Problem-oriented Decision Support in Manufacturing Industry

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Abstract. Decision-making in manufacturing organizations involves detecting and attacking problems continuously and hence requires very large volumes of problem-oriented knowledge. This paper firstly analyzes the features of problem knowledge and proposes a series of knowledge-based reasoning rules to yield knowledge from original problem evidence. Then a reasoning mechanism controlling the reasoning process is established on the basis of these rules and embedded to a knowledge-based decision support system (KB-DSS) .The problem-oriented KB-DSS can support the interactive analysis of problems and interpret reasoning results in a format understandable and useful for decision-making process. This combination of problem-oriented knowledge reasoning and traditional decision support system provides useful and effective approaches for management practice in manufacturing industry.

Introduction

As the decision environment of 21 century promises to become more complex because of the large number of factors involved, the uncertain relationships among factors and a host of other issues, decision-making in organizations have always been difficult and messy[1]. In this situation, model management systems and knowledge- based decision support systems (KB-DSS), based on theories and methods from artificial intelligence and expert systems are developed to provide smart support for decision- makers [2]. The KB-DSS is now evolving into a border notion of DSS serving as knowledge sources connecting decision-makers with diverse knowledge.

Different kinds of control mechanism have been established in DSS relying on different requirements in decision-making. The early DSS is mostly probability controlled, which requires large sample sets and high computational cost [3].With the development of artificial intelligence, a new mechanism is developed without knowledge input by users and relies on machine learning to acquire knowledge from a large number of instances automatically, some popular algorithms is involved such as Bayesian network, support vector machines and similarity-based algorithms [4]. However, this kind of mechanism cannot provide intelligible explanations for users [5]. Later, a new DSS control mechanism based on reasoning rules emerges in which rules are mapped to state space graph searching and have strong explanatory ability. As the traditional reasoning rules have weak knowledge structural features and be restricted to linear reasoning, in this paper a series of reasoning rules are proposed which is combined with the graph-searching in knowledge model and hence are highly structured and versatile [6,7,8].

This paper is organized as follows. Section 2 elaborates the reasoning rules and control mechanism in detail. Section 3 establishes a KB-DSS and demonstrates an example. The conclusions are presented in Section 4.

Control Mechanism of Knowledge Reasoning

The knowledge of problems and the causalities between problems is a kind of uncertain knowledge. For example in the stamping process of car manufacturing, the product defects are

probably caused by defective raw material, the life expectancy of equipment ,so the reasons to production problems are uncertain[9,10]. In real world, there are probably a bunch of reasons leading to one question, i.e. the causalities of a certain question are uncertain.

This paper introduces a kind of structure to depict uncertainty of causalities called casual net. A simple example of causal net is shown as Fig 1. In this structure, the circle node V_j represents the questions and the triangle node r_i represents causality among questions. So Fig.1 expresses the cause-effect relationship between questions $\{V_o, V_1\}$ and questions $\{V_2, V_3\}$, this kind of causality is denoted as $\{r_1\}$.
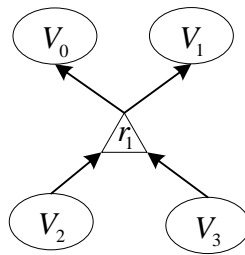

Fig.1 Causality Structure

In this structure, the causality nodes can depict the causality independently and therefore make implicit knowledge of causalities explicit. A problem space restoring all possible causalities in a certain fields is available with this structure [11, 12].

Rule-based knowledge reasoning can be described as a process of starting from the original data, executing the production rules in the knowledge casual net and yielding some conclusions or performing some actions.

The formulation of production rules is: Antecedent→Consequent. The antecedents are the premises of rules and the consequents are the conclusions or actions of rules [7].

To generate reason explanations from original problem data, this paper establishes a series of reasoning rules to realize searching in the causal net and get available conclusions.. These rules controlling the knowledge reasoning process comprise the whole reasoning mechanism in knowledge-based decision support system.

The reasoning rules are presented as follows.

rule 1:

$$\text{IF } < r_i, V_j >=1 \quad \text{THEN} \quad R(r_i) = 1 \text{ ELSE} \quad R(r_i) = 0 \; ; i = 1,2,\dots,k_0 \quad (1\text{-}1)$$
$$\text{IF } R(r_i) = 1 \quad \text{THEN} \quad \text{Compose } r_i \text{ into } S_1 ; \quad i = 1,2,\dots,k_0 \quad (1\text{-}2)$$
$$\text{IF } R(r_i) = 0 \quad \text{THEN} \quad \text{DEL}(r_i) ; \quad i = 1,2,\dots,k_0 \quad (1\text{-}3)$$

(i) $< r_i, V_j >$ -computed as the value of vector from r_i to V_j. It is mapped to the directed edge pointing from causality nodes r_i to question node V_j in the causal net;

(ii) $R(r_i)$-computed as the relevancy of causality nodes r_i to question node V_j according to the value of $< r_i, V_j >$.

Compose causality nodes r_i into set S_1 whose value of R is 1, i.e. $S_1 = \{r_i || R(r_i) = 1\}$.

Executing rule 1 will traverse the whole causal net to search all related causality nodes r_i to question node V_j and obtain the structure of V_j in the causal net displayed in Fig.2.
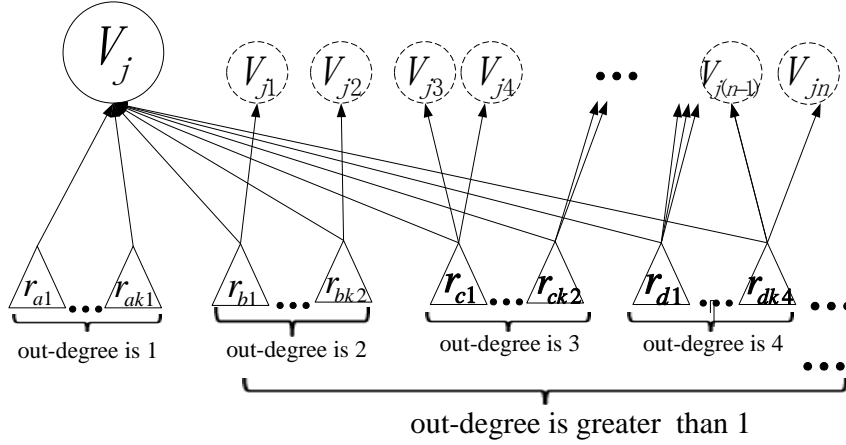
Fig.2 Structure of Question V_j

rule 2:

IF $M(r_{i\prime}) = 1$ THEN $SM(r_{i\prime}) = 1$ELSE $SM(r_{i\prime}) = 0$; $i\prime = 1,2, \ldots, k_1$ (2-1)
IF $SM(r_{i\prime}) = 1$ THEN Compose $r_{i\prime}$ into S_2 ; $i\prime = 1,2, \ldots, k_1$ (2-2)
IF $SM(r_{i\prime}) = 0$ THEN Compose $r_{i\prime}$ into S_3 ; $i\prime = 1,2, \ldots, k_1$ (2-3)

(i) $M(r_{i\prime})$ - computed as the out-degree of causality nodes $r_{i\prime}$;

(ii)$SM(r_{i\prime})$ -computed as the structural match degree of causality nodes $r_{i\prime}$ to question node V_j;

Executing rule 2 will calculate $SM(r_{i\prime})$ of causality node $r_{i\prime}$ according to its out-degree $M(r_{i\prime})$. If $M(r_{i\prime})$ is 1, it means the causality node $r_{i\prime}$ has causality only with question V_j and we consider it completely structural matched with question V_j, so we set its SM as 1. And if $M(r_{i\prime})$ is not 1, it means the causality node $r_{i\prime}$ has causality with other potential question besides V_j, so we set SM as 0, i.e. the causality node $r_{i\prime}$ is not 100% structural matched with question V_j. Then compose causality nodes $r_{i\prime}$ into set S_2 whose value of SM is 1, i.e.$S_2 = \{r_{i\prime} || SM(r_{i\prime}) = 1\}$. Compose causality nodes $r_{i\prime}$ into set S_3 whose value of SM is 0, i.e.$S_3 = \{r_{i\prime} || SM(r_{i\prime}) = 0\}$.

rule 3:

IF $P(r_i) > P(r_j)$ THEN $Rank(r_j) > Rank(r_j)$

(i) $P(r_j)$ - computed as the casual strength of causality nodes r_j ;

In the perspective of probability of frequency, the parameter $C(r_j)$ which represents the frequency of causality r_j in historical records can be an indicator to depict the probability. So in a complete event group comprised of causality nodes $\{r_1, r_2, \ldots r_i, \ldots, r_k\}$, the probability of element r_j is computed as formula (1).

$$P(r_j) = \frac{c(r_j)}{\sum_1^k c(r_j)} \ . \tag{1}$$

(ii) $Rank(r_j)$ – computed as the rank of causality nodes r_j ;

Executing rule 3 will rank the elements in set S_2 and S_3 according to their casual strength and form set S_2' and S_3' respectively.

rule 4:

IF $R'(V_{j\prime}) = 1$ THEN Compose $V_{j\prime}$ into S_2''; $j\prime = 1,2, \ldots, k_2$ (4-1)
IF $R'(V_{j\prime}) = 0$ THEN DEL $(V_{j\prime})$; $j\prime = 1,2, \ldots, k_2$ (4-2)

$R'(V_{j\prime})$ – computed as the relevancy of question node $V_{j\prime}$ to causality nodes r_k

The following three steps illustrate the procedure of executing rule 4.

Step1. Select the kth element i.e. causality node r_k in set S_2';

Step2. Compute the value of $R'(V_{j'})$ according to the value of vector $< V_{j'}, r_k >$;

Step3. Compose question node $V_{j'}$ into set S_2'' if the value of $R'(V_{j'})$ is 1.

The elements in set S_3' are the reason explanations to question V_j yielded by rules executing presented above. And it would be provided to the users as decision supports. According to real effect (whether it can support reason analyzing for certain question $V_{j'}$), rule 5 will be chosen to execute on S_3' in the control mechanism.

rule 5:

$$\text{IF } R(r_{k'}) = 1 \text{ AND } < V_{j''}, r_{k'} > = 1 \text{ AND } r_{k'} \in S_3'$$

$$\text{THEN } Compose\ V_{j''}\ into\ S_3''' \text{ ELSE } DEL(r_{k'}); j'' = 1, 2, \ldots, k_2 \quad (5\text{-}1)$$

(i) $R(r_{k'})$ – computed as the relevancy of causality nodes $r_{k'}$ to question node V_j.

(ii) $R(V_{j''})$ – computed as the relevancy of question node $V_{j''}$ to causality node $r_{k'}$.

The following four steps illustrate the procedure of executing rule 5.

Step1. Select the k'th element i.e. causality node $r_{k'}$ in set S_3';

Step2. Reset the value of $R(r_{k'})$ according to the confirming results of potential questions;

Step3. Compose causality node $r_{k'}$ into set S_3'' if the value of $R(r_{k'})$ is 1;

Step4. Generate new reason explanations and compose them into set $S3'''$, referring to rule 4.

Executing rule will update the problem evidence and the value of $R(r_{k'})$ in the reasoning system and then search new reason explanations referring to rule 4.

Fig. 3 illustrates the structure of reasoning mechanism controlling the process of knowledge reasoning.
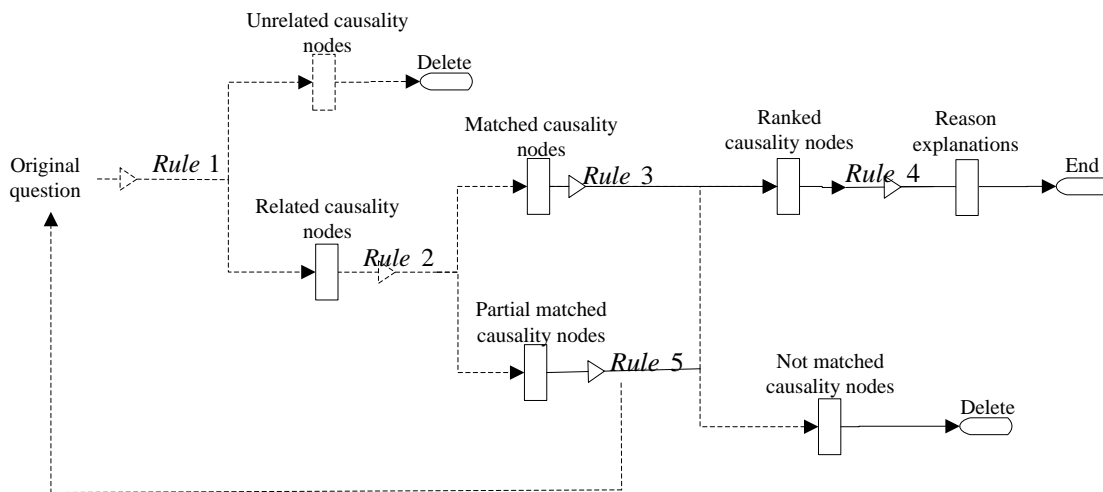

Fig.3 Reasoning Mechanism

System Structure and Example Analysis

The knowledge representation model and reasoning mechanism presented above will be applied to a KB-DSS to deliver appropriate reasoning results to the decision makers. Fig. 4 displays the structure of a KB-DSS.
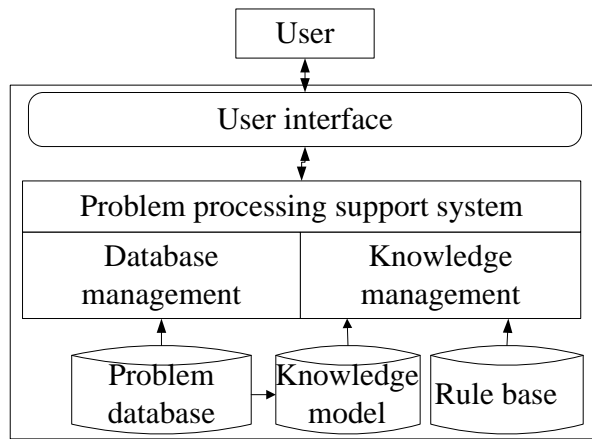
Fig.4 Structure of KB-DSS

The problem database collects and stores data in the certain problem field and generates a casual net through the structure presented above. When a user input questions through the interface, the problem processing support system (PPS) searches the causal net and matches rules in rule base to yield possible reason explanations to original questions [13]. These explanations are provided as support for problem attacking.

To verify the validity of the methods presented above, an example is shown below in this paper. Some production data from the stamping workshop of a car manufacturing plant are extracted to generate a causal net of stamping problems as shown in Fig. 5.
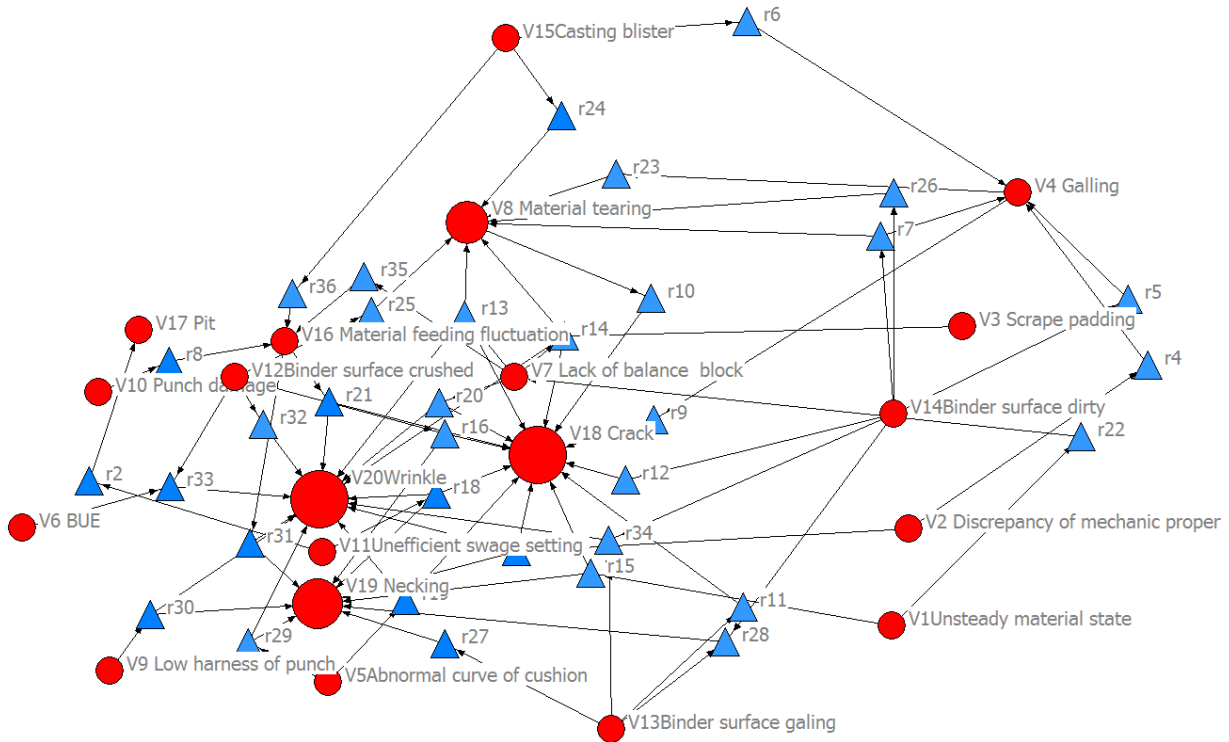

Fig.5 A casual net of stamping problems

A prominent question crack (V_{18}) is analyzed in the following steps:

Step 1: Search all the causalities between nodes in causal models with *rule 1*.The result is displayed in Fig. 6. $S_1 = \{r_9, r_{10}, r_{11}, \dots, r_{14}, r_{17}, r_{18}\}$
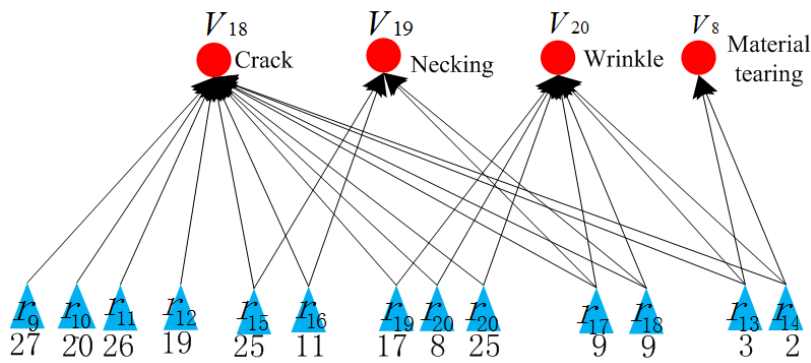
Fig.6 Structure of Question V_{18}

Step 2: Divide set S_1 into set S_2 and set S_3 with *rule 2*. $S_2 = \{r_9, r_{10}, r_{11}, r_{12}\}$ and $S_3 = \{r_{15}, r_{16,\ldots}, r_{17}, r_{18}\}$.

Step 3: Rank the elements in set S_2 and S_3 and form corresponding set $S_2'=\{r_{11}, r_9, r_{10}, r_{12}\}$ and set $S_3'=\{r_{15}, r_{21,\ldots}, r_{13}, r_{14}\}$ with *rule 3*.

Step 4: Generate the reason explanations of question crack (V_{18}) with *rule 4*.The results in this step are binder surface galling(V_{13}),material tearing(V_8),binder surface dirty(V_{14}).

Step 5: Yield new reason explanations and relevant set S_2'' 、 S_3''' by executing *rule 5*. According to the evidence by confirming question necking(V_{19}),winkle(V_{20}) and material tearing(V_8) the reasoning results are binder surface galling(V_{13}),material tearing(V_8) and binder surface dirty(V_{14}),etc.

These reason explanations are in perfect accordance with the expert knowledge in stamping production.

Conclusion

To realize intelligent decision support, this paper introduces the casual net to represent the problem knowledge and then establishes a control mechanism comprised of five reasoning rules to yield reasoning explanation as decision supports. These simple and tractable rules are harmonized with the casual net and can provide effective support for decision makers in the KS-DSS. An example analyzed at the end of this paper verifies the validity of the control mechanism and its applicability in manufacturing industry. We believe that the proposed KS-DSS could be beneficial to many organizational decision-making processes.

Acknowledgement

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