Adaptive Fuzzy Higher Order Petri Nets for Knowledge Representation an Reasoning

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***Abstract* — Petri Net (PN) is effective graphical, mathematical, simulation, and control tool for Discrete Event Systems (DES). But, with the growth in the complexity of modern industrial, and communication systems, PN found themselves inadequate to address the problems of uncertainty, and imprecision in data. This gave rise to amalgamation of Fuzzy logic with Petri nets and a new tool emerged with the name of Fuzzy Petri Nets (FPN). Although there had been a lot of research done on FPN and a number of their applications have been anticipated, but Petri nets and Fuzzy Petri nets as modeling formalism are not adaptable according to the changes of the arc weight. Weights are the parameters that represent the new incoming data of the system modeled by a (Fuzzy) Petri net. The weight changes meet the system changes in a variety of application domains (e.g. Intelligent E-learning, Computer Numerical Control, Weather Forecasting, and Expert systems). In this paper, introduce a new class of Fuzzy Petri nets that takes into account the weight changes of the arc in the Fuzzy reasoning process. This class gives the formal description of the model, an algorithm for learning the weights without the need to transfer into a neural network, an algorithm for the fuzzy reasoning.**

***Key Words* — knowledge representation, knowledge reasoning, Petri nets, learning and fuzzy reasoning algorithm.**

I. INTRODUCTION

In Artificial Intelligence, knowledge representation is a combination of data structures and interpretive procedures that leads to knowledgeable behavior [1]. The state and properties of an intelligent system vary such that the system exhibits continuous dynamic, e.g. intelligent E-learning, computer numerical control, weather forecasting, and expert systems. Specifically, intelligent E-learning exhibits continuous dynamic due to the continuous contribution of human expert's behavior and changes of objectives [2]. Uncertain knowledge representation and processing is a hot issue the expert system has been always studying [3]. Based on the elaboration on the structure and category of the expert system, there are eight methods for uncertain knowledge representation and processing, including deterministic theory, subjective Bayesian approach, fuzzy theory, evidence theory, grey system theory, concept maps, rough set theory [4]. PN is effective tool for graphical modeling, mathematical modeling, simulation, and real time control by the use of places and transitions [5]. However, there is an intuitive need for a system, which would be able to address uncertainties and imprecision of the real world systems, because of increase in the complexity of industrial and communication systems. Fuzzy logic proved to be an appropriate complement because of its possible nature to handle vague data [6].

Weights are the parameters that represent the new incoming data of the system modeled by a Petri net (PN) or Fuzzy Petri net (FPN) [7]. However, PN's and FPN's ignore the value of the arc weight. PN's and FPN's use arc weight to describe the relation between its markings. Consequently, as a modeling formalism they are not adaptable according to the changes of the arc weight. The dynamics of a Petri net are only governed by the firing of its transition. For dynamic systems such as intelligent E-learning, computer numerical control, and weather forecasting require modeling approaches capable of adjusting the system parameters. In this paper, Higher-Order Petri Nets (HOPN's) are introduced as a general class of PN's by extending the concept of higher-order synaptic weights in artificial neural networks to an arc in PN's.

II. BACKGROUND

The representation of expert knowledge and the reasoning process of the knowledge rules are two key issues when developing an expert system [1]. The inference engine of an expert system serves as a tool that selects the appropriate parts of the knowledge base according to the input. The output of an expert system is, for example, a recommendation to take a set of actions. Many knowledge representation methods have been developed, which include: weighted fuzzy production rules (WFPRs); disjunctive logic programming; semantic network; [2] extended hierarchical censored production rules; fuzzy Petri nets (FPNs); ontology; and the entity relation propagation diagram/tree. The evidential reasoning (ER) approach is that both precise data and subjective judgments with uncertainty can be consistently modeled under the unified framework. The ER approach provides a novel procedure for aggregating multiple attributes based on the distributed assessment framework and the evidence combination rule of the D-S theory [3].

FPNs are also a promising modeling tool to represent fuzzy production rules of rule-based expert systems [4]. FPNs are formal and general graphical models of rule based expert systems and can represent logical knowledge in an intuitive and visual way. FPNs can naturally model logical and mathematical arrays and allow checking the properties of modeled systems utilizing the major characteristics of Petri nets such as correctness, consistency, and reach ability tree. FPNs can capture the dynamic nature of fuzzy rule-based reasoning with marking evolution or express the dynamic behavior of a system in algebraic forms [5]. Fuzzy Petri nets (FPN's) can be combined with different techniques and theories such as fuzzy sets [6], neural networks, object-oriented programming, knowledge based systems, learning systems, and process control to support fuzzy reasoning. These include FPN's to analytically represent the knowledge of fault diagnosis in manufacturing systems and an iterative algorithm based on max-algebra to deduce the consequence–antecedent relationship [7] . Few adjustable FPN's are proposed. An algorithm for adjusting thresholds is presented but weights adjustments were realized by test design. An adjustable model is proposed which transforms FPN into a neural network (NN). Thus, parameters of the corresponding NN can be trained. However, it is only suitable for OR/AND logic neurons. An adaptive FPN model for adjusting certainty factors is introduced. However, the model does not consider the fuzzy beliefs of the output places, and is difficult to manage when the system is complex. A generalized FPN's with two knowledge representation parameters, input weight and output weight, for multilevel fuzzy reasoning is introduced. A weakness of the model occurs when knowledge system is updated since the two parameters are assumed to be fixed in the whole analysis process.

III. Previous Work Done

In Artificial Intelligence, knowledge representation is a combination of data structures and interpretive procedures that leads to knowledgeable behavior. Therefore, it is required to investigate such knowledge representation technique in which knowledge can be easily and efficiently represented in computer. Vassev et. al. [1] state that using this technique system can easily process and humans can easily perceive the results. Kesarwani et. al. [2] compares various knowledge representation techniques and proves that integrated approach is a more efficient and more accurate knowledge representation scheme. Lin-li et. al. [3] state that uncertain knowledge representation and processing is a hot issue the expert system has been always studying. Based on the elaboration on the structure and category of the expert system, this paper describes eight methods for uncertain knowledge representation and processing, including deterministic theory, subjective Bayesian approach, fuzzy theory, evidence theory, grey system theory, concept maps, rough set theory, and set pair analysis, and looks forward to the future research direction of uncertain knowledge representation and processing.

The two most important issues of expert systems are the acquisition of domain experts' professional knowledge and the representation and reasoning of the knowledge rules that have been identified by Kishan et. al. [4]. First, during expert knowledge acquisition processes, the domain expert panel often demonstrates different experience and knowledge from one another and produces different types of knowledge information such as complete and incomplete, precise and imprecise, and known and unknown because of its cross-functional and multidisciplinary nature. Second, as a promising tool for knowledge representation and reasoning, fuzzy Petri nets (FPNs) still suffer a couple of deficiencies. The parameters in current FPN models could not accurately represent the increasingly complex knowledge-based systems, and the rules in most existing knowledge inference frameworks could not be dynamically adjustable according to propositions' variation as human cognition and thinking. Hu-Chen et. al. [5] present a knowledge acquisition and representation approach using the fuzzy evidential reasoning approach and dynamic adaptive FPNs to solve the problems mentioned.

Although a promising tool for knowledge representation and reasoning, fuzzy Petri nets (FPNs) still suffer from some deficiencies. First, the parameters in current FPN models, such as weight, threshold, and certainty factor do not accurately represent increasingly complex knowledge-based expert systems and do not capture the dynamic nature of fuzzy knowledge. Second, the fuzzy rules of most existing knowledge inference frameworks are static and cannot be adjusted dynamically according to variations of antecedent propositions by Anuradha et. al.[6]. To address these problems, Qing-Lian et. al. [7] Presents a new type of FPN model, dynamic adaptive fuzzy Petri nets, for knowledge representation and reasoning. And also propose a max-algebra based parallel reasoning algorithm so that the reasoning process can be implemented automatically.

IV. Existing Methodology

A. Fuzzy Petri Nets (FPNs)

Knowledge representation is another issue that limits the application of an expert system. FPNs are an extension of Petri net, which have been widely applied in many areas, such as production rescheduling, knowledge learning, exception handling, and fault diagnosis. FPNs are a promising modeling tool for expert systems and have a couple of attractive advantages. First, FPNs are formal, general graphical models of rule-based expert systems and can represent logical knowledge in an intuitive and visual way. Second, FPNs allow the properties of modeled systems to be checked using the major characteristics of Petri nets, such as correctness, consistency, and reach ability. Third, FPNs capture the dynamic nature of fuzzy rule-based reasoning by marking evolution and allow one to express the dynamic behavior of a system, for example, in algebraic forms. Finally, FPNs improve the efficiency of fuzzy rule-based reasoning. A complex fuzzy expert system reasoning path can be reduced to a simple sprouting tree by applying a reach ability tree-based reasoning algorithm and simple matrix operations are used when max-algebra is adopted as an inference engine [5].

B. Dynamic Adaptive Fuzzy Petri Nets (DAFPN)

A new modified FPN, namely DAFPN, and a max-algebra based concurrent algorithm for this model. In contrast to earlier FPNs, the DAFPN has the following features [7].

1) The weights of propositions were assigned to each input arc of a transition, so the same place with different transitions had different corresponding input weights after WFPRs were mapped onto DAFPNs.

2) The certainty factor of a rule is replaced by several output certainty factors assigned to each output arc of a transition. This avoids the shortcoming common in most existing FPN models, i.e., the whole rule is assigned only one certainty factor even if a rule contains two or more consequents.

3) In our definition, distinct threshold values were not only assigned to each proposition in the antecedent part of a

composite production rule but to the propositions in the consequent part of a composite production rule. This can not only prevent or reduce rule misfiring, but also dynamically adjust knowledge rules with the change of antecedent propositions.

4) The improved inference model provided a new mechanism and approach for forward reasoning. Computational complexity of the given algorithm is only relative to the number of iterations and is not affected by the number of rules. Compared to reach ability tree-based reasoning algorithms, our method does not require the enumeration of all potential paths from the starting places to the terminating ones, thus leading to a more efficient method.

5) Fuzzy knowledge in expert systems can be adjusted automatically according to the changing environment through our DAFPN model. This is an innovation over other models.

V. Analysis And Discussion

As a tool for fuzzy knowledge representation and reasoning, existing FPN models still have some deficiencies.

1) A proposition is assigned only one weight and the weight is assigned to one place in the FPN model. This may be unreasonable when a proposition is shared by different rules at the same time; consequently, the same place with different transitions has the same weight after fuzzy production rules (FPRs) are mapped into FPNs.

2) Similarly, when the consequent part has two or more propositions in a rule, the whole rule is assigned only one certainty factor to its transition in the FPN model. In fact, when a rule contains two or more consequents, the influence of the transition to its output places may be different.

3) A proposition or rule is generally assigned only one threshold value and the threshold value is assigned to its place or transition in the FPN model. Some FPN models do not even consider thresholds or only assign a single value to all FPRs. These may be unreasonable limitations, given the increasing complexity of today's knowledge-based systems.

4) The fuzzy reasoning algorithms of many FPNs are implemented using a reach ability tree-based method that is not suitable for parallel reasoning such methods often require the enumeration of all possible paths, such that the final truth degrees can be properly evaluated, leading to a less efficient reasoning algorithm.

5) Although most existing FPN models are flexible, and some can even learn, the rules in their models are still fixed and cannot be adjusted dynamically according to varying antecedent propositions. In view of the complexity of today's knowledge-based systems, the application of FPNs will be severely limited if knowledge representation models cannot accurately express various kinds of expert knowledge, and knowledge reasoning frameworks do not have the ability to dynamically adapt with changing antecedent propositions.

To overcome the limitations of FPNs by proposing a new type of FPN model, dynamic adaptive fuzzy Petri nets (DAFPNs), for knowledge representation and reasoning. The structure of a DAFPN is a more generic form than those proposed in previous literature. Moreover, inspired by the work and present a max-algebra reasoning algorithm for the rule-based reasoning systems modeled with DAFPNs. The fuzzy reasoning algorithm has parallel reasoning, and can be used to efficiently solve complicated problems.

Research is on the following directions. First, a program to execute the proposed reasoning algorithm needs to be developed, so that DAFPNs can be used to handle complex problems at higher speed. Second, introducing other knowledge representation parameters into DAFPNs, such as global weights and time factors needs to be investigated. Third, the combination with fuzzy evidential reasoning theory should be examined so that the DAFPNs can deal with incomplete and uncertain information.

Petri nets, Fuzzy Petri nets and DAFPNs as modeling formalism are not adaptable according to the changes of the arc weight. Weights are the parameters that represent the new incoming data of the system modeled by a (Fuzzy) Petri net. The weight changes meet the system changes in a variety of application domains (e.g. Intelligent E-learning, Computer Numerical Control, Weather Forecasting, and Expert Systems). In this paper, introduce a new class of Fuzzy Petri nets that takes into account the weight changes of the arc in the Fuzzy reasoning process. Give the formal description of the model, an algorithm for learning the weights without the need to transfer into a neural network, an algorithm for the fuzzy reasoning.

VI. Proposed Methodology

Higher-Order Petri Nets (HOPN's) are introduced as a general class of PN's by extending the concept of higher-order synaptic weights in artificial neural networks to an arc in PN's. The major difference between HOPN's and PN's is the definition of the input arc and the weight. In PN's, the arc links only one place to transition and in HOPN's, the input arc links one or more input places to transition. The weight changes according to the changes of its corresponding arc. Fuzzy higher order Petri nets are used for managing uncertainty in expert systems. Here, introduce adaptive fuzzy higher order Petri net (AFHOPN) that has the learning ability as NN's and can be used for knowledge representation and reasoning. In addition, AFHOPN is suitable for vague and dynamic knowledge. Based on transition firing rules, that develops a back propagation learning algorithm to ensure the convergence of the weights.

Here, introduce the fuzzy reasoning algorithm for computing the fuzzy beliefs of places and an algorithm for updating the input and output weights. In The fuzzy reasoning algorithm, Consider input as the fuzzy beliefs (truth values) of the input places and the values of the weights and output is the truth values of the output places (goal places). If the transition is enabled then calculate the truth values and make token transmission. Assume P is one of the output places of a fired transition T. There are three conditions; if a place has only one input transition then add a token to P with the truth value produced by its input transition; If a place has one input transition with n (n > 1) input arcs, and it fired by s (s 6 n) of its input arcs then add a token to P with the maximum truth value produced by the transition with respect to all s input arcs; If a place has m (m > 1) input transitions and k (k 6 m) of its input transitions fired, then select the transition that gives the maximum output and add a token to output place P with the truth value produced by this transition. Let T is equal to T _

Current enabled transition and continues until Current enabled transition is equal to φ.

After applying the fuzzy reasoning algorithm, the truth values of a set of antecedences and consequences are changed. So, the parameters (weights) must be adjusted according to the new truth values of the input and the output places. This leads us to introduce an algorithm for updating the input and the output weights.

The learning algorithm

Input: The truth values of a set of antecedent propositions and the truth values of a set of consequent propositions.

Output: Input and output weights

Repeat

1. Build the set of user input places.
2. Build the set of initially enabled transitions.
3. Calculate the input weights
4. Calculate the output weights according to the types of firing rules.

Until (Current enabled transition = φ).

VII. Possible Outcomes And Results

AFHON model has the capability of dynamic adjustment of parameters. The weights in fuzzy production rules play an important role in the changes of the parameters. Therefore, the algorithm for updating the weights can be used to predict further changes by learning the weights. In the sense of Knowledge representation aspect, the problem (its specification) is mapped directly onto the topology of the adaptive fuzzy higher order Petri net. Data structure is compact in AFHOPN model and fuzziness is at places and weights. In this model, Fuzzy sets are continuous and adaptive comparatively in Petri Nets.

Conclusion

Based on transition firing rules and a back propagation learning algorithm, introduced an adaptive fuzzy higher order Petri net (AFHOPN) that is dynamically adjusted the parameters of the system modeled by the net, allowed a structural representation of vague and dynamic knowledge, and it has a systematic procedure for supporting fuzzy reasoning. Future research will focus on the following directions. First, a program to execute the proposed reasoning algorithm needs to be developed, so that AFHOPN can be used to handle complex problems at higher speed. Second, the combination with fuzzy evidential reasoning theory should be examined.

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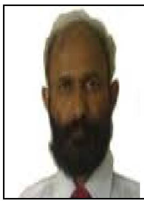

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