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Iterative learning belief rule-base inference methodology using evidential reasoning for delayed coking unit

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ABSTRACT

The belief rule-base inference methodology using evidential reasoning (RIMER) approach has been proved to be an effective extension of traditional rule-based expert systems and a powerful tool for representing more complicated causal relationships using different types of information with uncertainties. With a predetermined structure of the initial belief rule-base (BRB), the RIMER approach requires the assignment of some system parameters including rule weights, attribute weights, and belief degrees using experts' knowledge. Although some updating algorithms were proposed to solve this problem, it is still difficult to find an optimal compact BRB. In this paper, a novel updating algorithm is proposed based on iterative learning strategy for delayed coking unit (DCU), which contains both continuous and discrete characteristics. Daily DCU operations under different conditions are modeled by a BRB, which is then updated using iterative learning methodology, based on a novel statistical utility for every belief rule. Compared with the other learning algorithms, our methodology can lead to a more optimal compact final BRB. With the help of this expert system, a feedforward compensation strategy is introduced to eliminate the disturbance caused by the drum-switching operations. The advantages of this approach are demonstrated on the UniSim™ Operations Suite platform through the developed DCU operation expert system modeled and optimized from a real oil refinery.

1. Introduction

Expert systems (ES) are a branch of applied artificial intelligence (AI), and were developed by the AI community in the mid-1960s. The basic idea behind ES is simply that expertise, which is the vast body of task-specific knowledge, is transferred from a human to a computer. This knowledge is then stored in the computer and users call upon the computer for specific advice at a specific conclusion. Then like a human consultant, it gives advices and explains, if necessary, the logic behind the advice (Giarratano & Riley, 1989; Jackson, 1998). In the last five decades, a large number of ES methodologies have been proposed in literatures, and applications implemented in industry fields (Duan, Yang, Li, Gui, & Deng, 2008; Liao, 2005).

Among these, the rule-based ES has been proved to be an effective and quite understandable tool. However, it is inevitable to deal with uncertainty caused by vagueness intrinsic to human knowledge and imprecision or incompleteness resulting from the limit of human knowledge (Yang, Liu, Wang, Sii, & Wang, 2006). It is therefore necessary to use a scheme for representing and processing the vague, imprecise, and incomplete information in conjunction with precise data. These methods for representing and reasoning with uncertain knowledge, such as Bayesian probability theory (Jensen, 1996), Dempster–Shafer (D–S) theory of evidence (Binaghi & Madella, 1999) and rough set theory (Pawlak, 1991), have attracted much attention in academic research (Yang Liu, Wang, Sii, & Wang, 2006). Nevertheless, it is impossible for us to use only one of these methods to solve the real problem, which may contain different kinds of uncertainties. In order to develop a generalized knowledge representation scheme and inference methodology to deal with these hybrid uncertainties, a new approach was proposed for building a hybrid rule-base using a belief structure and for inference in the rule-based system using the evidential reasoning theory by Yang et al. (Wang, Yang, Xu, & Chin, 2006; Xu et al., 2007; Yang Liu, Wang, Sii, & Wang, 2006; Yang, Liu, Xu, Wang, & Wang, 2007). The methodology, based on D–S theory of evidence, decision theory and fuzzy set theory, is referred to as a generic belief rule-base inference methodology using evidential reasoning approach – RIMER (Yang Liu, Wang, Sii, & Wang, 2006). The RIMER approach provides a more informative and flexible scheme than the traditional IF-THEN rule-base for

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knowledge representation, and is capable of capturing vagueness, incompleteness, and nonlinear causal relationships. In recent years, RIMER has already been applied to the safety analysis of off-shore systems (Liu, Yang, Wang, & Sii, 2005), pipeline leak detection (Xu et al., 2007; Zhou, Hu, Yang, Xu, & Zhou, 2009; Zhou, Hu, Yang, Xu, & Zhou, 2011), clinical decision support systems (Kong, Xu, Liu, & Yang, 2009) and stock trading expert systems (Dymova, Sevastianov, & Bartosiewicz, 2010).

In recent years, delayed coking technology is playing a more and more important role in modern oil refineries (Anthony, Kruse, & Ewy, 1996; Ellis, Paul, & Session, 1998; Friedman, 2005; Haseloff, Friedman, & Goodhart, 2007; Rodríguez-Reinoso, Santana, Palazon, Diez, & Marsh, 1998; Valyavin, Khukhrin, & Valyavin, 2007). It is a thermal cracking process used in petroleum refineries to upgrade and convert petroleum residuum (bottoms from atmospheric and vacuum distillation of crude oil) into liquid and gas product streams leaving behind a solid concentrated carbon material, petroleum coke. With short residence time in the furnace tubes, coking of the feed material is thereby "delayed" until it reaches large coking drums downstream of the heater.

Nevertheless, delayed coking is such a petrochemical process with strong coupling, non-linearity, long time-delay. It is the only main process in a modern petroleum refinery that is a batch-continuous process (Ellis, Paul, & Session, 1998). The flow through the tube furnace is continuous. The feed stream is switched between two drums. One drum is on-line filling with coke while the other one is being steam-stripped, cooled, coke removed, pressure tested, and warmed up. Thus, it is hard to implement effective automatic control to this unit (Friedman, 2005; Haseloff, Friedman & Goodhart, 2007; Zhou, Wang, & Jin, 2009). First, most of operations in drum-switching process are performed manually based on operators' experiences. As a result, the impact on the downstream unit such as the fractionator varies with different operators, fresh feed and also switching time. Second, the delayed coking fractionator is such a complex tower with multi-component and multi-side-draw. On one hand, there are strong non-linearity and large time-delay. On the other hand, it can not be ignored that great disturbance will be brought into the whole process because of the periodic drum-switching operation, which is hard for the traditional PID controller to eject effectively. During the past decade, various advanced process control (APC) technologies have been applied in DCU operations (Elliott, 2003; Haseloff Friedman & Goodhart, 2007). For example, a multivariate model predictive controller was designed and implemented on the fractionator of a DCU in a refinery company in China by Zhao et al. (Zhao, Chu, Su, & Huang, 2010). Whereas, in most APC technologies, to the best of our knowledge, the drum-switching disturbance has not been handled well so far (Yu, et al.,2011). Thus, it is quite important to develop efficient and robust techniques for such complex process. In our previous work (Yu et al., 2011), a rule-based expert system of intelligent switching expert system for DCU operations was established and a feedforward control strategy based on iterative learning was introduced to eliminate disturbances arising from the drum-switching operations. While nevertheless, it is a traditional rule-based expert system, and these simple rules can not represent more complicated causal relationships with uncertainties.

In this paper, a novel iterative learning belief rule-base inference methodology using evidential reasoning (IL-RIMER) is proposed and applied to construct a DCU operation expert system for providing optimal operating information for the field operators. Then a feedforward compensation strategy is incorporated into this expert system and implemented to smooth the operating process while drum-switching. In the following Section 2, the RIMER theory will be reviewed briefly, followed by a detailed description of the IL-RIMER scheme in Section 3. Then Section 4 shows how a DCU operation expert system can be developed using the IL-RIMER methodology proposed, based on the field data from a real oil refinery. And the effectiveness and efficiency of this expert system is illustrated on the UniSim^{TM} Operations Suite platform subsequently. Finally the paper is concluded in Section 5, followed by some acknowledgments. The basic idea of our algorithm was previously explored by Yu et al. (Yu, Huang, Jiang, & Jin, 2011). This paper represents a significant extension in terms of experimental methodology, parameterization, and analysis.

2. The RIMER theory

2.1. Belief rule-base

A BRB, which captures the dynamic of a system, consists of a collection of belief rules defined as follows (Yang Liu, Wang, Sii, & Wang, 2006):

$$R_k : \text{IF } x_1 \text{ is } A_1^k \wedge x_2 \text{ is } A_2^k \ldots x_{T_k} \text{ is } A_{T_k}^k \text{ THEN } \{(D_1,\beta_{1k}), \quad (D_2,\beta_{2k}),\ldots,(D_N,\beta_{Nk})\} \tag{1}$$

with a rule weight θ_k and attribute weight $\delta_{k1},\delta_{k2},\ldots,\delta_{kT_k}$, where $x_1,x_2,\ldots,x_{T_k}$ represents the antecedent attributes in the kth rule R_k, $A_i^k(i=1,2,\ldots,T_k,k=1,2,\ldots L)$ is the referential value of the ith antecedent attribute in the kth rule R_k, $A_i^k \in A_i, A_i=\{A_{ij}, j=1,2,\ldots J_i\}$ is a set of referential value of the ith antecedent attribute, J_i is the number of the referential value, $\theta_k(\in R^+, k=1,2,\ldots,L)$ is the relative weight of the kth rule R_k, $\delta_{k1},\delta_{k2},\ldots,\delta_{kT_k}$ are the relative weights of the T_k antecedent attributes used in the kth rule R_k, and β_{ik} $(i=1,2,\ldots,N,k=1,2,\ldots,L)$ is the belief degree assessed to D_j which denotes the jth consequent. If $\sum_{i=1}^{N}\beta_{ik}=1$, the kth rule R_k is said to be complete; otherwise, it is incomplete. Note that "$\wedge$" is a logical connective to represent the "AND" relationship. In addition, suppose that T is the total number of antecedent attributes used in the rule base.

2.2. Belief rule-base inference methodology using evidential reasoning approach

Given an input to the system, $U(t)=\{U_i(t), i=1,2,\ldots,T_k\}$, how can the rule-base be used to inference and generate an output? As mentioned earlier, T_k is the total number of antecedents in the rule-base, $U_i(t)(i=1,2,\ldots,T_k)$ is the ith attribute, which can be one of the following types (Yang Liu, Wang, Sii, & Wang, 2006): continuous, discrete, symbolic and ordered symbolic.

Before the start of an inference process, the matching degree of an input to each referential value in the antecedents of a rule needs to be determined so that an activation weight for each rule can be generated. This is equivalent to transforming an input into a distribution on referential values using belief degrees and can be accomplished using different techniques such as the rule or utility-based equivalence transformation techniques (Yang, 2001; Yang, Liu, Xu, Wang & Wang, 2007).

Using the notations provided above, the activation weight of the kth rule R_k, w_k, is calculated as (Yang Liu, Wang, Sii, & Wang, 2006):

$$\omega_k = \frac{\theta_k a_k}{\sum_{i=1}^{L}\theta_i a_i} \tag{2}$$

where a_k is called the normalized combined matching degree, which can be calculated by

$$a_k = \prod_{i=1}^{T_k}(a_i^k)^{\overline{\delta}_{ki}} \tag{3}$$