CHAPTER 2

LITERATURE REVIEW

This chapter is divided two parts. First part, it describes a modeling of rinsing process in many industrial sectors, which is used a base model to develop for recycled plastic industry. Second part, it reviews an application of dynamics optimization in chemical engineering filed.

2.1 Modeling of Rinsing Process

Giebler E (2004) proposed a steady state model of counter-current rinsing systems. The model is formulated in a compact matrix form that, in contrast to conventional descriptions, can be applied to a wide range of special cases by use of adequate matrices and vectors. The necessary formation rules are presented for a simple cascade rinsing system and for rinsing systems with pre-rinsing, imperfect mixing and spray rinsing.

W. Silalertruksa, P. Kittisupakorn and S. Boonyanant (2001) applied a rinsing model in Zinc and Chromium plating industry and used it to optimize minimum fresh water consumption. The result found that factory could be decreased excess water usage in rinsing process by proper rinse water flow rate control. From optimize technique obtained 7 percent reduction of fresh water usage.

Fullen, W. John (2000) developed a model for rinse water reduction. The first step in making rinse water use reductions is to determine the required amount of water for any specific process. The difference between common current practices and how much water is needed define over half of the potential rinse water reduction obtainable. Incoming water flow rates can be estimated by developing mathematical models based on means of mass balances. Model for double counter current and single heated rinse tank is formulated at steady state and transient conditions.

Lou, H.R. and Huang, Y.L. (1999) proposed a model-based dynamic simulator for cleaning and rinsing. This research presents a set of dynamic models for characterizing the cleanness of parts, the change of chemical concentrations in cleaning tanks, and the pollution level in rinsing tanks. The models have been implemented as a dynamic simulation tool. The tool is used for platers to check the operational status of their plating lines, to determine optimal settings of chemical and rinsing water, to identify waste reduction opportunities, and to estimate economical and environmental incentives.

Torsten Bohlin (1994) used a grey box identification to find a model of strip steel rinsing process. The purpose of the study is twofold: First, to find a working procedure for carrying out interactive system identification, especially using the grey box identification tool. The procedure comprises a sequence of hypothesis testing and parameter fitting, and involves the designer closely in the interactive 'loop' to contribute 'engineering sense'. Final, to explain the choice between internal-noise, external-noise, or no-noise (deterministic) structures, in particular whether the result may be worth the effort of using optimal state-variable filtering.

B. Sohlberg (1993) studied an optimal control of a steel strip rinsing process. Modeling and identification of the process is based on knowledge about the process and measured data from the process. In the model, the worn parts are modeled explicitly and estimated on line by an Extended Kalman Filter. The process is influenced by changing production variables. It is measurable but not controllable. The model is expressed in a discrete state space form, which makes the model suitable for optimal control.

Amadi, Sebastian I. (1985) studied a modeling and simulation of rinsing process for a printed circuit board production. A typical rinse process in a plating shop is modeled and simulated on a computer. Mathematical equations were developed for a rinse process whose configuration includes a stagnant drag-out rinse and a final constant volume and variable volume spray rinse. The model equations were simulated on the computer. Factors that affect final effluent discharge were also considered.

2.2 Dynamic Optimization

Victor M. Zavalaa, Antonio Flores-Tlacuahuac and Eduardo Vivaldo-Lima (2004) applied the dynamic optimization concept in a polyurethane copolymerization reactor. A kinetic–probabilistic model is used to describe the nonlinear step-growth polymerization of a mixture of low- and high-molecular-weight diols, and a low-molecular-weight diisocyanate. The main objective is the maximization of the molecular weight distribution (MWD) under a desired batch time, subject to a large set of operational constraints, while simultaneously avoiding the formation of polymer network (gel molecule). It was found that process operation is greatly enhanced by the semibatch addition of 1,4-butanediol and diamine, and the manipulation of the reactor temperature profile, allowing to obtain high molecular weights while avoiding the onset of the gelation point.

Richard Fabera, Tobias Jockenh ovelb and George Tsatsaronisc (2004) presented an approach for the dynamic optimization of energy and chemical engineering processes with the simulated annealing algorithm. They developed an optimization methodology, which finds optimal control strategies requiring a minimum of user input. The methodology we propose uses rigorous dynamic Simulink models based on first principles in a black-box approach. The presented approach based on the SA algorithm has the potential to find the global optimum and it does not need any additional information than the dynamic model itself.

Bing Zhang, Dezhao Chena and Weixiang Zhaoc (2004) sloved dynamic optimization problems of chemical process with numerical methods, a novel algorithm named iterative ant-colony algorithm (IACA). The main idea was iteratively execute ant-colony algorithm and gradually approximate the optimal control profile. The results of the case studies demonstrated the feasibility and robustness of this novel method. IACA approach can be regarded as a reliable and useful optimization tool when gradient is not available.

Ioan Cristian Treleaa, Mariana Titicab and Georges Corrieua (2002) presented the possibility of obtaining various desired final aroma profiles and reducing the total process time using dynamic optimization of three control variables:. temperature, top pressure and initial yeast concentration in the fermentation tank. The optimisation is based on a sequential quadratic programming algorithm, on a dynamic model of the alcoholic fermentation and on an aroma production model.

B. Chachuat, N. Roche and M.A. Latifi (2001) applied dynamic optimization technique in small size wastewater treatment plants. The problem is stated as a hybrid dynamic optimization problem, which is solved using a gradient-based method. They found minimization of the energy consumption and satisfy discharge requirements under specified constraints with process and physical constraints. The comparison between usual rule-based control policies and optimized strategies showed that the optimized aeration profiles lead to reductions of energy consumption of at least 30%.