BRIDGE DAMAGE ASSESSMENT THROUGH FUZZY PETRI NET BASED EXPERT SYSTEM

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ABSTRACT: The reliability of the techniques adopted for damage assessment is important for bridge management systems. It is widely recognized that the use of expert systems for bridge damage assessment is a promising direction toward bridge management systems. However, several important issues need to be addressed, such as the management of uncertainty and imprecision, the efficiency of fuzzy rule based reasoning, and the need of an explanation facility to increase confidence about the assessment results. To address the issues arising from using expert systems, this paper is aimed at developing an expert system for assessing bridges based on an expert system shell, which is called the fuzzy Petri net based expert system (FPNES). Major features of FPNES include the ability to reason using uncertain and imprecise information, knowledge representation through the use of hierarchical fuzzy Petri nets, a reasoning mechanism based on fuzzy Petri nets, and an explanation of the reasoning process through the use of hierarchical fuzzy Petri nets. Therefore, this expert system for assessing bridges does not impose any restriction on the inference mechanism. Furthermore, this approach offers more informative results than other systems. An application to the damage assessment of the Da-Shi bridge in Taiwan is used as an illustrative example of FPNES.

INTRODUCTION

In recent years, many countries have been aware of bridge problems and have initiated the development of bridge management systems to assist their decision-makers in establishing efficient repair and maintenance programs. Basically, bridge management systems consist of several modules to record the inventory data of bridges, store the inspection results, evaluate the damage states of bridges, propose maintenance and retrofit schemes, estimate the maintenance and retrofit cost, and allocate the available funds appropriately. The reliability of the technique adopted for evaluating bridge states is playing an important role in bridge management systems. Damage assessment for a bridge is a process to evaluate the damage state of the bridge based on visual inspection and empirical tests. However, it is a difficult task due to a lack of complete understanding of the mechanism of bridge deterioration. Bridge structures are too complex to analyze completely, and therefore, numerical simulations require a host of simplified assumptions. Nevertheless, an experienced engineer who has closely studied these problems over the years could use his heuristic knowledge to achieve the task. The use of expert systems for damage assessment has been widely recognized as a promising solution for alleviating the lack of experts.

An expert system is a computer program that emulates the problem-solving ability of human experts. Separating the knowledge base from the inference procedure makes it easy to extend and modify knowledge collected from all possible sources. Expert systems can perform task much more efficiently than experts, and can even be accessed through the Internet without time and space barriers to serve as a ‘‘knowledge server’’ (Eriksson 1996). Recently, researchers have begun to investigate the use of expert systems to assess damage assessment—for example, Yao (1980), Ishizuka et al. (1982), Ogawa et al. (1985a,b), Furuta et al. (1991, 1996), Ross et al. (1990), Hadipriono and Ross (1991), Shiraishi et al. (1991), Krauthammer et al. (1992), Miyamoto et al. (1993), and Kushida et al. (1997).

Several important issues need to be addressed in using expert systems for damage assessment of bridges:

- The descriptions of heuristic damage assessment knowledge by experts usually take the form of natural language that contains intrinsic imprecision. For example, experts may treat the extent, degree, and seriousness of a defect as linguistic variables that have fuzzy values. Therefore, a mechanism that can cope with imprecise information in expert system is essential.
- Uncertain and imprecise information involved in the damage assessment usually makes the problem harder. Therefore, a reasoning mechanism that can deal with uncertain and imprecise information is crucial for damage assessment.
- To consider the efficiency of fuzzy rule based reasoning, it is important that fuzzy facts (input or inferred) find the matched fuzzy rules efficiently, rather than scanning through all the fuzzy rules.
- In order to increase the confidence about the assessment results, an explanation facility that can describe how the conclusions are derived is instrumental for a computer-aided tool designed especially for damage assessment.

To address the first two issues, the writers have proposed a possibilistic logic based approach (Lee et al. 1998) to handling uncertain and imprecise information. The writers have also proposed a fuzzy Petri net approach to addressing the last two issues. The writers have proposed a framework of integrated expert systems based on proposed fuzzy Petri nets, called fuzzy Petri net based expert systems (FPNES) (Lee et al. 1999). This paper is aimed at developing an expert system for assessing bridges based on FPNES. Unlike other researchers’ systems, our expert system does not impose any restriction on the inference mechanism, that is, the intended meaning is not required to be intact; meanwhile, the confidence level can be partially certain. Furthermore, it offers more informative results because the explanation provided in the system and the confidence level of the conclusions can be used as a way of justification on whether to take the recommendations into account or not. An application to the damage assessment of the Da-Shi bridge in Taiwan is used as an illustrative example of FPNES. The result through FPNES not only matches the ex-

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perts' judgments, but also provides more information than experts do.

FUZZY PETRI NET BASED EXPERT SYSTEM

FPNES, a framework of integrated expert systems based on the proposed fuzzy Petri net, has been proposed by Lee et al. (1999) and is briefly described in this section. Major features of FPNES include the ability to reason using uncertain and fuzzy information, explanation of the reasoning process through the use of hierarchical fuzzy Petri nets, and a reasoning mechanism based on fuzzy Petri nets.

REASONING FOR UNCERTAIN AND FUZZY INFORMATION

The distinction between imprecise and uncertain information can be best explained by the canonical form representation (i.e., a quadruple of attribute, object, value, and confidence) proposed by Dubois and Prade (1988). Imprecision implies the absence of a sharp boundary of the value component of the quadruple, whereas uncertainty is related to the confidence component of the quadruple, which is an indication of the reliability of the information.

To represent uncertain imprecise information, a fuzzy proposition with a fuzzy valuation has been chosen by Lee et al. (1998), denoted as

$$(r, \tau) \tag{1}$$

where r is fuzzy proposition of the form "X is F" [i.e., X is a linguistic variable (Zadeh 1975, 1976) and F is a fuzzy set in a universe of discourse U]; and τ is a fuzzy valuation. It should be noted that for every formula (r, τ) (called a truth-qualified fuzzy proposition), we assume τ is larger than or equal to $\tau(r|\pi)$ [i.e., $\tau(r|\pi)$ is the real fuzzy truth value derived from r and a possibility distribution π], which means $\mu_\tau(t)$ is the upper bound of the possibility that r is true to a degree t. The fuzzy set is to represent the intended meaning of imprecise information, while the fuzzy truth value serves as the representation of uncertainty for its capability to express the possibility of the degree of truth.

An inference rule for truth-qualified fuzzy propositions has been expressed as follows:

$$\begin{array}{c} (r_1 \wedge r_2 \wedge \cdots \wedge r_n) \rightarrow q, \tau_1 \\ r'_1, \tau_2 \\ r'_2, \tau_3 \\ \vdots \\ r'_n, \tau_{n+1} \\ \hline q', \tau_{n+2} \end{array} \tag{2}$$

where r_i, r'_i $(i = 1 \sim n)$, q, and q' are fuzzy propositions and characterized by "X_i is F_i," "X_i is F'_i" and "Y is G," "Y is G'," respectively; τ_j $(j = 1 \sim n + 2)$ are fuzzy valuations for truth values and defined by $\mu_{\tau_j}(t)$. F_i and F'_i are the subsets of U_i; G and G' are the subsets of V. There are three major steps for deriving q' and τ_{n+2} of (2):

- The fuzzy rules and fuzzy facts with fuzzy truth-values are transformed into a set of uncertain classical propositions with necessity and possibility measures.
- The possibilistic entailment is performed on the set of uncertain classical propositions.
- We reverse the process in the first step to synthesize all the classical sets obtained in the second step into a fuzzy set, and to compose necessity and possibility pairs to form a fuzzy truth-value.

Hierarchical Fuzzy Petri Nets

To increase the efficiency of rule based reasoning, two issues are particularly relevant: the possibility of exploiting concurrency, and the use of smart control strategies. To achieve these goals, the writers have proposed the use of fuzzy Petri nets to model fuzzy rule based reasoning (Lee et al. 1998). Furthermore, the explanation of how to reach conclusions is expressed through the movements of tokens in fuzzy Petri nets.

There are several rationales behind basing a computational paradigm for expert systems on Petri net theory. First, Petri nets achieve the structuring of knowledge within rule bases, which can express the relationships among rules and help experts construct and modify rule bases. Second, Petri nets' graphic nature provides the visualization of dynamic behavior of rule based reasoning. Third, Petri nets make it easier to design an efficient reasoning algorithm. Fourth, Petri nets' analytic capability provides a basis for developing a knowledge verification technique. Last, the underlying relationship of concurrency among rules activation can be modeled by Petri nets, which is an important aspect where real-time performance is crucial.

Fuzzy Petri Nets: Definition

A fuzzy Petri net *FPN* is defined as a quintuple:

$$FPN = (FP, UT, A, W, M_0) \tag{3}$$

where $FP = \{(p_1, F_1), (p_2, F_2), \ldots, (p_m, F_m)\}$ is a finite set of fuzzy places, where p_i represents a fuzzy condition and F_i is a fuzzy subset of U_i to represent the fuzzy set of the condition; $UT = \{(t_1, \tau_1), (t_2, \tau_2), \ldots, (t_n, \tau_n)\}$ is a finite set of uncertain transitions, where t_j represents the causal relationship of fuzzy conditions and τ_j is a fuzzy truth value to represent the uncertainty about the causal relationship of fuzzy conditions; A is a set of arcs; W is a weight function; and $M_0 = \{M(p_1), M(p_2), \ldots, M(p_m)\}$ is the initial marking, where $M(p_i)$ is the number of tokens in p_i.

Each token is associated with a pair of fuzzy sets (F'_i, τ_i) (called an uncertain fuzzy token). Fuzzy places with uncertain fuzzy tokens can be interpreted as uncertain fuzzy facts related to the fuzzy conditions modeled by the fuzzy places.

Fuzzy Rule Based Reasoning and Fuzzy Petri Nets

It is widely recognized that fuzzy Petri nets are a promising modeling mechanism for formulating fuzzy rule based reasoning. The three key components in fuzzy rule based reasoning —fuzzy propositions, fuzzy rules, and fuzzy facts—can be formulated as places, transitions, and tokens, respectively. The mapping between fuzzy rule based reasoning and fuzzy Petri nets has been made below.

- *Fuzzy places:* Fuzzy places correspond to fuzzy propositions. The fuzzy sets, attached to the fuzzy places, represent the values of fuzzy propositions. Fuzzy input and fuzzy output places of a truth-qualified transition are used to represent the antecedent and conclusions parts of a truth-qualified fuzzy rule, respectively.
- *Uncertain fuzzy tokens:* An uncertain fuzzy token represents a truth-qualified fuzzy fact. The fuzzy sets and fuzzy truth-values are attached to uncertain fuzzy tokens to represent the values and our confidence level about the observed facts, respectively.
- *Uncertain transitions:* Uncertain transitions are classified into four types: inference, aggregation, duplication, and aggregation-duplication transitions. The inference transitions represent the truth-qualified fuzzy rules; the aggre-

gation transitions are designed to aggregate the conclusion parts of rules that have the same linguistic variables; the duplication transitions are used to duplicate uncertain fuzzy tokens to avoid the conflict problem; and the aggregation-duplication transitions link the fuzzy propositions with the same linguistic variables. These have been formally defined below.

Type 1: Inference Transition (t^i). An inference transition serves as modeling of a truth-qualified fuzzy rule. A truth-qualified fuzzy rule having multiple antecedents is represented as

$$(r_1 \wedge r_2 \wedge \cdots \wedge r_n) \rightarrow q, \tau_1 \tag{4}$$

where r_i and q are of the forms of "X_i is F_i" and "Y is G," respectively. In Fig. 1, after firing the inference transition t_1^i, the tokens will be removed from the input places of t_1^i, a new token will be deposited into the output place of t_1^i, and the fuzzy set and the fuzzy truth value attached to the new token are derived by three steps: transformation, inference, and composition.

Type 2: Aggregation Transition (t^a). An aggregation transition is used to aggregate the conclusions of several truth-qualified fuzzy rules that have the same linguistic variable, and to link the antecedent of a truth-qualified fuzzy rule that also has the same linguistic variable. For example, there are m truth-qualified fuzzy rules having the same linguistic variable in the conclusions, denoted as

$$(r_1 \rightarrow q_{11}, \tau_1), (r_2 \rightarrow q_{12}, \tau_2), \cdots, (r_m \rightarrow q_{1m}, \tau_m) \tag{5}$$

where q_{1i} is "Y is G_{1i}." In Fig. 2, after firing the aggregation transition t_{m+1}^a, the tokens in input places of t_{m+1}^a will be removed, a new token will be deposited into the output place of t_{m+1}^a, and the fuzzy set and the fuzzy truth value attached to the new token are derived by three steps: transformation, aggregation, and composition.

Type 3: Duplication Transition (t^d). The purpose of duplication transitions is to avoid the conflict by duplicating the token. For example, there are l truth-qualified fuzzy rules having the same linguistic variable in the antecedents, denoted as

$$(r_{11} \rightarrow q_1, \tau_1), (r_{12} \rightarrow q_2, \tau_2), \cdots, (r_1 \rightarrow q_{1l}, \tau_l) \tag{6}$$

where r_{1i} means "X_i is F_{1i}." They are linked by a duplication transition shown in Fig. 3. After firing the duplication transi-

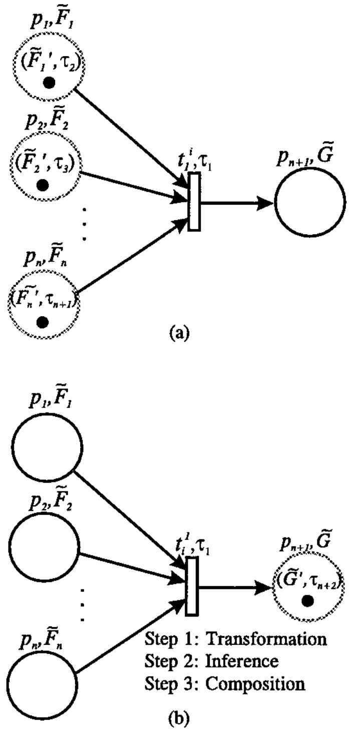


FIG. 1. Modeling Fuzzy Rule Based Reasoning through Fuzzy Petri Nets (a) before Firing Inference Transition t_1^i; (b) after Firing t_1^i

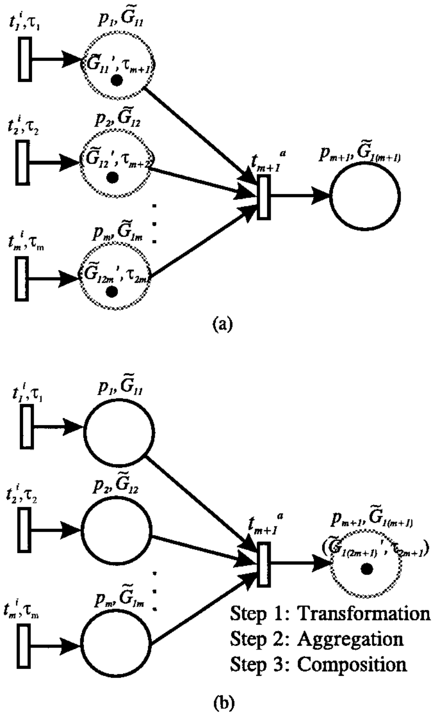


FIG. 2. Modeling Aggregation of Conclusions by Aggregation Transition (a) before Firing t_{m+1}^a; (b) after Firing t_{m+1}^a

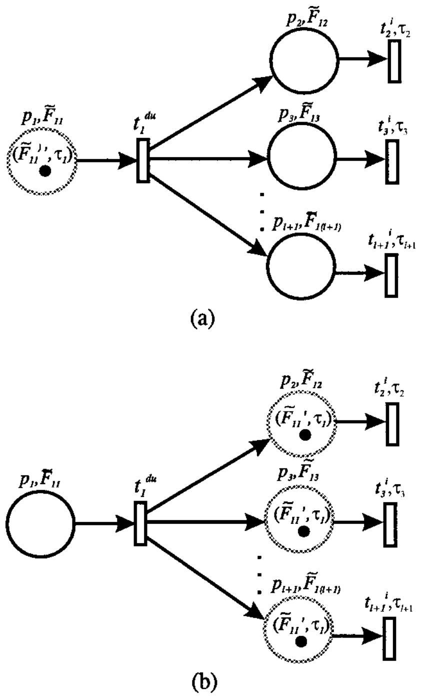


FIG. 3. Modeling Duplication of Uncertain Fuzzy Token through Fuzzy Petri Nets (a) before Firing Duplication Transition t_1^d; (b) after Firing t_1^d

tion t_1^d, the tokens in the input place of t_1^d will be removed, new tokens will be added into the output places of t_1^d, and the fuzzy sets and the fuzzy truth values attached to the new tokens are not changed.

Type 4: Aggregation-Duplication Transition (t^{ad}). An aggregation-duplication transition is a combination of an aggregation transition and a duplication transition. It is used to link all fuzzy propositions that have the same linguistic variable. For example, there are *m* truth-qualified fuzzy rules having a same linguistic variable in the conclusions and *l* truth-qualified fuzzy rules having the same linguistic variable in the antecedents, denoted as

$$(r_1 \to q_{11}, \tau_1), (r_2 \to q_{12}, \tau_2), \cdots, (r_m \to q_{1m}, \tau_m) \qquad (7a)$$

$$(q_{1(m+1)} \to s_1, \tau_{m+1}), q(_{1(m+2)} \to s_2, \tau_{m+2}), \cdots,$$

$$(q_{1(m+1)} \to s_1, \tau_{m+1}) \qquad (7b)$$

where s_i means "*Z* is H_i." They are linked by an aggregation-duplication transition shown in Fig. 4. After firing the aggregation-duplication transition t_1^{ad}, the tokens in the input places of t_1^{ad} will be removed, new tokens will be deposited into the output places of t_1^{ad}, and the fuzzy sets and the fuzzy truth values attached to the new tokens are derived by three steps: transformation, aggregation, and composition.

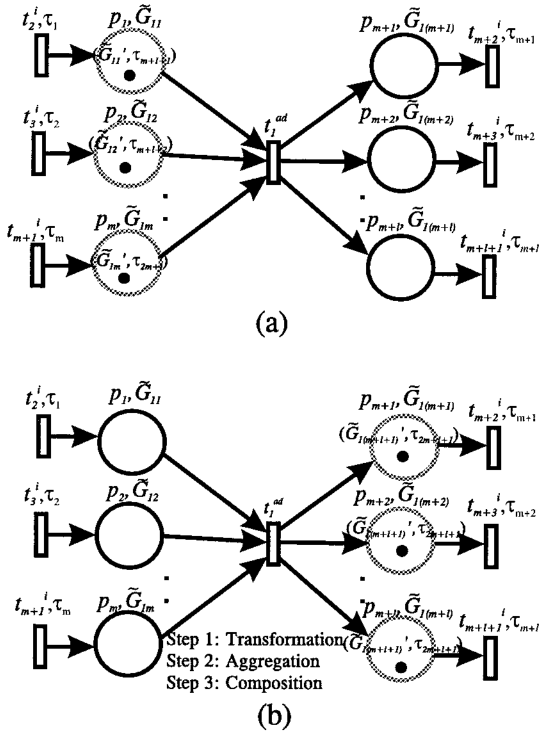
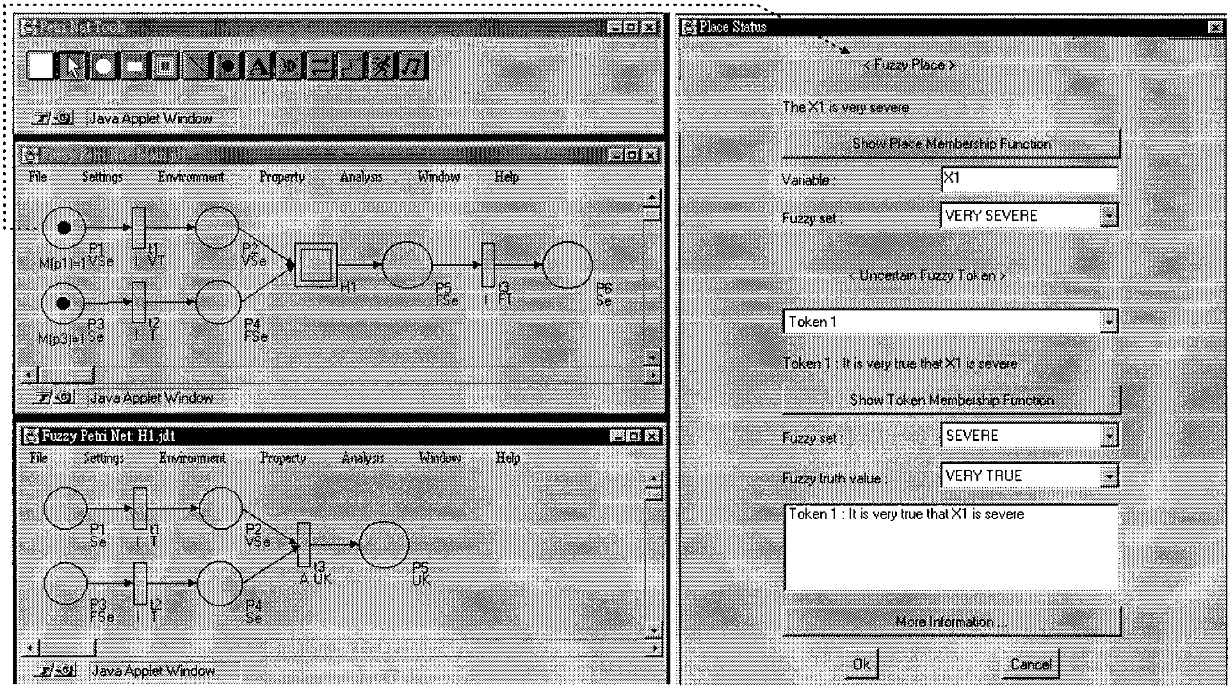


FIG. 4. Modeling Aggregation-Duplication of Uncertain Fuzzy Token through *FPN* (a) before Firing Aggregation-Duplication Transition t_1^{ad}; (b) after Firing t_1^{ad}

Hierarchical Fuzzy Petri Nets

To overcome the complexity arising from large sizes of rule bases and fuzzy Petri nets, two important features, modularized rule bases and hierarchical fuzzy Petri nets, have been adopted in FPNES. Modularization is used to partition rule bases into smaller parts for organizing rules. In a hierarchical fuzzy Petri net, each hierarchy contains a fuzzy Petri net that may or may not contain other hierarchies. The connections between hierarchies are achieved by defining importing and exporting fuzzy places (Fig. 5). That is, an exporting fuzzy place with respect to a hierarchy is defined as a fuzzy place that is connected to the hierarchy by an arc from the fuzzy place to the hierarchy; an importing fuzzy place with respect to a hierarchy is defined as a fuzzy place connected to the hierarchy by an arc from the hierarchy to the fuzzy place. In a graphical representation, a hierarchy is drawn as a double-lined square to connect the importing or exporting fuzzy places. A hierarchical fuzzy Petri net that contains a main hierarchy *H*0 and hierarchy *H*1 is illustrated in Fig. 5(a). The status of the fuzzy place *P*1 in Fig. 5(a) is shown in Fig. 5(b). In this figure, the fuzzy Petri net in the middle window is the main hierarchy at the top level of the hierarchical structure,



< Fuzzy Place >

The X1 is very severe

Variable : X1

Fuzzy set : VERY SEVERE

< Uncertain Fuzzy Token >

Token 1

Token 1 : It is very true that X1 is severe

Fuzzy set : SEVERE

Fuzzy truth value : VERY TRUE

Token 1 : It is very true that X1 is severe

(a) (b)

FIG. 5. (a) Hierarchical Fuzzy Petri Net; (b) Place Status for *PI* in *Ho*

and the fuzzy Petri net in the bottom window is hierarchy $H1$ at the second level. In $H0$, fuzzy places $P2$ and $P4$ are the exporting fuzzy place with respect to hierarchy $H1$, and fuzzy place $P5$ is the importing fuzzy places with respect to hierarchy $H1$. In the hierarchy $H1$, fuzzy places $P1$ and $P3$ are the importing fuzzy places with respect to $H0$, and fuzzy place $P5$ is the exporting fuzzing place with respect to $H0$. When a token is inserted into the fuzzy place $P2$ in $H0$, it will be transited into hierarchy $H1$ and added to place $P1$ in hierarchy $H1$. Similarly, once a token enters into place $P4$ in $H0$, it will be sent into hierarchy $H1$ and reaches the fuzzy place $P3$ in $H1$. After firing transition $t1$, $t2$, and $t3$ in hierarchy $H1$, the token arrives the fuzzy place $P5$ in $H1$ and then enters the fuzzy place $P5$ in $H0$.

There are two main benefits by having a hierarchical structure in the system: (1) the notion of hierarchy makes easy the handling of complex systems through decomposition; and (2) a hierarchical Petri net facilitates the reusability, that is, each hierarchy can be considered as a reuse unit.

Transforming Modularized Fuzzy Rule Bases into Hierarchical Fuzzy Petri Nets

The explanation of how to reach conclusions is expressed through the movement of tokens in hierarchical fuzzy Petri nets. The first step toward this goal is to transform modularized fuzzy rule bases into hierarchical fuzzy Petri nets. To bridge the gap between fuzzy rule based expert systems and fuzzy Petri nets, it is important to have a mechanism to automatically transform modularized fuzzy rule bases into hierarchical fuzzy Petri nets. In our earlier paper (Lee et al. 1999), two algorithms have been involved in the transformation. One is to transform modularized fuzzy rule bases into a hierarchical incidence matrix. The other is to transform the hierarchical incidence matrix into a hierarchical fuzzy Petri net.

Reasoning Mechanism Based on Fuzzy Petri Nets

To consider the efficiency of fuzzy rule based reasoning, it is crucial that fuzzy facts (input or inferred) find the matched fuzzy rules efficiently, rather than scanning through all the fuzzy rules. Fuzzy Petri nets offer an opportunity to achieve this goal by using transitions and arcs to connect fuzzy rules as a net based structure. A data-driven reasoning algorithm has been developed by the writers; for details about the reasoning algorithm, see Lee et al. (1998).

Overview of FPNES Tool

FPNES has been implemented in Java with a client-server architecture, encompassing four main parts: fuzzy Petri net system (FPNS), user interface, transformation engine, and knowledge bases (Fig. 6). Java has been adopted as the programming language for the FPNES tool for its capability of running on multiple platforms through the Internet.

FPNS is a modeling and analysis tool for fuzzy Petri nets, and serves as an inference engine, and explanation facility in FPNES. FPNS mainly contains the simulator and analyzer for fuzzy Petri nets. It provides the basic constructs for hierarchical fuzzy Petri nets (e.g., hierarchies, fuzzy places, uncertain transitions, arcs, and uncertain fuzzy tokens). After judging the firing conditions, the simulator will compute the fuzzy sets and move tokens. The analyzer performs the tasks of analyzing the properties of fuzzy Petri nets, such as incidence matrix, reachability trees, and state equations.

Users can edit modularized fuzzy Petri rule bases in the client site, including the assignments of linguistic variables, truth-qualified fuzzy rules, the relationship of modules, and modularized structures of input facts. When users finish editing the modularized fuzzy rule bases and the corresponding facts, and decide to run them, the data is then sent to the transformation engine and transformed to a hierarchical fuzzy Petri net in FPNS. After FPNS processes the hierarchical fuzzy Petri net with the aid of the reasoning algorithm, it sends the results back to users. The results are presented in a hierarchical fashion to provide a flexible explanation facility.

DAMAGE ASSESSMENT

To develop our modularized rule bases for damage assessment of bridges, we define the scope of knowledge domain,

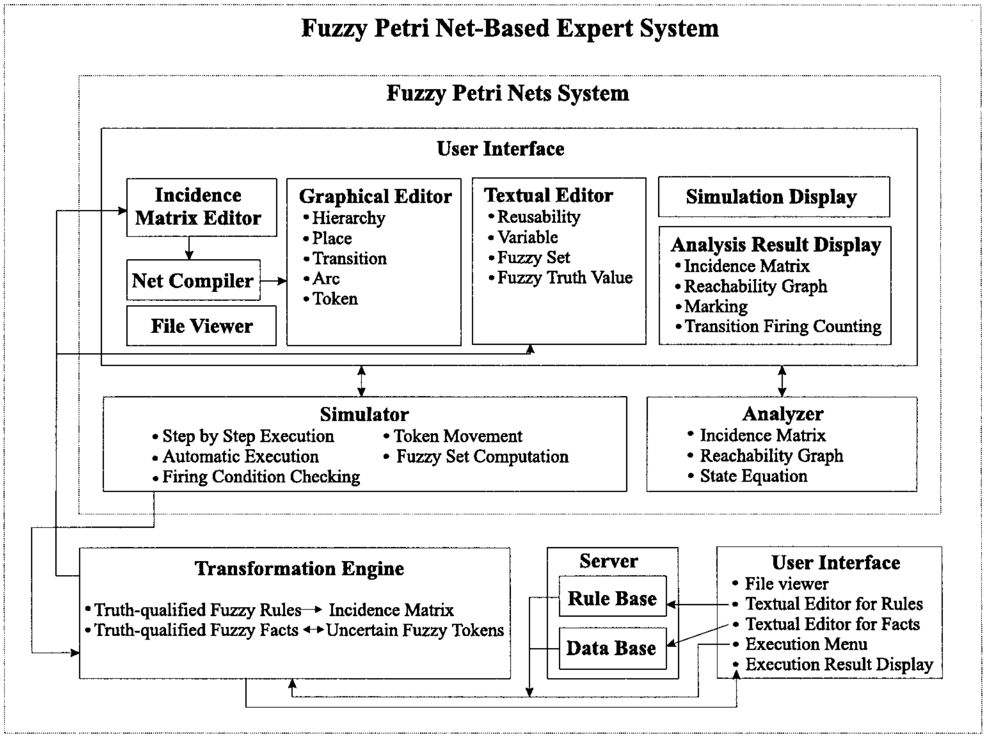


FIG. 6. Overview of FPNES Tool

describe the process of linguistic assessment, and discuss how to construct the modularized rule bases.

Knowledge Domain

The type of defects that could occur in a bridge depends upon the construction materials, environmental conditions, and external loadings. Nowadays, prestressed concrete bridges are widely used in Taiwan. However, some of them become implicit threats to the public because they have served for a long period of time and lots of defects are developing. To start with, the scope of the system is limited to (1) the concrete bridges that have prestressed concrete I-girders and hammerhead piers; and (2) the defects that occur most commonly and influence the load-carrying capacity.

Linguistic Assessment

In order to keep a bridge functioning, each component serves several functions to meet demands such as traffic loading, earthquakes, erosion, and environmental corrosion. Based on the observed defects, an expert can identify what kind of function is insufficient, judge the effect, and determine the damage level. The inference procedure for experts to assess bridge damage is described as follows:

1. A team of inspectors visually investigates each component of a bridge and records the observed defects, such as cracking, delamination, spalling, honeycomb, efflorescence, corrosion, and movement.
2. Based on the defect symptoms, such as locations and patterns, experienced bridge engineers can identify the possible causes of the defects.
3. The possible causes can induce what kinds of functions are eliminated due to the defects.
4. The damage level of each defect is evaluated according to the quantitative description of its symptoms.
5. The levels of functional insufficiency are inferred based on the damage levels of the defects.
6. The assessment of damage can be estimated by aggregating both the functional insufficiency and its levels.

The expression of observed defects by inspectors is viewed as the input of the system. Defects affecting the load-carrying capacity of bridges include (1) concrete discontinuities caused by overloadings, such as shear or flexure cracks, delaminations, and spalls; (2) component displacements such as rotational movement and settlement; and (3) soil scours due to rushing flood. Various patterns and locations of the defects are used to determine the possible causes and effects on the functionality, and the magnitude of each defect relates to the level of damage.

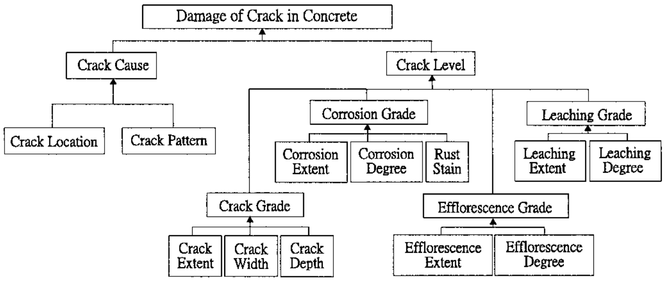


FIG. 7. Factors Related to Cracking in Concrete

The level of damage, severity of defects, and intensity of confidence about descriptions are expressed linguistically and are considered as linguistic variables. The severity of damage in terms of linguistic variables is classified into seven fuzzy levels, such as (1) very severe [i.e., $\mu(x) = x^8$]; (2) severe [i.e., $\mu(x) = x^4$]; (3) fairly severe [i.e., $\mu(x) = x^2$]; (4) fair [i.e., $\mu(x) = x$]; (5) fairly slight [i.e., $\mu(x) = x^{1/2}$]; (6) slight [i.e., $\mu(x) = x^{1/4}$]; and (7) very slight [i.e., $\mu(x) = x^{1/8}$], where x is a real number between zero and one, and denotes the degree of damage. The intensity of confidence about rules or facts is also considered in terms of linguistic variables with values such as (1) very true [i.e., $\mu(t) = t^2$]; (2) true [i.e., $\mu(t) = t$]; (3) fairly true [i.e., $\mu(t) = t^{1/2}$]; (4) fairly false [i.e., $\mu(t) = (1 - t)^{1/2}$]; (5) false [i.e., $\mu(t) = 1 - t$]; (6) very false [i.e., $\mu(t) = (1 - t)^2$]; and (7) unknown [i.e., $\mu(t) = 1$], where t is a real number between zero and one, and denotes the degree of truth.

Modularized Rule Bases

Crack, delamination, spalling, movement, and scour are five main defects in our system. Cracking is the most common defect and can be discovered in any kind of concrete structure. Its location and pattern are used to determine whether a crack affects the load-carrying capacity. The level of severity of a crack should not be determined directly without full consideration of the factors involved. the factors could include but are not necessarily limited to those shown in Fig. 7, and the related fuzzy rules of module ''crack in I-girder'' are presented in Fig. 8. Delamination is separation along a plane nearly parallel to the surface of the concrete. Spalling is a depression resulting from the dislodgment surface of concrete. It is typically found in old concrete structures and not in young concrete. Before developing into a depression, spalling may be presented as a delamination below the concrete surface. Sometimes it is as deep as the reinforcing steel.

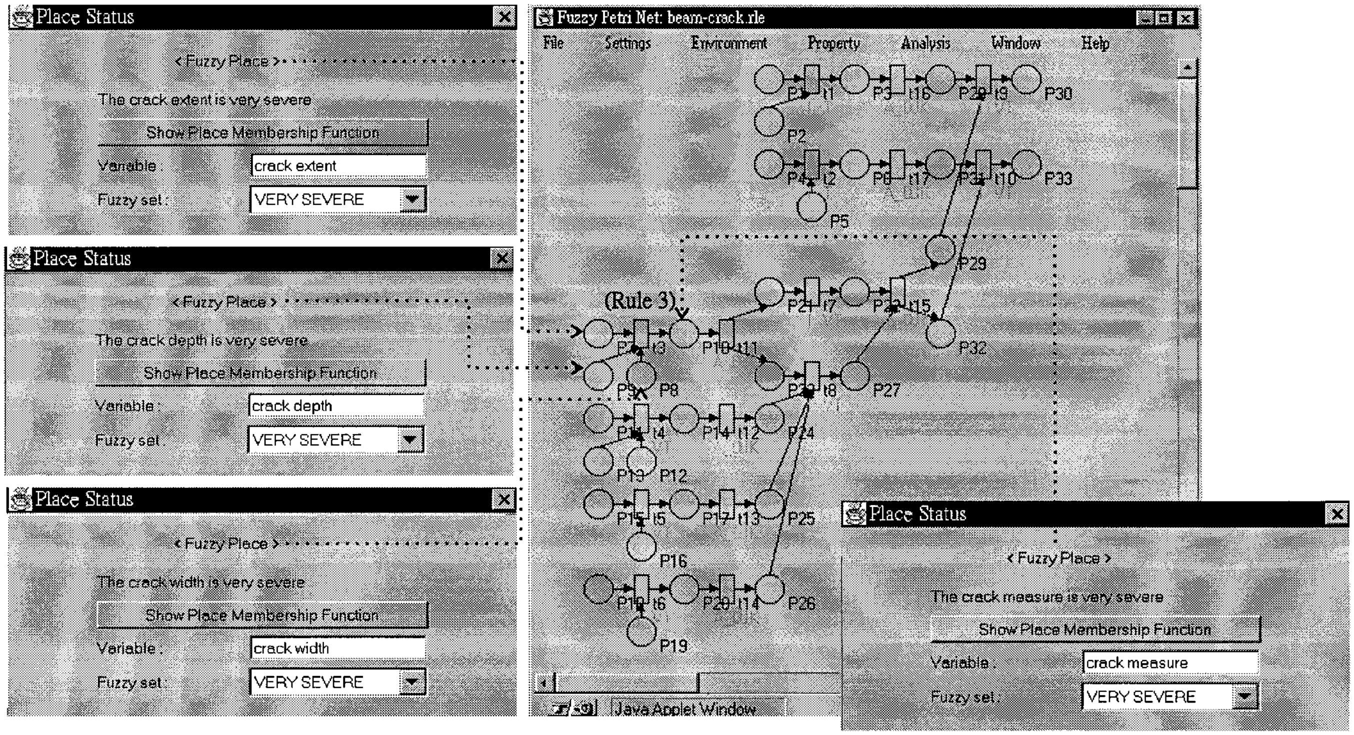
Vertical movement such as differential settlement can produce serious distress in a bridge structure. Rotational movement of substructure can be considered to be the result of unsymmetrical settlement or lateral movements. Piers, abutments, and walls may undergo this type of movement. The degree of damage depends on the extent of vertical and rotational movement. The recommendation of strengthening or repairing is based on the possible cause. Scour of the substructure support is one of the more frequent factors that may cause or lead to structural failure or foundation distress. Scour is the removal of the streambed, backfill, slopes, or other supporting material, by stream tidal action, dredging, propeller backwash, etc. The degree of damage depends on the extent of exposure of foundation and the extent of deterioration of foundation.

⋮

Rule 3: IF crack extent is very severe AND crack width is very severe AND crack depth is very severe
THEN crack measure very severe, very true
Rule 4: IF corrosion extent is very severe AND corrosion degree is very severe AND rust stain is very severe
THEN corrosion grade is very severe, very true
Rule 5: IF efflorescence extent is very severe AND efflorescence degree is very severe
THEN efflorescence grade is very severe, very true
Rule 6: IF leaching extent is very severe AND leaching degree is very severe THEN leaching grade is very severe, very true

⋮

FIG. 8. Part of Rule Base for Crack in I-Girder



< Fuzzy Place >

The crack extent is very severe

Variable : crack extent

Fuzzy set : VERY SEVERE

< Fuzzy Place >

The crack depth is very severe

Variable : crack depth

Fuzzy set : VERY SEVERE

< Fuzzy Place >

The crack width is very severe

Variable : crack width

Fuzzy set : VERY SEVERE

< Fuzzy Place >

The crack measure is very severe

Variable : crack measure

Fuzzy set : VERY SEVERE

FIG. 9. Fuzzy Rule Petri Net Transformed from Rule Base of Crack in I-Girder

The whole rule base is subdivided into a lot of modules in order to overcome the complexity arising from too large sizes of the rule bases and to make the rules well organized. At present there are 34 modules in this system, in which 216 truth-qualified fuzzy rules and 224 recommendations are included. Seven modules related to the cracking in concrete, five modules dealing with the delamination in concrete, five modules concerning the spalling in concrete, two modules about the movement of foundation, and two modules handling to the scour of support are constructed. Furthermore, two modules are used to evaluate the insufficiency of shear or flexure resistance, and 11 modules are used to assess the damage levels of components; 216 truth-qualified fuzzy rules and 224 recommendations are accommodated in these modules. As was mentioned previously, fuzzy Petri nets' graphical representation can help us construct and modify fuzzy rule bases. Fig. 9 shows the fuzzy Petri nets after the transformation of the rule bases of a crack in an I-girder.

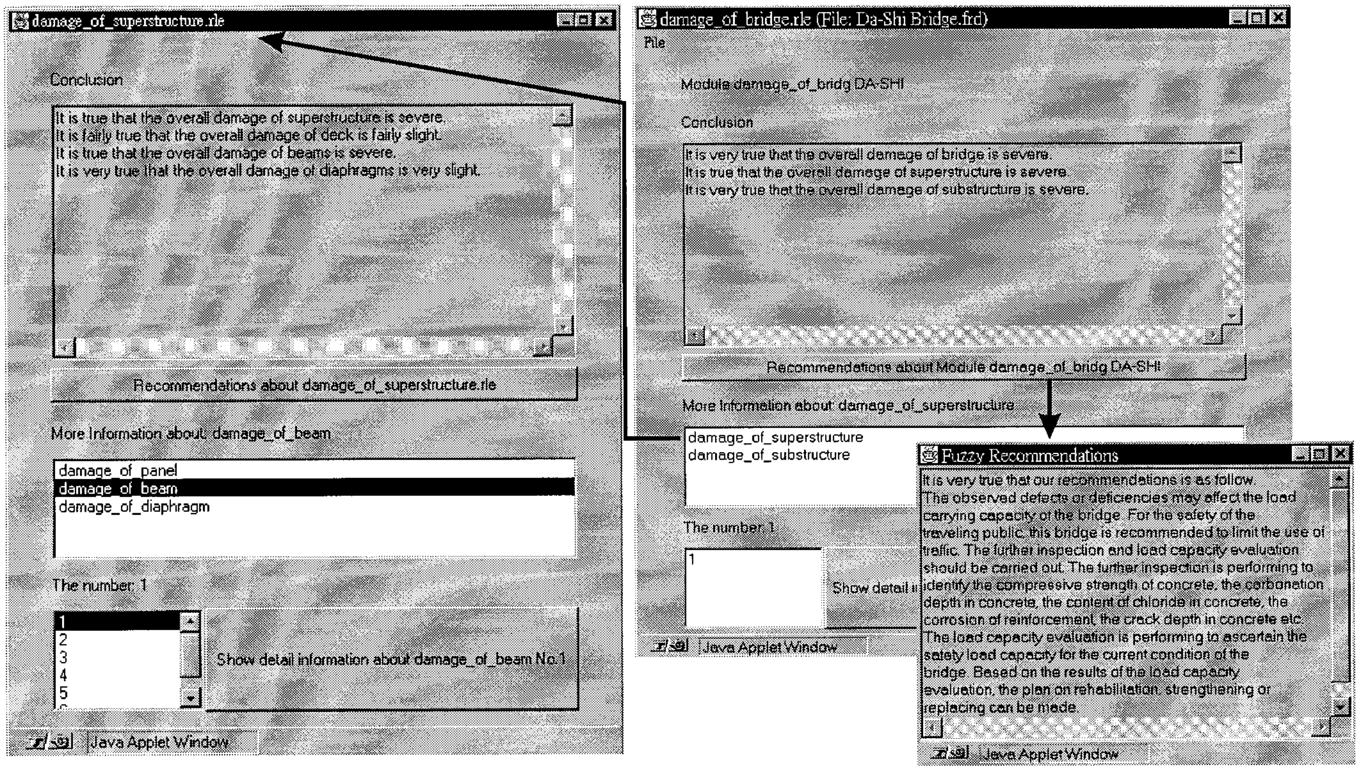
EXAMPLE

To demonstrate the use of FPNES, the Da-Shi bridge located in northern Taiwan was considered. It was rebuilt in 1960 as a simply supported, 12-spanned bridge, 550 m long and 7.8 m wide, across the Da-Han river. This bridge consists of 12 decks, 36 prestressed concrete I-girders, 120 diaphragms, 11 piers, and two abutments.

In 1997, this bridge was inspected by the Center of Bridge Engineering Research at National Central University. Visual inspection revealed that many minor cracks accompanied with efflorescence spread over eight panels within deck 7. The PCI girders S9G1, S9G2, S9G3 in span 9 and S10G1, S10G2, S10G3 in span 10 had severe flexure, shear cracks, and some spalls. There were two diaphragms where several spalls were found. The foundations of piers P1 to P6 were exposed up to 5 m above the ground level, and some of them suffered severe spalling. Furthermore, pier 2 had rotational movement.

After executing FPNES for damage assessment of the Da-Shi bridge, the hierarchical fuzzy Petri nets were constructed based on the modularized rule bases, and uncertain fuzzy tokens were transformed into these nets in order to fire transitions and perform the reasoning mechanism. The results of damage assessment using FPNES for the Da-Shi bridge were expressed in a hierarchical fashion to serve as an explanation mechanism to facilitate the retrieval of detailed information on damaged components from the top down to lower levels (Fig. 10). The recommendations embedded in rule bases were also provided on an if-needed basis. As a result, the damage to the Da-Shi bridge was evaluated to be severe with strong confidence (i.e., very true) since the overall damage to the superstructure was severe with common confidence (i.e., true) and the overall damage to the substructure was also severe with strong confidence (i.e., very true). The severity of superstructure results from the overall damage to decks was fairly slight with fair confidence (i.e., fairly true), the overall damage to I-girders was severe with common confidence (i.e., true), and the overall damage to diaphragms was very slight with strong confidence (i.e., very true). Meanwhile, the severity of substructure as derived from the overall damage of piers was severe with strong confidence (i.e., very true). The FPNES results not only match the experts' judgments, but also provide more information than experts do, because the explanation provided in the system and the confidence level associated with the conclusions can be used to justify whether to take the recommendations into account.

The following recommendations were made with strong confidence (i.e., very true). The observed defects or deficiencies may affect the load-carrying capacity of the bridge. For the safety of the traveling public, traffic on the bridge should be limited. A second inspection and load capacity evaluation should be made. The second inspection is used to identify the compressive strength of concrete, the carbonation depth in concrete, the content of chloride in concrete, the corrosion of reinforcement, the crack depth in concrete, etc. The load capacity evaluation is performed to ascertain the safety load capacity for the current condition of the bridge. Based on the results of the load capacity evaluation, a plan can be made for rehabilitating, strengthening, or replacing the bridge.



It is true that the overall damage of superstructure is severe.
It is fairly true that the overall damage of deck is fairly slight.
It is true that the overall damage of beams is severe.
It is very true that the overall damage of diaphragms is very slight.

It is very true that the overall damage of bridge is severe.
It is true that the overall damage of superstructure is severe.
It is very true that the overall damage of substructure is severe.

It is very true that our recommendations is as follow.
The observed defects or deficiencies may affect the load carrying capacity of the bridge. For the safety of the traveling public, this bridge is recommended to limit the use of traffic. The further inspection and load capacity evaluation should be carried out. The further inspection is performing to identify the compressive strength of concrete, the carbonation depth in concrete, the content of chloride in concrete, the corrosion of reinforcement, the crack depth in concrete etc. The load capacity evaluation is performing to ascertain the safety load capacity for the current condition of the bridge. Based on the results of the load capacity evaluation, the plan on rehabilitation, strengthening or replacing can be made.

FIG. 10. Results of Damage Assessment for Da-Shi Bridge Using FPNES

CONCLUSION

This research has resulted in the development of a fuzzy Petri net based expert system (FPNES) for bridge damage assessment, which contains a reasoning mechanism to deal with uncertain and imprecise information, a fuzzy Petri nets approach to modeling fuzzy rule based reasoning, and a tool supporting the damage assessment of bridges. Unlike other researchers' systems, our expert system does not impose any restriction on the inference mechanism, that is, the intended meaning is not required to be intact; meanwhile, the confidence level can be partially certain. Furthermore, it offers more informative results because the explanation provided in the system and the confidence level of the conclusions can be used to justify whether to take the recommendations into account. An application to the damage assessment of the Da-Shi bridge in Taiwan is used as an illustrative example of FPNES. The FPNES results not only match the experts' judgments, but also provide more information than experts do.

Future research will consider issues related to damage assessments that remain to be addressed further: (1) how to enhance FPNES to involve numerical data such as earthquake records, experimental results, and load testing information; and (2) how to integrate the numerical data and linguistic assessment into an overall evaluation.

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APPENDIX I. REFERENCES

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APPENDIX II. NOTATION

The following symbols are used in this paper:

A = set of arcs;
F, G = fuzzy set;
FP = finite set of fuzzy places;
FPN = fuzzy Petri net;
H = hierarchy;
M_0 = initial marking;
$M(p_i)$ = number of tokens in p_i;
p = fuzzy place;
p_i = fuzzy condition;
q, r, s = fuzzy proposition;
t = truth degree;
t_j = causal relationship of fuzzy conditions;
t^a = aggregaton transition;
t^{ad} = aggregation-duplication transition;
t^d = duplication transition;
t^i = inference transition;
U, V = universes of discourse;
UT = finite set of uncertain transitions;
W = weight function;
X, Y, Z = linguistic variable;
$\mu(x)$ = membership function;
π = possibility distribution; and
τ = fuzzy truth value.