ABSTRACT

Development of control relevant models with excellent predictive capability is a challenging task for a batch process due to the non-linear dynamics and varying operating conditions within the batch and batch-to-batch. First principles-based models do not provide a remedy to this problem in most cases as they are tedious to develop and strenuous to solve for complex processes. Incidentally, industrial processes are warehouses of a large amount of multivariate data. Hence, data-driven modelling approaches can be conveniently used in this juncture. Traditional approaches of the data-based modeling methods focus on global approaches, however, developing a single global model for the entire batch process may not be a reasonable option because operating conditions change dynamically in industrial processes and may warrant updating the model online. The first part of the thesis focuses on the development of a novel data-driven dynamic model based on the local modeling approach i.e., Just-in-Time Learning (JITL) framework for batch process modeling. The accuracy of the underlying model under the JITL framework is based on the 'similarity measure' used to extract the relevant data from the massive historical database similar to the query point, and the 'weighting strategies' adopted. The proposed formulation incorporates a 'query profile' instead of a 'query point', with a view to bring in the dynamic modeling capabilities. A new 'searching strategy' based on 'profile similarity' is proposed for taking into account the time-varying dynamics of the batch processes. Further, a new 'weighting strategy' is introduced to ensure that the complete dynamics of the batch processes are captured and also to accommodate the outliers in the historical database.

The second part of this thesis focuses on the data-driven control of batch processes.

Control of batch processes is difficult due to their complex nonlinear dynamics and unsteady-state operating conditions within batch and batch-to-batch. Advanced control strategies like Model Predictive Control (MPC) used in the process industries for batch process control employs mathematical programming to solve a constrained, possibly non-convex, optimisation problem. The key issue here is that the online computational burden at each time step to obtain the optimal control input profile is very high. This limits the implementation of these approaches for complex nonlinear, high-dimensional dynamical systems, despite the advancement in computational hardware and numerical methods. Further, the performance of a model-based controller is highly dependent on the availability of an accurate process model. For a complex and nonlinear process, the availability of such a model is a limitation as it requires significant prior knowledge and expertise. Plant-model mismatch occurs even if there is a slight variation in the real process and its approximate model, leading to inaccurate predictions of the performance variable, such as product yield. Even if the process model is available, the controller performance deteriorates in the presence of uncertainties and process drifts. Batch-to-batch variations that occur due to raw material fluctuations, cleaning, etc., are a source of uncertainty that further deteriorate the closed-loop performance. In this juncture, the development of a control strategy that does not entirely rely on the knowledge of the accurate dynamics of the system and can handle the stochastic dynamics and plant-model mismatches is extremely useful. Model-free Reinforcement Learning (RL), where the agent (analogous to the controller) learns the optimal control action (analogous to control input) by directly interacting with the operational environment (analogous to the process), offers a potential alternative to traditional model-based approaches for process control. RL frameworks with actor-critic architecture have recently become popular for the control process systems where both the state and action spaces are continuous. Subsequent works focus on the development of Actor-Critic RL based controller by developing two novel Actor-Critic RL algorithms, namely, (i) Twin Actor Twin Delayed Deterministic Policy Gradient (TATD3), a deterministic RL algorithm, and (ii) Twin Actor Soft Actor-Critic (TASAC), a stochastic RL algorithm, for batch process control by incorporating an 'en-

semble of actors' in the Actor-Critic algorithms for training the policies to achieve an overall optimal policy for batch process control.

The efficacies of the developed approaches in this work are evaluated by simulation studies on batch process case studies. In a nutshell, the overall objective is to develop a data-driven dynamic model and a model-free RL-based controller for complex, nonlinear batch processes to ensure optimal operation of the batch processes.

KEYWORDS: data-driven model; just-in-time learning; reinforcement learning; deep-Q-learning; deep deterministic policy gradient; actor-critic algorithms; batch process control