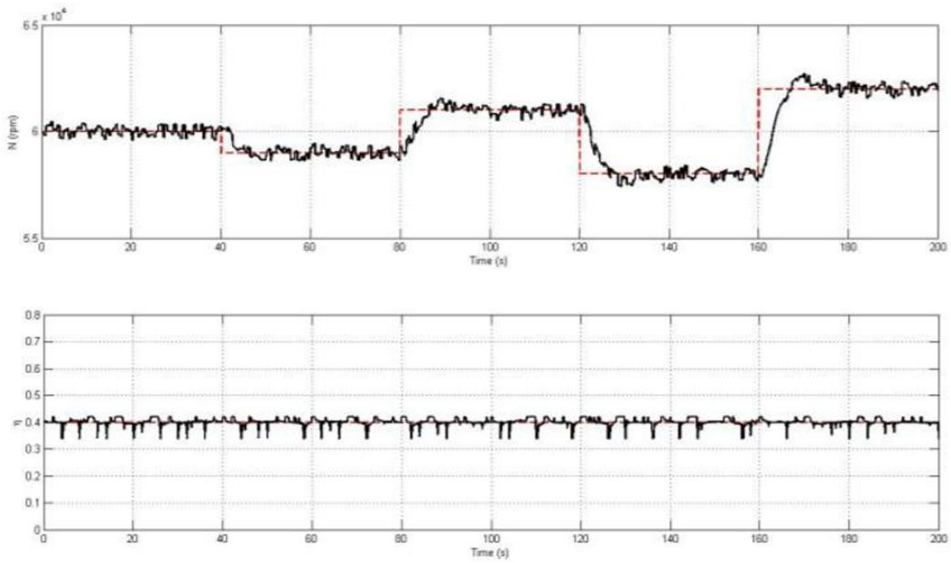


Figure 5. Ideal and actual (a) shaft rotational speed and (b) total efficiency

Set point tracking control ability is performed in previous simulations. In the following, disturbance rejection ability is checked for the predictive control system based on MOO. For this purpose, noise disturbance is investigated. Disturbance checked here are occurred in measurement system. Results are shown in Figure 6. As it is shown in Figure 6, there are no types of instability or creation of large errors in the system.

(a)

(b)

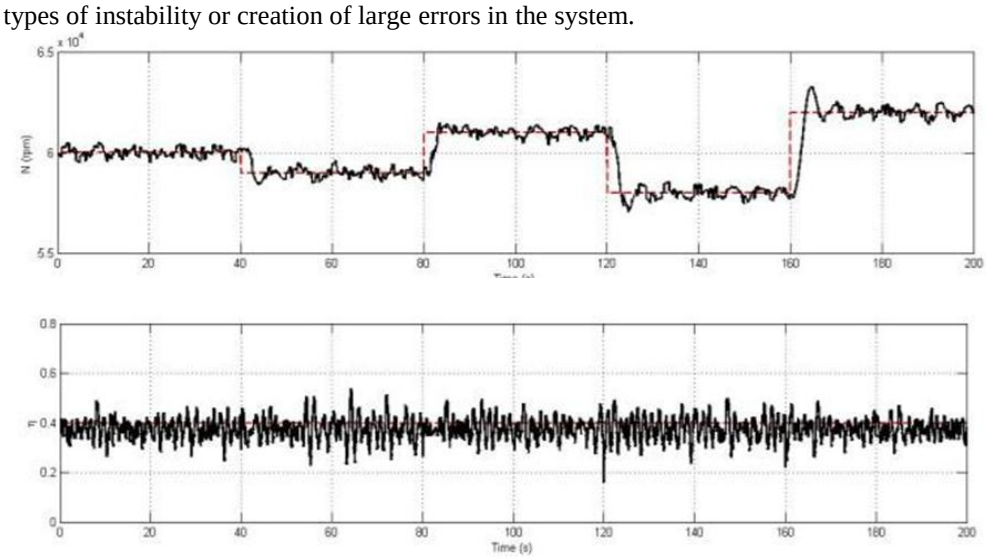


Figure 6. MOPSO method outputs ((a) shaft rotational speed and (b) total efficiency) after applying noise disturbance, combination of disturbance rejection and reference tracking

## 4. Conclusion

In this study, we used a novel technique for design predictive control called intelligent multi-objective nonlinear model predictive control (IMO-NMPC) method. In fact, we used the combination of intelligent computational techniques such as multi-objective particle swarm optimization in the NMPC implementation and application over a complex control problem, such as industrial gas turbine system. In this method, all the specified control objectives and system constraints must be addressed simultaneously.

In this paper, the multi-objective particle swarm optimization approach is utilized in multi-objective nonlinear model predictive control (MO-NMPC) structure to obtain best control manipulators values in each step time. We evaluated the designed controller in two different scenarios. In the first case, we checked the suitability of controller in reference tracking state. We changed the rotational speed of the gas turbine main shaft and the controller function was to track desired rotational speed with minimum acceptable changes in total efficiency. As shown in the first scenario's results, both concerns were addressed in a prominent manner. In the next scenario, transducers' noise was added to the systems to get closer to real condition. Although the reference tracking error was increased in this situation, the system operation is appropriate in both disturbance rejection and reference tracking at the same time.

The evaluation of this method indicated that using multi-objective optimization schemes, such as MOPSO in NMPC structure improve its performance significantly.

By applying some extensions into multi-objective optimization algorithm, and in order to modify them as a dynamical model, its responses became more appropriate. As other suggestions for future research, we can use dynamic multi objective PSO algorithm called DVEPSO in our next studies to develop mentioned results. In addition, other multi-objective optimization methods, such as: NSGA-II (Li et al., 2016; Mobin et al., 2015), NSGA-III (Tavana et al., 2016), the artificial bee colony algorithm (Vadarnikjoo et al., 2015), the imperialist competitive algorithm (Borghei et al., 2015), and the general variable neighborhood search algorithm (Komaki et al., 2015) can be applied in the MO-NMPC problem; and the performance of different algorithms can be compared (Alaei et al., 2016; Fazelzarandi and Kayvanfar, 2015; Kayvanfar et al., 2011).

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