Journal of Southeast University (English Edition) Vol. 25, No. 4, pp. 536 – 540 Dec. 2009 ISSN 1003—7985

Hierarchical decision-making system for real-time freeway incident response

Yang Shunxin Ni Fujian Chen Fei

(School of Transportation, Southeast University, Nanjing 210096, China)

Abstract: The artificial intelligence technique is used to generate a freeway incident response plan. The incident response framework based on rule-based reasoning, case-based reasoning and Bayesian networks reasoning is presented. First, a freeway incident management system (RK-IMS) based on rule-based reasoning is developed and applied for incident management in the northern section of the Nanjing-Lianyunguang Freeway. Then, field data from the two-year long operations of the RK-IMS are analyzed. Representations of incident case structures and Bayesian networks (BNs) structures related to incident responses are deduced. Finally, the k-nearest neighbor (k-NN) algorithm is applied to calculate the similarities of the cases. The preplan generation and the control strategy by integrating the k-NN algorithm are also developed. The model is validated by using incident data of the year 2006 from the RK-IMS. The comparison results indicate that the proposed algorithm is accurate and reliable.

Key words: freeway incident; decision-making; rule-based reasoning; case-based reasoning; Bayesian networks

By the end of December 2008, the total mileage of freeways in China had exceeded sixty thousand kilometers, ranking No. 2 in the world. In order to meet the national economic development requirements, the Ministry of Transport of the People's Republic of China established a Chinese National Freeway Network Plan suggesting that the freeway network come to eighty-two thousand kilometers and cover a population of more than one billion, which is close to the eighty-eight thousand kilometers scale in America. This will greatly improve the China's transportation status and promote a faster development of the Chinese economy. However, with the dramatic increase in the freeway traffic volume in recent years, various types of traffic accidents obviously occur.

Researches and empirical practices in many countries have proved that the key to freeway operation management is to deal with the traffic incident management of nonrecurring congestion, by which the realization of high traffic volume, speed and freeway traffic safety can be guaranteed. An incident management system, which has been carried out since the 1960s in Chicago, USA, is an important subsystem of a freeway management system. However, the application of incident management based on an intelligent system in China is still in its initial stages. It is far behind the rapid development of highway construction.

Since the 1979s, many studies have been focused on freeway incident responses. The methods used in these studies can be generally classified into several categories: reinforcement learning[1], case-based reasoning[2–3], support vector regression[2], the sequential hypothesis testing method[4], rule-based reasoning[5–7], neural networks[8], knowledge-based systems[9], probability density functions[10], data mining[11], risk-based reasoning[12], and Bayesian networks (BNs)[13]. The process of emergent freeway incidents features a high demand for real-time response, intricate associated factors, and time-dependent field data information with inadequate accuracy. The quick development of the state of freeway incidents calls for a plan with strong prediction ability and comparability with incidents. This paper focuses on the application of the artificial intelligence theory and techniques to generate the process plan and mainly discusses the combination of rule-based reasoning, case-based reasoning (CBR) and Bayesian networks reasoning in freeway incidents responses. Due to the high similarity among freeway incidents, CBR with less calculation complexity is employed to provide real-time matches in the case base for emergencies as well as quick responses. Nevertheless, the amount of data obtained from field operations is huge and the correlations among them are complex, incomplete, and imprecise, which results in difficulties in selecting similar cases and appropriate rules. Meanwhile, Bayesian networks feature the advantage of indicating data with complex correlations and impreciseness. Therefore, it is of great significance to study the generation of incident process plans under Bayesian networks with incomplete and imprecise information.

1 Rule-Based Reasoning

Knowledge is formalized and organized by knowledge representation. A widely used representation is a production rule, or a rule, in short. A rule consists of an IF part and a THEN part (also called a condition and an action). The piece of knowledge represented by the production rule is related to the line of reasoning being developed. If the IF part of the rule is met, the THEN part can be concluded. Expert systems whose knowledge is represented in the form of rules are called rule-based systems.

1.1 Knowledge acquisition

Decision-making of incident management is a comprehensive job involving various types of resources, personnel and expert knowledge of many aspects. The latter requires much basic knowledge. In fact, when a serious incident happens, the manpower and material resources of many aspects are often employed across regions or go beyond powers. Thus, with regard to knowledge, the more detailed the better.

Received 2009-07-01.

Biography: Yang Shunxin (1971—), male, doctor, lecturer, shunxin.yang@gmail.com.

Foundation item: The Natural Science Foundation of Jiangsu Province (No. BK2008308).

Citation: Yang Shunxin, Ni Fujian, Chen Fei. Hierarchical decision-making system for real-time freeway incident response[J]. Journal of Southeast University (English Edition), 2009, 25(4): 536 – 540.

Knowledge in the knowledge base of this system mainly results from several aspects as follows:

1) Large quantities of documents related to incident management and expert systems from home and abroad.

2) Consultation with staff in related departments of incident management, including the freeway management center, the monitoring center, the clearance team, freeway patrols and so on.

3) Historical incidents record.

1.2 Implementation of response rule base

The response procedures begin once the incident is verified. In the process of the formulation of a response plan, all types of incidents are first broadly classified as vehicle and non-vehicle incidents, and each has several sub-classes. This allows the identification of all services required at the incident site based on the incident's characteristics. Then, a list of tasks performed by each agency and interagency is identified. The response procedures are used as the basis for the development of the response rule base. The rule base constitutes the core of the system response module. These rules are collected through personal interviews and some literature studies during the assessment of user requirements. The knowledge base consists of forty-three different sets of rules. An example of rule base sets is shown in Tab. 1.

Tab. 1 Rules for variable message signs and changeable speed limitation sign

Incident severity index		Disseminate information on VMS	Speed limitation/($km \cdot h^{-1}$)
1		Incident ahead, speed-down	80
2		Incident ahead, speed-down	60
3	No division	Incident ahead, speed-down	40
	Division	Incident ahead, detour advised	30
4	No division	Incident ahead, speed-down	20
	Division	Incident ahead, detour advised	20

2 Case-Based Reasoning

2.1 Framework of emergency system for freeway incidents

Improvements on the case-based reasoning work process are made according to the basic principle of case-based reasoning. The corresponding emergent freeway incident system is proposed as shown in Fig. 1.

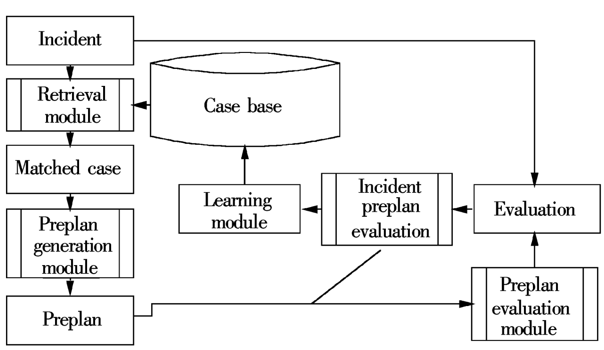

Fig. 1 Incident management process based on CBR

2.2 Case-based design

A case base is the most crucial part of an emergency system for freeway incidents. It determines the efficiency and effectiveness of the emergency system. With regard to the case-based design, the case structure has to be determined first. In the emergency system for freeway incidents, a complete case should include three parts: case description, decision preplan and evaluation of effectiveness.

2.2.1 Case description

The incident description part of cases records the detailed information related to the incident when it happens. Therefore, it is the crucial part of case retrieval. Generally speaking, the incident description part mainly includes two aspects: basic information of freeway incidents and information of freeway incident loss.

2.2.2 Decision preplan

The data in the decision preplan indicate the detailed situations of each participating emergency department when freeway incidents occur. They include the information about the time when police patrols, the administrative department, the clearance team, the medical and rescue departments are called, the time these departments arrive at the incident scene, traffic management and control, the time for incident treatment, and numbers of vehicles dispatched. Besides, a complete decision preplan should include the information about dispatching resources, disseminating information and diverting the traffic.

2.3 Design of incident retrieval module

Two goals should be achieved in this module. One is that the amounts of similar incident cases searched should be as few as possible, and the other is that the searched information of incident cases related to or similar to the actual incident should be as much as possible. Here, we employ the deep retrieval based on knowledge, which assigns different weight values to incident attributes according to their respective importance. The distance measurement or the k-nearest neighbor (k-NN) algorithm obtains the similarities between two cases by calculating the distance of the two objects within the characteristic vector space. A freeway incident case can be described by a feature vector $\boldsymbol{X}' = \{X_1, X_2, \ldots, X_N\}$, where $X_i (1 \leqslant i \leqslant N)$ is the characteristic value of the corresponding incident. The distance between two incident cases $\boldsymbol{X}$ and $\boldsymbol{Y}$ can be defined[13] as

$$D(\boldsymbol{X}, \boldsymbol{Y}) = \left(\sum_i W_i (X_i, Y_i)^2 \right)^{1/2} \tag{1}$$

where W_i is the weight coefficient of X_i.

2.4 Example

As shown in Tab. 2, a similar case is selected from the case base.

Tab. 2 Example of case structure

Basic information	Costs of incidents	Resources dispatch	Information dissemination
Incident type: traffic incident; Location: Lianshui-Gaogou section; Time: 8:23 A. M. ; State of traffic flow: free flow; State of pavement: dry; Weather: foggy, visibility = 300 m	Number of blocked lanes: 1; Number of vehicles seriously damaged: 1; Type of seriously damaged vehicles: car; Number of people slightly injured: 2; Number of people seriously injured: 1; Number of deaths: 0	Patrol department: Patrol Department of Lianshui; Clearance department: Lianshui Clearance Team; Number of trailers: 1; Type of trailers: compact; Hospital: 120 Rescue Center of Lianshui; Number of ambulances: 2	CCTV1: incidents ahead, please drive with caution

3 BNs Reasoning

3.1 Development of BNs model

There are two methods for constructing BNs. One is by consulting experts, and the other is by data analysis. Here, we apply the first method by consulting two experts in the field of freeway incident management. This model is established by GeNie software as shown in Fig. 2. An example illustrating the conditional probability tables (CPT) of the node NumberofFatal is given in Tab. 3.

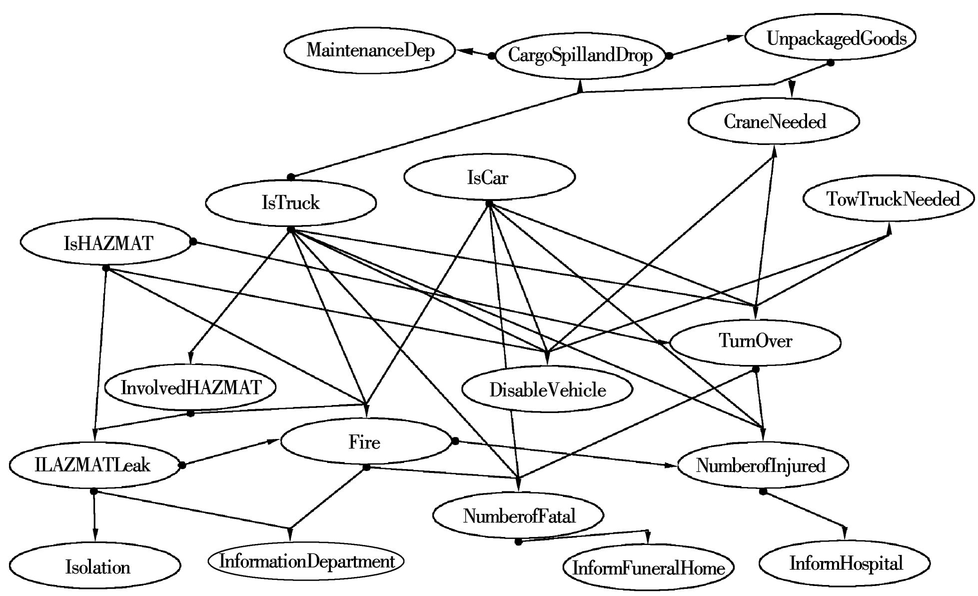

Fig. 2 Primary variables in BNs model for incident response

Tab. 3 Conditional probability table associated with node NumberofFatal

Parent notes				NumberofFatal		Number of instances
Fire	Turnover	isCar	isTruck	Yes	No	
Yes	Yes	Yes	Yes	0. 802 3	0. 1977	23
Yes	Yes	Yes	No	0. 751 1	0. 248 9	16
Yes	Yes	No	Yes	0. 756 7	0. 243 3	2
Yes	Yes	No	No	0. 500 0	0. 500 0	2
Yes	No	Yes	Yes	0. 430 0	0. 570 0	4
Yes	No	Yes	No	0. 310 0	0. 690 0	3
Yes	No	No	Yes	0. 250 0	0. 750 0	3
Yes	No	No	No	0. 050 0	0. 950 0	5
No	Yes	Yes	Yes	0. 720 0	0. 280 0	20
No	Yes	Yes	No	0. 410 0	0. 590 0	16
No	Yes	No	Yes	0. 580 0	0. 420 0	23
No	Yes	No	No	0. 303 4	0. 696 6	18
No	No	Yes	Yes	0. 150 0	0. 850 0	139
No	No	Yes	No	0. 120 0	0. 880 0	56
No	No	No	Yes	0. 050 0	0. 950 0	78
No	No	No	No	0. 050 0	0. 950 0	8

Notes: "NumberofFatal = Yes" denotes that there are some personal fatalities; "NumberofFatal = No" denotes that there are no personal fatalities.

3.2 Model validation

As shown in Fig. 3, an incident occurs at midnight and the initial information received by the operator on duty at the monitoring center is just that cars and trucks are involved in the incident. Then, on the basis of Bayesian networks reasoning, we can calculate that the probability of a vehicle turning over is 5%. The probability for the need of a tow truck is 39%, and 30% for the need of a crane. For an incident under these conditions, the value of vehicle failures is "Yes" with a probability of 30%, 15% for vehicles fires, 6% for the leak of hazardous materials, 43% for people who may get injured and so on. These probabilities obtained from Bayesian networks reasoning provide preferable reference information for the next action of these related departments, and remind operators at the monitoring center to pay more attention to these predictions with higher probabilities. Then, when the operators get the real information of the incident a few minutes later, they can be more fully prepared and thus their reaction time can be greatly reduced.

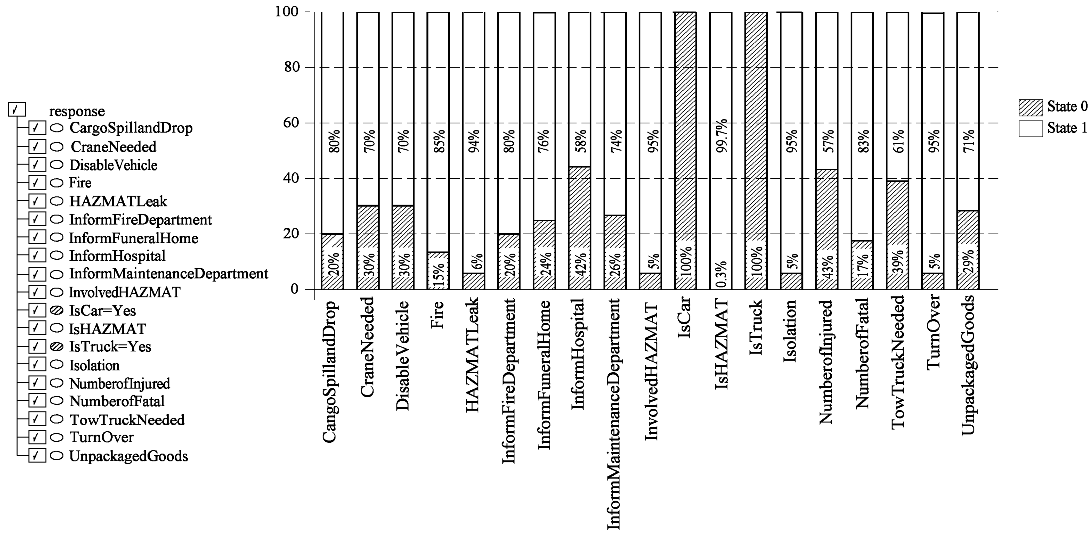

Fig. 3 Top-down inference

4 Algorithm Architecture

Freeway incident response is a decision-making process. As time goes by, more information of incidents can be obtained. Preplans are generated simultaneously by rule-based reasoning, case-based reasoning and Bayesian networks reasoning. The preplan lists are updated with the incident information continuously acquired. To be more specific, rule-based reasoning is more practical in field operations and the preplan provides clear instructions for operators. Meanwhile, Bayesian networks reasoning and case-based reasoning are more related to probabilities, which provide predictions for the need of further actions. As shown in Fig. 4, preplans 1, 2, 3 are generated by rule-based reasoning, Bayesian networks reasoning and case-based reasoning, respectively. Each preplan is labeled with the exact reasoning method from which it is generated. In the actual situation, it is up to the operators to select the suitable preplans generated by using the three reasoning methods. For instance, with regard to ordinary incidents, operators can select the preplan generated directly by rule-based reasoning.

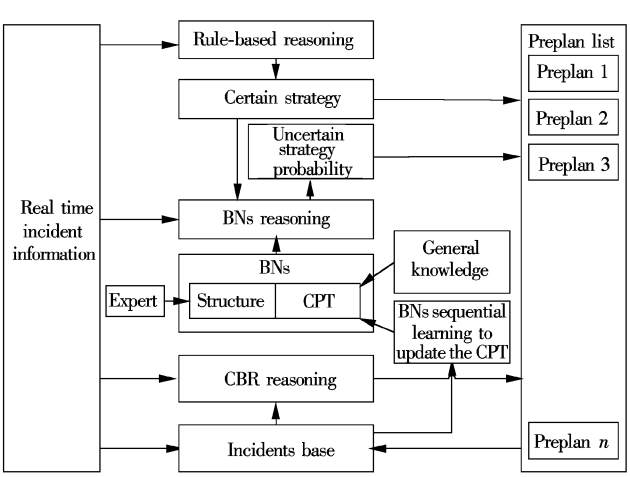

Fig. 4 Generation and control of preplan

Anyway, when it comes to some rarely occurring incidents, such as hazardous materials spill, very few related rules are established. At the same time, due to their complex process nature, it is difficult to extract and establish unified rules. Therefore, case-based reasoning provides a reference for operators to choose related actions. The prediction of further incidents status and the corresponding actions can be obtained from Bayesian networks reasoning. Moreover, when the incident is finally disposed of, the parameters of BNs can be relearned based on the sequential updating model by the incident database consisting of incident information and incident response preplans.

5 Conclusions

The complete theory, method and realization framework for generating real-time preplans are proposed by applying CBR reasoning, rule-based reasoning and BNs reasoning under emergent freeway incidents. The emergency management system for freeway incidents has been successfully applied in the northern section of the Nanjing-Lianyungang Freeway for almost two years, from which the collected data can provide beneficial help for future researches.

1) As for rule-based reasoning, although we define it a deterministic one in the above application, it can be applied to make effective incident responses under uncertainties by adding uncertainty factors.

2) As for case-based reasoning, the current case structure is monotonous and time-consuming when searching for the matching cases. More detailed classification of inputting incident cases are needed to accelerate the searching time for the matching cases.

3) As for Bayesian networks reasoning, further research is needed on the selection of the sample cases for the calculation of CPT.

References

[1] Jacob C, Abdulhai B. Automated adaptive traffic corridor control using reinforcement learning: approach and case studies [J]. *Transportation Research Record*, 2006, **1959**: 1 − 8.

[2] Chowdhury M, Sadek A, Ma Y, et al. Applications of artificial intelligence paradigms to decision support in real-time traffic management [J]. *Transportation Research Record*, 2006, **1968**: 92 − 98.
[3] Adel W S. Case-based reasoning for real-time traffic flow management [D]. Charlottesville, VA, USA: School of Engineering and Applied Science of University of Virginia, 1998.
[4] Madanat S, Cassidy M J, Teng H, et al. Decision-making system for freeway incident response using sequential hypothesis testing methods [J]. *Transportation Research Record*, 1996, **1554**: 228 − 235.
[5] Arti G. Application of knowledge-based expert systems to incident management on freeways [D]. Amherst, MA, USA: Department of Civil Engineering of University of Massachusetts, 1992.
[6] Stephen R, Neil A. A real-time expert system approach to freeway incident management [R]. Berkeley, CA, USA: University of California at Berkeley, 1991.
[7] Stephen R. A knowledge-based decision support architecture for advanced traffic management [J]. *Transportation Research Part A*, 1990, **24**(1): 27 − 37.
[8] Papageorgiou M, Messmer A, Azema J, et al. A neural network approach to freeway network traffic control [J]. *Control Eng Practice*, 1995, **3**(12): 1719 − 1726.
[9] Filippo L, Stephen R. Development and evaluation of a knowledge-based system for traffic congestion management and control [J]. *Transportation Research Part C*, 2001, **9**(6): 433 − 459.
[10] Rust P, Abde-Rahim A, Hassan A. Evaluation freeway diversion route plans in integrated incident management systems under uncertainties [C]//*Proceedings of the Fourth International Symposium on Uncertainty Modeling and Analysis*. College Park, MD, USA, 2003: 46 − 60.
[11] Lee D, Jeng S. Integrated freeway incident management using data mining and expert systems [R]. Irvine, CA, USA: University of California at Irvine, 2004.
[12] Ghada M H. Risk-based decision support model for planning emergency response for hazardous materials road accidents [D]. Waterloo, Ontario, Canada: University of Waterloo, 2004.
[13] Nilsson N J. *Artificial intelligence*: *a new synthesis* [M]. San Fransisco, CA, USA: Morgan Kaufmann Publishers Inc, 1998.

高速公路事件实时响应层次决策支持系统

杨顺新　倪富健　陈　飞

（东南大学交通学院，南京 210096）

摘要： 应用人工智能技术产生高速公路事件响应预案，提出了基于规则推理、案例推理和贝叶斯网络推理 3 种方法的事件响应框架. 首先，建立了基于规则推理的高速公路事件管理系统（RK-IMS），并应用于宁连高速公路北段事件管理过程中. 然后，通过分析 RK-IMS 系统 2 年的运营数据，确定了事件案例的结构表示与事件响应的贝叶斯网络结构. 最后，应用 k 近邻算法计算相似性案例，并研究了基于该算法的预案产生和控制策略. 利用 2006 年 RK-IMS 事件管理系统的实际数据对模型进行了验证. 对比分析结果表明，该方法是有效可信的.

关键词： 高速公路事件；决策支持；规则推理；案例推理；贝叶斯网络
中图分类号： U491