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A two-level measurement-based dynamic optimization strategy for a bioreactor in penicillin fermentation process ☆

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ABSTRACT

One measurement-based dynamic optimization scheme can achieve optimality under uncertainties by tracking the necessary condition of optimality (NCO-tracking), with a basic assumption that the solution model remains invariant in the presence of all kinds of uncertainties. This assumption is not satisfied in some cases and the standard NCO-tracking scheme is infeasible. In this paper, a novel two-level NCO-tracking scheme is proposed to deal with this problem. A heuristic criterion is given for triggering outer level compensation procedure to update the solution model once any change is detected *via* online measurement and estimation. The standard NCO-tracking process is carried out at the inner level based on the updated solution model. The proposed approach is illustrated *via* a bioreactor in penicillin fermentation process.

1. Introduction

The optimization of dynamic processes has received growing attentions for years because of the demands in reducing production cost, improving product quality and satisfying safety requirements [1–4]. Some new techniques are proposed for solving dynamic optimization problems. A hybrid improved genetic algorithm (HIGA) is proposed to deal with the problem of convergence in dynamic optimization [5]. An approach that combined differential evolution (DE) algorithm and control vector parameterization (CVP) is proposed to improve the computing efficiency [6]. However, due to the uncertainties from model mismatch and process disturbances, the optimal solutions based on nominal models are usually infeasible in practical applications [7,8]. Hence, open-loop optimization is insufficient under uncertainties.

With the rapid development in measurement technology, two measurement-based optimization methods show great potential. As shown in Fig. 1(a), the measurements are used to update the process model, and the numerical optimization procedure is implemented based on the updated model. The model refinement and optimization are carried out at each sampling instant, referred to as repeated optimization method [9–11]. In Fig. 1(b), measurements are used to adjust the optimal inputs directly by tracking the necessary conditions of optimality (NCO) in a closed-loop control scheme based on a special solution model, referred to as the NCO-tracking method [7]. Without any explicit model updating or online re-optimization, its computation burden is much less than that with the repeated optimization method.

The NCO-tracking method has received lots of attentions because neither the knowledge about possible uncertainties nor the explicit model updating is needed for its online implement [12]. Bonvin *et al.* used it to implement optimal grade transition for polyethylene reactors [12]. Zhang *et al.* also introduced NCO-tracking into optimal grade transition in polymerization processes under uncertainty and proposed a new method to extract the solution model [13]. Srinivasan *et al.* proposed to change set of active constraints using a barrier-penalty function, so the assumption regarding the active set is not required in NCO-tracking [14]. Bonvin and Srinivasan addressed the role of NCO in structuring dynamic real-time optimization schemes [15]. By using NCO-tracking in the optimization layer and self-optimizing control (SOC) in the lower control layer, Jäschke and Skogestad demonstrated that the two methods complement each other, with SOC giving fast optimal correction for expected disturbances and the model free NCO-tracking procedure compensating other disturbances on a slower time scale [16].

In many investigations, the structure of solution model is assumed to be invariant under all kinds of process uncertainties in

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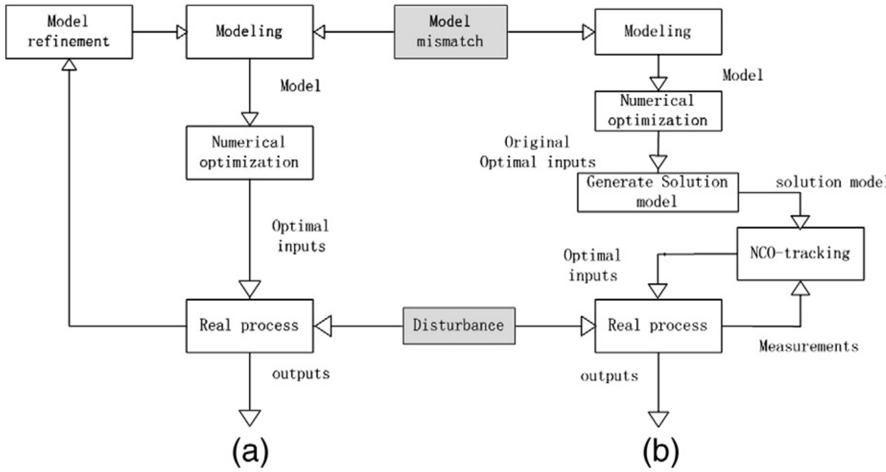

Fig. 1. Two schemes of measurement-based dynamic optimization.

the NCO-tracking scheme [7]. This assumption is considered to be satisfied in most cases for the following two reasons. First, the impact from parameter mismatch and process disturbances is limited, *e.g.*, a parameter may deviate from its nominal value but the deviation is limited [17]. Second, basic understanding of the process, such as mechanism, dynamic characteristics as well as typical uncertainties, is usually provided, so the solution model obtained by numerical optimization can reflect the basic structure of the optimal input profiles for various uncertainties.

However, it is almost impossible to analyze the effects of all kinds of uncertainties because of the high complexity in modern industrial processes. Therefore, the rationality of the assumption cannot be guaranteed. One research about the optimal grade transition in polymerization processes [18] showed that inactive path constraint in the solution model could become active under disturbances. That is, the structure of solution model is changed.

With a possible change of the solution model, a supervisory system must be provided to monitor the change and compensate it timely, otherwise the control scheme based on an inappropriate solution model will not meet the necessary conditions of optimality. A special NCO-tracking approach has been proposed by Kadam *et al.* [18] to handle this problem, in which several kinds of possible changes in the solution model, *e.g.*, activation of nominally inactive path constraint, are found by offline analysis. An overriding control scheme is used to adjust the control strategy in real time if any of these changes occurs online. The main drawback of this approach lies in the difficulty to construct a candidate set of possible solution model change since it requires human experience and physical insight into the dynamic process, which is analytically expensive and often impossible to obtain.

In this paper, a two-level strategy for NCO-tracking scheme is proposed, in which the assumption on invariant solution model is not required. The scheme consists of an outer level and an inner level. The outer level is used to update the solution model when it changes under the uncertainties and the inner one is used to implement NCO-tracking based on the current solution model. A trigger unit is embedded into this two-level strategy to decide whether the solution model should be updated. With monitoring function in the trigger unit and compensation procedure in the outer level, the new NCO-tracking scheme can be normally implemented even if the solution model changes. Introducing the basic ideas of the repeated optimization, the two-level NCO-tracking scheme is proposed. The scheme is illustrated *via* a bioreactor in penicillin fermentation production.

2. Dynamic Optimization and NCO-tracking

Consider the following terminal-cost dynamic optimization problem:

$$\min_{\boldsymbol{u}(t),t_\mathrm{f}} \phi(\boldsymbol{x}(t_\mathrm{f})) \tag{P1}$$

$$\text{st.}\quad \dot{\boldsymbol{x}}(t) = f(\boldsymbol{x}(t),\boldsymbol{u}(t),t),\quad \boldsymbol{x}(t_0)=\boldsymbol{x}_0 \tag{1}$$

$$h(\boldsymbol{x}(t),\boldsymbol{u}(t)) \le 0 \tag{2}$$

$$e(\boldsymbol{x}(t_\mathrm{f})) \le 0 \tag{3}$$

$$t \in [t_0, t_\mathrm{f}] \tag{4}$$

where $\phi(\cdot)$ denotes the terminal-cost objective function, $\boldsymbol{x} \in \mathbb{R}^{n_x}$ denotes the vector of state variables (states) with initial condition $\boldsymbol{x}_0$, $\boldsymbol{u} \in \mathbb{R}^{n_u}$ denotes the vector of control variables (inputs), $h(\boldsymbol{x}(t), \boldsymbol{u}(t))$ is the mixed state-input path constraints, $e(\boldsymbol{x}(t_\mathrm{f}))$ is the terminal constraints, ξ_1, ξ_2 and σ are the dimensions of these constraint vectors, with $\xi_1+\xi_2=\xi$, and t_0 and t_f are the initial time and final time.

Using Pontryagin's minimum principle, problem (P1) can be reformulated as minimizing the Hamiltonian function in the following form

$$\min_{\boldsymbol{u}(t),t_\mathrm{f}} H(t) = \boldsymbol{\lambda}^\mathrm{T} f(\boldsymbol{x},\boldsymbol{u},t) + \boldsymbol{\mu}^\mathrm{T} h(\boldsymbol{x},\boldsymbol{u},t) \tag{P2}$$

$$\text{st.}\quad \dot{\boldsymbol{x}}(t) = f(\boldsymbol{x}(t),\boldsymbol{u}(t),t),\quad \boldsymbol{x}(t_0)=\boldsymbol{x}_0 \tag{5}$$

$$\dot{\boldsymbol{\lambda}}^\mathrm{T} = -\frac{\partial H}{\partial \boldsymbol{x}},\quad \boldsymbol{\lambda}^\mathrm{T}(t_\mathrm{f}) = \left.\frac{\partial \overline{\phi}}{\partial \boldsymbol{x}}\right|_{t_\mathrm{f}} \tag{6}$$

$$\boldsymbol{\mu}^\mathrm{T} h = 0, \boldsymbol{\nu}^\mathrm{T} e = 0 \tag{7}$$