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D-FNN based soft-sensor modeling and migration reconfiguration of polymerizing process

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ABSTRACT

A soft-sensor modeling method based on dynamic fuzzy neural network (D-FNN) is proposed for forecasting the key technology indicator convention velocity of vinyl chloride monomer (VCM) in the polyvinylchloride (PVC) polymerizing process. Based on the problem complexity and precision demand, D-FNN model can be constructed combining the system prior knowledge. Firstly, kernel principal component analysis (KPCA) method is adopted to select the auxiliary variables of soft-sensing model in order to reduce the model dimensionality. Then a hybrid structure and parameters learning algorithm of D-FNN is proposed to achieve the favorable approximation performance, which includes the rule extraction principles, the classification learning strategy, the precedent parameters arrangements, the rule trimming technology based on error descendent ratio and the consequent parameters decision based on extended Kalman filter (EKF). The proposed soft-sensor model can automatically determine if the fuzzy rules are generated/eliminated or not so as to realize the nonlinear mapping between input and output variables of the discussed soft-sensor model. Model migration method is adopted to realize the on-line adaptive revision and reconfiguration of soft-sensor model. In the end, simulation results show that the proposed model can significantly enhance the predictive accuracy and robustness of the technical-and-economic indexes and satisfy the real-time control requirements of PVC polymerizing production process.

1. Introduction

With VCM as a raw material, the suspension method to produce PVC resin is a kind of typical intermittent chemical production process. The traditional polymerization monomer conversion ratio is controlled to lower than 85%. However with the development of bigger polymerizer, the increase in conversion ratio of every polymerizer has an important significance for enhancing the production capability of the polymerizer device and reducing the production costs. Different conversion ratios have a certain influence on the molecular weight of PVC, porosity, absorption rate of plasticizer, VCM residue and thermal stability. Research on a soft-sensor model of PVC polymerizing process has not been carried out research in a related field. Therefore the present paper proposes a hybrid soft-sensor modeling method to predict the conversion rate and velocity, which is used as the operation guide for the PVC polymerizing process [1].

Dynamic fuzzy neural network (DFNN) is a hybrid model of fuzzy theory and neural network method, whose function is equivalent to the TSK fuzzy system [2]. Based on the problem complexity and precision demand, D-FNN model can be constructed combining the system prior knowledge. An improved fuzzy neural network modeling method [3] was proposed to realize the soft-sensor of molten index in the polymerization process, in which a hybrid learning method based on LM algorithm and a steepest descend method to train the network parameters. Simulation results show that the model has the merits of not sensitive to initial values, fast convergence velocity and high forecasting precision. The particle swarm algorithm (PSO) is adopted to optimize the parameters of the fuzzy neural network to set up a soft-sensor model of acrylonitrile yield [4]. I-Hsum and Lian-Wang [5] proposed an interval type-2 fuzzy system is integrated with an observer-based hierarchical fuzzy neural controller, which can greatly reduce the number of adjusted parameters. Hsu-Kun et al. proposed the maximum likelihood estimators used in nonparametric maximum likelihood fuzzy neural networks (MFNNs) for nonlinear regression problems and simple weight updating rules based on gradient descent and iteratively reweighted least squares (IRLS) will be derived [6]. Mounir and Mohamed [7] proposed a self organizing map-based initialization for hybrid training based on a two stage learning approach for feedforward neural networks. The weights between input and hidden layers are firstly adjusted by Kohonen algorithm with fuzzy neighborhood, whereas the weights connecting hidden and output layers are adjusted using gradient descent method.

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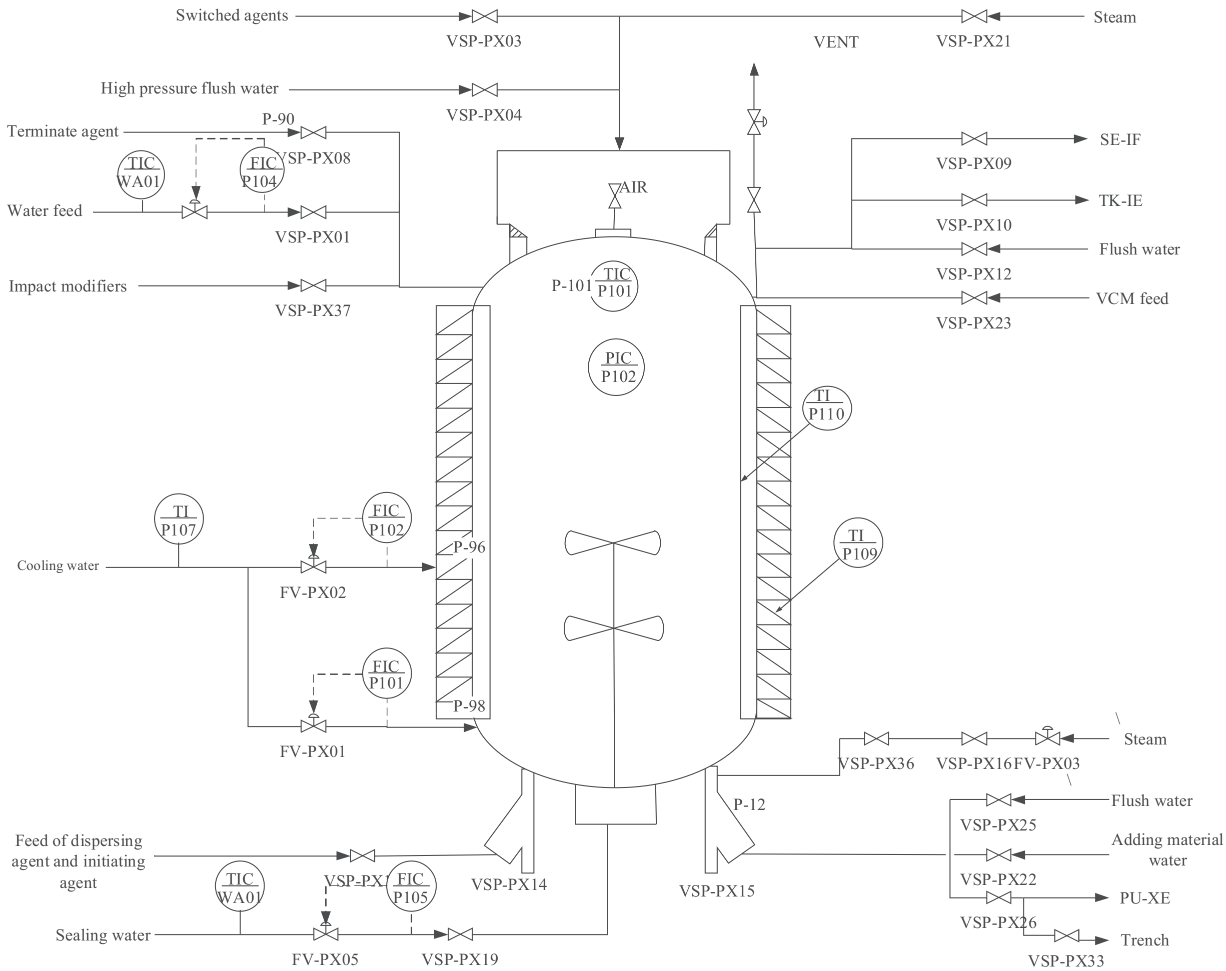

Fig. 1. Technique flowchart of polymerization apparatus.

Hung-Ching et al. proposed an adaptive self-constructing fuzzy neural network (ASCFNN) controller for a real inverted pendulum system, where the Mahalanobis distance (M-distance) method in the structure learning is also employed to determine if the fuzzy rules are generated/eliminated or not [8]. D-FNN is also successfully applied in many fields, such as function approximation, permanent-magnet synchronous motor drive control [9,10].

The paper proposed a D-FNN soft-sensor modeling method to predict the VCM convention velocity of the PVC polymerizing process. Simulation results show the effectiveness of the proposed model. The paper is organized as follows. In Section 2, the PVC polymerizing process is introduced. The model dimension reduction based on kernel principal component analysis is presented in Section 3. In Section 4, the D-FNN soft-sensor modeling method of polymerization process is summarized. In Section 5, the reconfiguration of soft-sensor model based on model migration is introduced. In Section 6, experiment and simulation results are introduced in details. Finally, the conclusion illustrates the last part.

2. PVC polymerizing process

In PVC polymerizing process, all kinds of raw materials and auxiliary agents are placed into the reaction kettle. They are fully and evenly dispersed under the function of stirring. Then, we begin to ventilate the cooling water to the clip set of the reaction kettle and baffle plate constantly in order to remove homopolymer. When the conversion rate of VCM reaches a certain value, there is a proper pressure drop. Then, the reactions are terminated and the finished product is created. A flowchart of the typical PVC polymerization kettle production process is shown in Fig. 1 [1].

2.1. Hot balancing mechanisms of polymerizer

Polymerizing reaction of SG-5 is analyzed as follows. VC is a feed of 26 ton. The conversion ratio is 80%, the reaction temperature is 57 °C and the polymerizing reaction thermal is 1600 kJ/kg. Emigrating heat includes four sections: Q_1–Q_4.

Q_1 is the heat flow of the jacket as given by Eq. (1).

$$Q_1 = K_J \cdot F_1 \cdot \Delta t_{mJ} \tag{1}$$

where K_J = 2500 kJ/m^2 h is the overall coefficient of heat transfer of the jacket, F_1 = 72 m^2 is the jacket area, and Δt_{mJ} is the inlet and outlet mean temperature difference of cooling water.

Q_2 is the heat flow of the baffle as given by Eq. (2).

$$Q_2 = K_D \cdot F_2 \cdot \Delta t_{mD} \tag{2}$$

where K_D = 4853 kJ/m^2 h is the overall coefficient of heat transfer of the baffle, F_2 = 4 m × 4.5 m is the baffle cooling area, and Δt_{mD} is the inlet and outlet mean temperature difference of the baffle cooling water.

Q_3 is the heat flow of the feed water as given by Eq. (3).

$$Q_3 = C \cdot w_1 \cdot (t_2 - t_1) \tag{3}$$

where C = 4.167 kJ/kg °C is the specific heat of water, w = 750 kJ/h is the water feed value, t_1 is the temperature of the feed water, and t_2 is the polymerizer temperature.