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Fuzzy Petri nets for knowledge representation and reasoning: A literature review

Hu-Chen Liu[a,b], Jian-Xin You[b], ZhiWu Li[c], Guangdong Tian[a,d,*]

[a] School of Management, Shanghai University, Shanghai 200444, PR China
[b] School of Economics and Management, Tongji University, Shanghai 200092, PR China
[c] School of Electro-Mechanical Engineering, Xidian University, Xi'an 710071, PR China
[d] Transportation College, Jilin University, Changchun 130022, PR China

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ABSTRACT

Fuzzy Petri nets (FPNs) are a potential modeling technique for knowledge representation and reasoning of rule-based expert systems. To date, many studies have focused on the improvement of FPNs and various new algorithms and models have been proposed in the literature to enhance the modeling power and applicability of FPNs. However, no systematic and comprehensive review has been provided for FPNs as knowledge representation formalisms. Giving this evolving research area, this work presents an overview of the improved FPN theories and models from the perspectives of reasoning algorithms, knowledge representations and FPN models. In addition, we provide a survey of the applications of FPNs for solving practical problems in variety of fields. Finally, research trends in the current literature and potential directions for future investigations are pointed out, providing insights and robust roadmap for further studies in this field.

1. Introduction

Fuzzy Petri nets (FPNs) are a modification of classical Petri nets (PNs) for dealing with imprecise, vague or fuzzy information in knowledge based systems, which have been extensively used to model fuzzy production rules (FPRs) and formulate fuzzy rule-based reasoning automatically. An FPN is a marked graphical system containing places and transitions, where graphically circles represent places, bars depict transitions, and directed arcs denote the incidence relationships from places to transitions or from transitions to places. The main characteristics of an FPN are that it supports structural organization of information, provides visualization of knowledge reasoning, and facilitates design of efficient fuzzy inference algorithms. All these render FPNs a potential modeling methodology for knowledge representation and reasoning in expert systems (Chen et al., 1990; Liu et al., 2013a; Yeung and Tsang, 1994a).

Since the introduction of FPNs for supporting approximate reasoning in a fuzzy rule-based system (Looney, 1988), they have received a great deal of attention from academics and practitioners in the domain of artificial intelligence. However, the earlier FPNs, as indicated in the academic literature, are plagued by a number of shortcomings, and are not suitable for increasingly complex knowledge-based systems. Therefore, a variety of alternative models have been put forward in the literature to enhance the knowledge representation power of FPNs and to implement the rule-based reasoning more intelligently. Besides, FPNs have been widely used by researchers and practitioners to manage different kinds of engineering problems in many fields. To the best of our knowledge, however, no research is found to present a thorough review on FPNs as a knowledge representation formalism. This paper aims to summarize and analyze the existing approaches to enhance the performance of FPNs, and further introduce in depth the applications of FPNs to solve real-world problems. Related articles published in international journals between 1988 and 2016 are gathered and reviewed. The specific objectives of this review are:

- To establish sources of improvements around FPNs and identify those aspects that attract the most attention in the FPN literature.
- To describe the development of FPNs and find the approaches that are prevalently applied.
- To uncover gaps and trends in the current FPN literature and highlight future directions for research.

This study not only provides evidence that some alternative models are better than former FPNs, but also aids both practitioners and researchers in applying FPNs more effectively. The paper's goal is to also provide a spur to further study this area in depth and develop

* Correspondence to: School of Management, Shanghai University, 99 Shangda Road, Shanghai200444, PR China.
E-mail addresses: huchenliu@foxmail.com (H.-C. Liu), tiangd2013@163.com (G. Tian).

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richer knowledge on FPNs to help industrialists build effective expert systems for intelligent decision making.

The rest of this paper is organized in the following way. First, some background knowledge regarding FPRs and FPNs, and the major aspects of research on FPNs are presented in Section 2. Section 3 reviews the improved FPN approaches from the perspectives of reasoning algorithms, knowledge representations and FPN models. In Section 4 we introduce the applications of FPNs in different engineering areas. Section 5 describes some general observations based on statistical analysis results of this review. Section 6 discusses the main findings of this literature survey and gives suggestions for the future work. Finally, Section 7 concludes the paper.

2. FPRs and FPNs

2.1. FPRs

FPRs have been comprehensively used to represent, capture and store vague expert knowledge in decision systems. Each rule is usually expressed in the form of a fuzzy if-then rule in which both the antecedent and the consequent are fuzzy terms expressed by fuzzy sets. If an FPR consists of either AND or OR connectors, then it is called a composite or compound FPR (Chen, 1996).

To enhance the representation and reasoning capabilities of FPRs, the weight parameter (Tsang et al., 2004; Yeung and Tsang, 1997) has been incorporated into fuzzy if-then rules, obtaining the weighted FPRs (WFPRs). Let R be a set of WFPRs, i.e.,$R = \{R_1, R_2, \ldots, R_n\}$, the form of the ith rule can be presented as

$$R_i\text{: IF } a \text{ THEN } c \ (\text{CF} = \mu), \quad Th, w \tag{1}$$

where a and c are the antecedent and consequent parts of the rule, respectively, which comprise one or more propositions with fuzzy variables. The parameter $\mu\,(\mu \in [0, 1])$ is the certainty factor indicating the belief strength of the rule,$Th = \{\lambda_1, \lambda_2, \ldots,\lambda_m\}$ is a set of threshold values specified for each of the propositions in the antecedent, and $w = \{w_1, w_2, \ldots, w_m\}$ is a set of weights assigned to all propositions in the antecedent, showing the relative importance of each proposition in the antecedent contributing to the consequent.

In general, WFPRs can be divided into five types as listed below (Ha et al., 2007; Liu et al., 2013a; Yeung and Ysang, 1998):

Type 1. A simple weighted fuzzy production rule

R: IF a THEN c (μ; λ; w)

Type 2. A composite weighted fuzzy conjunctive rule in the antecedent

R: IF a_1 AND a_2 AND…AND a_m THEN c (μ; $\lambda_1, \lambda_2, \ldots,\lambda_m$; $w_1, w_2, \ldots,w_m$)

Type 3. A composite weighted fuzzy conjunctive rule in the consequent

R: IF a THEN c_1 AND c_2 AND…AND c_m (μ; λ; w)

Type 4. A composite weighted fuzzy disjunctive rule in the antecedent

R: IF a_1 OR a_2 OR…OR a_m THEN c (μ; $\lambda_1, \lambda_2, \ldots,\lambda_m$; $w_1, w_2, \ldots,w_m$)

Type 5. A composite weighted fuzzy disjunctive rule in the consequent

R: IF a THEN c_1 OR c_2 OR…OR c_m (μ; λ; w).

In many practical applications, the rules of Types 4 and 5 are not allowed to appear in a knowledge base since they can be transferred into several rules of Type 1. The following rules are several typical examples of WFPRs:

R_1: IF it is hot THEN the humidity is low (μ=0.9);
R_2: IF John is fat AND John is tall AND John is a man THEN he is heavy (μ=1.0);
R_3: IF fever is high AND cough is heavy AND blood pressure is normal THEN pneumonia (μ=0.8);
R_4: IF regulator semiconductor is broken THEN exciter is not enough (μ=0.9; λ=0.2; w =1.0);
R_5: IF frequency is higher than normal value AND double frequency is smaller than normal value AND amplitude changes obviously as the loads change THEN rotor is hot bending (μ=0.9; λ_1 =0.3, λ_2 =0.3, λ_3 =0.2; w_1 =0.5, w_2 =0.3, w_3 =0.2).

It is worth noting that R_4 and R_5 are WFPRs derived from the fault diagnosis of aircraft generator (Liu et al., 2016a).

2.2. PNs and FPNs

PNs are a graphical and mathematical modeling method used to model and analyze discrete event systems (Cassandras and Lafortune, 2008; Li et al., 2012a, 2012b) such as communication, manufacturing and transportation systems. Tokens in the places represent the state of a system (Chen et al., 2014b; Li and Zhao, 2008; Zhang et al., 2015). A PN is formally defined as a 5-tuple (Murata, 1989):

$$\text{PN} = (P, T, F, W, M_0) \tag{2}$$

where P and T are finite sets of places and transitions, respectively, the flow relation between P and T is denoted by $F \subseteq (P \times T) \cap (T \times P)$, W: $F \rightarrow \{0, 1, 2, \ldots\}$ is a weight function, and M_0: $P \rightarrow \{0, 1, 2, \ldots\}$ is the initial marking. A PN example is shown in Fig. 1(a), where $P = \{p_1, p_2\}$, $T = \{t_1\}$,$F = \{(p_1, t_1), (t_1, p_1)\}$ and its initial marking is $M_0 = [3 \quad 0]^T$ at which t_1 is enabled. After t_1 fires, one token is removed from its input place, i.e., p_1, and deposited into its output place, i.e., p_2.

To deal with uncertainty in knowledge representation and reasoning, FPNs have been developed from the PN theory, where tokens representing the state of propositions are marked by a truth value between 0 and 1. By applying a PN formalism to fuzzy rule-based systems, it is able to visualize the structure of an expert system and express its dynamic proposition logic reasoning behavior efficiently. For example, in Fig. 1(b), we have $P = \{p_1, p_2\}$, $T = \{t_1\}$, $I(t_1) = \{p_1\}$,$O(t_1) = \{p_2\}$, $f(t_1) = \mu_1$, $\alpha(p_1) = \alpha_1$, and $\alpha(p_2) = 0$ based on the basic FPN defined in Eq. (3). For an FPN, a transition is said to be enabled if all of its input places are marked by a token and its real value is greater than or equal to a threshold value. The reasoning process of an FPN is executed by firing the rules and updating the truth degree vector at each reasoning step.

Due to the features of fuzzy rule-based systems, the major differences between PNs and FPNs are as follows (Gao et al., 2003; Hanna et al., 1996; Hu et al., 2011):

(1) In FPNs, the number of tokens in a place cannot be greater than one since a token is associated with a truth value between 0 and 1. A token does not represent an “object,” whereas it may likely do so in PNs.
(2) FPNs are always conflict-free nets because there is no “resource” concept in FPNs and a proposition may be shared by different rules at the same time. For example, in Fig. 2, the proposition d_3 is shared by two rules R_1 and R_2, which can utilize proposition d_3 simultaneously and reason in parallel.
(3) The tokens are not removed from the input places of a transition after it fires since the evaluation of the rules means the truth propagation of the propositions only. That is, the antecedent part remains verified although its consequent part may already be proved in the knowledge reasoning.