Combination Prediction Model of Traffic Accident Based on Rough Set

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Abstract. Vehicles accidents have become the first public nuisance in the world. A dramatic rise of traffic accidents results from sharp increase of vehicles with the rapid development of economy. Accident forecasting is designed to help decision-making and planning before casualty and loss occur. Calculating weight coefficient is a key for combination forecast. The result of the forecast will be straightly influenced if the selection of the weighting coefficient is illogicality. A new method of combination forecasting applied in traffic accident is showed in this paper. It is based on the rough sets theory, and the weighting coefficient of all the forecast methods is distributed, so that the calculation of the weighting coefficient will be more impersonal and simpler, and the result of the forecast will be more exactly. In this paper, two samples were used to check the accuracy of this method. The Percent of errors were approximately about 0.5%and 2.7%. Compared with another method for combination forecasting- artificial neutral network, the Percent of errors were 1.1% and 3.05%. Respectively.

Keywords: Combination forecasting, Rough sets theory, Traffic accident prediction, Weighting coefficient.

1 INTRODUCTION

Accident forecasting is to forecast the safety state based on the available information and observations. For either the analysis of accident trend or the identification of potential hazardous sources, accident forecasting is more and more important because of frequent accidents. In this field, the previous researches mostly focus on longitudinal surveys concerning an individual method.

Few studies have been done on comprehensive comparisons of different accident forecasting methods. To assist model users to select an appropriate model for a specific accident, this paper provides an overview of three major
accident forecasting methods and drive the method of calculate weighing coefficient. The three methods are mainly quantitative methods, but qualitative analysis more or less plays a role in the process of accident analysis, modeling and forecasting. These quantitative methods can be further classified into two principal groups time-series forecasting methods and causality forecasting methods.

1.1 Regression Method

There are two kinds of simple linear regression models. In the first, there is just one variable known as dependent variable and the other known as independent variable where dependent variable is desired one that must be estimated based on the other. Equation (1) shows the relation between dependent and independent variables where α and β are known as coefficients of simple regression model between dependent variables X and independent Y.

$Y = \alpha + \beta X$ (1)

model set relationship between independent variables X1, X2,. . . Xn, and dependent variable Y by the equation (2). In the equation (2), coefficients β0, β1, β2, β3 . . . and βn must be set based on minimizing the mean square errors between observations and model outputs.

$Y = \beta 0 + \beta 1\ X\ 1 + \beta 2\ X\ 2 + \beta 3\ X\ 3 + \ldots + \beta n\ X\ n$

When it is considered that the effect of independent variable on dependent one is power base, the model called weighted linear regression. There are also simple and multivariate regression model such as simple regression models but with the power of independent different from. Assuming the parameters described in the previous section regarding to power independent variables to p. In this case equation (3) is shown the relation between X and Y as respectively independent and independent variables and α, β, and p are parameters.

$$Y = \alpha + \beta X^{p} \quad (3)$$

Parameters are being calculated based on the minimum of mean or total square errors between observations and model outputs [8]. It is obvious that multivariate regression model can be defined when independent variables $X_1, X_2, \ldots\ldots$ and dependent variable Y are defined as equation (4)

$$Y = \beta_0 + \beta_1 X_1^{P_1} + \beta_2 X_2^{P_2} + \beta_3 X_3^{P_3} + \ldots + \beta_n X_n^{P_n} \quad (4)$$

Effective parameters can be discussed based on t-test value in simple regression models. The values obtained by regression model shown in table 2. To ensure that which of variables are effective in road accidents , with confidence interval of 95%, t-test values .

The model of regression forecasting is established according to the distribution law of past samples so as to give a best fit of the data. In the regression model, the dependent variable is modeled as a function of the independent variables, corresponding parameters and an error term,

$$Y = f\,(X, \beta) + \varepsilon.$$

Thereby a guess about the function form of regression equation must be made first. According to the types of accidents, we can specifically employ linear model, exponential model, power model, logarithmic model, polynomial model and so on. Sometimes, the form of regression function is known. When it is not known, we must apply a trial and error process. If the dependent variable is a count of rare events in a given period of time, Poisson or negative binomial regression is carried out to model the count data. Poisson regression model is a log linear model with the logarithm as the canonical link function. The model takes the form:

$$\ln\,[E\,(Y)] = \beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p,$$

and the mean accident frequency is $\lambda = E\,(Y)$ which can be interpreted by the Poisson distribution function. A characteristic of the Poisson distribution is that its mean is equal to its variance, which makes it inappropriate in circumstances where the observed variance is greater than the mean, which is known as overdispersion. In these cases, negative binomial (NB) model is used . However, traditional Poisson and negative binomial models are not applicable when many zero accidents are observed. Therefore, Zero-altered probability processes such as zero-inflated Poisson (ZIP) model and zero-inflated negative binomial (ZINB) model are proposed for this case . The dual-state models explicitly separate the true zero-state process from the parent count-data process, and allow for actors to influence both of these states. In safety programming ,the injury-severity of accidents is categorized into many levels. The accident frequencies of each severity level can be predicted by separate negative binomial models. Unfortunately, such an approach may introduce significant estimation errors because it presumes that the factors causing the occurrence of an accident are independent across severity outcomes. In fact, when the requency of one severity level changes, the frequencies of other levels are also likely to change. In this regard, Milton, hankar, and Mannering (2008) employed a mixed logit model. As a discrete choice model, this approach allows for the possibility that model parameters can distribute randomly.

1.2 Exponential Smoothing Method

Exponential smoothing method derives from the weighted average method, assuming that the importance of the data decreases non-linearly with the passage of time. It can eliminate the unexpected change in the time-series and learn the trend. The most important theoretical advance of exponential smoothing is the invention of a complete statistical rationale based on a new class of state-space models with a single source of errors. Each exponential smoothing method has two corresponding state-space models (Gardner, 2006).The simple exponential smoothing model N–N (no trend and no seasonality) is given by the formulas:

$$S_t = \alpha x_t + (1-\alpha) S_{t-1},$$

Where $\alpha\ (0 < \alpha < 1)$ is smoothing factor, St is smoothed statistics and $S_{t-1} = \hat{x}_t$ ($\hat{x}_t$ is the forecast value of x_t). Then, two parameters T_t and I_t are added to reflect trend and seasonality respectively. a helpful categorization for describing various exponential smoothing methods. Each method consists of one of four types of trend (None, Additive, Damped Additive, and Multiplicative) and one of three types of seasonality (None, Additive, and Multiplicative). Thus, there are 12 different methods. Subsequently, Taylor (2003) extended a Damped Multiplicative method. The method has the appeal of modeling

trends in a multiplicative fashion but it includes a dampening term, which should lead to more robust forecasting performance

1.2.1 Grey Model

A system is defined as a white one if the information in it is
known; a system will otherwise be a black box if nothing in it is clear. Grey forecasting obtains the estimation based on the theory of grey system, which is between a white system and a black-box system. Unlike other forecasting methods which need a large quantity of historical data to achieve better regularity of random variables, Grey theory generates new data sequence through the accumulated generating operation (AGO) technique. Using the AGO technique efficiently reduces noise by converting ambiguous original time-series data to a monotonically increased series. Grey model (GM) is capable of using as few as four data inputs to forecast the future value. Therefore, grey forecasting method is often applied to the accident with uncertain and insufficient information [19] (e.g., Mao & Chirwa, 2006; Zhang, Wang, & Zhao, 2007).
The most commonly used Grey model is the GM(1,1).

For an initial time sequence X(0), the form of GM(1,1) [7] $x^{(0)}(k) + az^{(1)}$, and the corresponding white differential equation is:

$$dx^{(1)}/dt + ax^{(1)} = b, \text{ where } X^{(1)} = AGO(X^{(0)}),\ z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}$$

(k-1),a and b denote the parameters requiring determination in the model. There are two ways to increase the forecasting accuracy of grey model. One is to improve modeling mechanism. GM(1,1) is fit for the change process with monotonous exponent law. But for the dynamic and swinging sequences, it is necessary to introduce a more general model such as the GM(M,N) model with M-order and N-element [7] (see Guo, 2007). In fact, grey model is likely to produce divergent errors. The larger the exponential coefficient of response function is, the bigger the error. In this regard, we can use the equation $z^{(1)}(k) = 1/2m\,[(m+1)x^{(1)}(k) + (m-1)x^{(1)}(k-1)$ as background value [7] (Mao & Chirwa, 2006). On the other hand, the forecasting accuracy can be improved by processing and updating data sequences, such as residual modification and information updates. The improved grey models include: Residual GM(1,1) model [6] (e.g., Hsu & Chen, 2003), new information GM model (e.g., Jiang, Yao, Deng, & Ma, 2004), and so on and so forth. If the accident data show much fluctuation or center–symmetry curve, the forecasting result obtained by grey model is unsatisfactory. A solution is the meritorious combination of grey forecast and Markov forecast. The new combined model is named Grey - Markov model [3] (e.g., Li, Hu, & Zhang, 2007). The accident data are seen as a Markov chain and their states are divided according to the difference between the grey forecast value and the raw data. The grey forecast value is obtained by a grey model at first. In this method, grey model is used to forecast the general trend, and Markov chain model is used to determine the transferred direction of the microcosmic vibration. The combination cannot only join the strengths of the two models but also make full use of the information [17] included in the raw data. However, there is not a given standard that can really unify and settle these kinds of accidents. ARMA(2,3) model is:

$$y(t) = -0.0348y(t-1) + 1.011y(t-2) + e(t)$$
$$+0.9335e(t-1) - 0.04159e(t-2) + 0.005696e(t-3)$$

1.3 Neural Networks

The above forecasting models have the pre-defined underlying relationship between dependent and independent variables which is sometimes hard to get from complex accidents. If this assumption is violated, the model could lead to erroneous estimation of accident likelihood [16] (Chang, 2005). In contrast, artificial neural networks (ANNs) [15], which can fit complex non-linear relationships between inputs and outputs within a black-box structure, has been evidenced to be a powerful tool for accident forecasting. The applications of ANNs to accident forecasting are divided into two kinds of modes: trend forecasting and causality forecasting. In the former mode, the inputs are time-series data (e.g., Xie, Lord, & Zhang, 2007). Jain and Kumar (2007) [10] indicated that ANNs also need the time series to be stationary so as to produce more accurate forecasts [11]. Therefore, the steps in time-series analysis such as detrending and de-seasonalisation are necessary to be carried out before gradually presenting the modified time-series data to the ANNs. The latter mode uses a set of influencing factors related to the accident as the inputs [2] (e.g., Chang, 2005; Santosh, Srivastava,Sanyasi Rao, Ghosh, & Kushwaha, 2009). In this mode, it is helpful to measure the contribution of each explanatory variable. The work has been done in the following aspects. Firstly, according to the influence analysis of input variables on the output [21] (reviewed by Gevrey, Dimopoulos, & Lek, 2003), the input variables which are belowa fixed threshold are excluded from the network. This allows the size of the network to be reduced and the redundancy in the

Table 1. Road Accident Statistics.

Year	**Accident**	**Fatality**	**Injury**
2001	80	25	107
2002	104	7	155
2003	50	22	174
2004	71	29	203
2005	40	12	99
2006	33	15	96
2007	30	11	101
Total:	**509**	**121**	**935**

Table 2. THE TRAFFIC ACCIDENT IN (2001- 2007).

Year	Actual accident	Forecasts regression	Forecasts Grey	Forecasts Exponential	Forecasts ARMA
2001	80	101.23	93.37	120.7	100.87
2002	104	114.21	119.59	101.11	108.33
2003	50	72.54	79.85	82.31	80.34
2004	71	87.76	75.43	97.54	80.56
2005	40	47.98	61.26	70.76	55.34
2006	33	65.67	73.54	50.34	42.49
2007	30	47.09	61.77	70.11	55.98

2 CALCULATE WEIGHTING COEFFICIENT

The keystone of the combination forecasting is to integrate the advantages of the other forecasting methods, and fit the information of other methods together, so that the precision of the combination forecasting results will be improved [12]. Weighting coefficient shows the reliability of each forecasting models, and influence the impact of forecasting directly, thus the calculation of the weighting coefficient is the key of the combination forecasting, and also is the difficulty. In this paper, the rough set theory [14] will be used for weighting coefficient calculations, and translate the problem into estimating the importance of the property in rough set. In the ordinary set theory, crisp sets are used. A set is then defined uniquely by its elements, to define a set we have to point out its elements. The membership function, describing the belongingness of elements of the universe to the set, can attain one of the two values. It means that any element is either in or outside the set under consideration.

This definition of the membership function does not take into account the uncertainty of being an element of a given set of elements. Rough set theory can deal with the uncertainty problems; represent a different mathematical approach to vagueness and uncertainty [4]. In 1982, Pawlak introduced the concept of a rough set.

This concept is fundamental to the examination of granularity in knowledge. It is a concept that has many applications in data analysis. The theory of rough sets is motivated by practical needs to interpret, characterize, represent, and process indiscernibility of individuals. Rough set theory provides a systematic method for representing and processing vague concepts caused by indiscernibility in situations with incomplete information or a lack of knowledge [13]. The idea is to approximate a subset of a universal set by a lower approximation and an upper approximation in the following manner. A partition of the universe is given. The lower approximation is the union of those members of the partition contained in the given subset and the upper approximation is the union of those members of the partition that have a nonempty intersection with the given subset. It is well known that a partition induces an equivalence relation on a set and vice versa. The properties of rough sets can thus the examined via either partitions or equivalence relations. The members of the partition or equivalence classes can be formally described by unary set theoretic operators, or by successor functions for upper approximation spaces. This axiomatic approach allows not only for a wide range of areas in mathematics to fall under this approach, but also a wide range of areas to be used to describe rough sets [20]-[21]. Suppose U is the set composed with all the research objects, and it is a finite and non-empty universe. R is the equivalence relation on U , and the equivalence genus procreated by R marked as:

$$[X]_R = \{y | xRy, y \in U\}.$$

The set composed by the entire equivalence genus marked as:

$$U / \hat{R} = \{[x]_R | x \in U\},$$

, it seen as a system. A conception or a category marked as X can seen as a subset of U .

$R\_(X) = \{x \mid [x]_R \subseteq X, x \in U\}$

is the lower approximation of X , it is doubtlessly belong to the set,

$R^-(X) = \{x \mid [x]_R \cap X \neq \phi, x \in U\}$

is the upper approximations; it is possibly belong to the set. card(Y) means the element number in set Y . Suppose R and Q are the equivalence relations on U , the degree of the dependence between R and Q is identified as (1)

$$r_Q(R) = \frac{\sum_{[X]_R \in (U/R)} card(Q\_([x]_R))}{card(U)} \qquad (1)$$

Obviously, $0 \leq \gamma_Q(R) \leq 1$, when $\gamma_Q(R) = 1$, R is all mostly depend on Q ; when (R) is close to 1, R is highly depend on Q .If the condition attribute ci has no influence to the set of decision attribute, the condition attribute ci is not so important for the system, and value of the importance can be calculated by (2):

$$\sigma_D(c_i) = \gamma_c(D) - \gamma_{C-\{c_i\}}(D) \qquad (2)$$

3 STEPS OF WEIGHTING COEFFICIENT CALCULATION

3.1 Establish the Relation Date Model

In the interest of calculation the weighting coefficient in the combination forecasting, the relation date model should be established first. Each forecasting method is seen as condition properties, so the set of it is:

$C = \{c_1, c_2, \cdots, c_m\}$

The forecasting objects y are seen as decision properties, so the set of it is Data in the period of t , The value of each forecasting method and the date of the forecasting object can be seen as the information of some research object ut , and it can be identified as:

$u_t = \{c_{1t}, c_{2t}, \cdots, c_{mt}; y_t\}$

So that:

$U = \{u_1, u_2, \cdots, u_n\}$

It also called sample set. The property of the research object is:

u_t is $c_i(u_i) = c_{it}(t = 1, 2, \cdots, n)$

And the information table is the relation date model about the forecasting method.

3.2 Types of Attributes

In order to catch the dependence and the importance of the date, first classical the object by the attributes, and then built the system. Always the qualitative attributes are used for classical classifiers, and the attribute dates should be set to 0,1 or others.

Simplification of the data can be achieved by dropping certain values of attributes, which are unnecessary for the system, by eliminating some of these values in such a way that we are still able to discern all elementary sets in the system. The procedure of finding core and redacts of the attributes. All Computations are performed based on the discernibility matrix, but the definition of the discernibility function is now slightly different. Instead of on discernibility function, we have to construct as many discernibility functions, as there are elementary sets in the system[8].

Continuous condition attributes present a problem, as in this case, a is cartelization is required. Both the number of sub ranges and their intervals has to be optimized. The number of sub ranges decides about the number of logical rules considered. The number of ruled is not given in advance, but is limited by the general requirement that the learning objects should confirm the rules.

3.3 Equations Calculate the Dependence between RD and

C. Calculate the Dependence:

$$r_{R_c}(R_D) = \frac{\sum_{[y]_{R_D} \in (U/R)} card(R_C \_([y]_{R_D}))}{card(U)} \quad (3)$$

D. Equations Calculate the Dependence between R_D and $R_{C-\{c_i\}}$ in each Forecasting Method:

$$r_{R_{C-\{c_i\}}}(R_D) = \frac{\sum_{[y]_{R_D} \in (U/R)} card(R_{-C-\{c_j\}}([y]_{R_D}))}{card(U)} \quad (i = 1,2,\cdots m) \quad (4)$$

E. Calculate the Importance of each Forecasting Method in the Combination Forecasting:

$$\sigma_D(c_i) = r_c(R_D) - r_{c-\{c_i\}}(R_D), i = 1,2,\cdots m \quad (5)$$

F. The Weighting Coefficient of each Forecasting Method:

$$\lambda_i = \frac{\sigma_D(c_i)}{\sum_{j=1}^{m} \sigma_D(c_i)}, i = 1,2,\cdots m \quad (6)$$

Preliminary analysis of accident data for the study locations could serve as a initial platform for systematic development of models that are capable of taking into account important variables explaining accidents and casualties. Given accident data available from the database of the Thailand Department of Highways Table 4 summarizes the number of accidents and casualties over the past seven year. The pattern of traffic accidents gradually declined over the yea tablers, decreased to the lowest of 43 cases in 2006, and then started to be on rise again in 2007 as shown in the While the fatalities were rather constant with small fluctuation as whole, the injuries showed a reverse trend with the highest number being recorded of 203 persons in 2004. After reaching its peak, the trend dropped to 99 persons in 2005 and remained relatively stable onwards. The total number of accidents occurred throughout this route were 509 cases with 121 fatalities and 101 injuries.

Table 3. THE IMPORTANCE AND THE WEIGHTING COEFFICIENT OF EACH FORCASTING METHOD.

Method	C1(regression)	C2(grey)	C3(exponential)	C4(arma)
Dependence	0.85714	0.71429	0.57143	0.57143
Importance	0	0.14286	0.28571	0.28571
Weighting coefficient	0	0.2	0.4	0.4

Table 4. Rough set estimation comparing with ANN.

Year	Actual accident	Forecasts regression	Forecasts Grey	Forecasts Exponential	Forecasts ARMA	ANN	Rough Set
2001	80	101.23	93.37	120.7	100.87	95.65	94.23
2002	104	114.21	119.59	101.11	108.33	115.55	109.23
2003	50	72.54	79.85	82.31	80.34	80.41	77.11
2004	71	87.76	75.43	97.54	80.56	88.67	85.23
2005	40	47.98	61.26	70.76	55.34	57.45	56.56
2006	33	65.67	73.54	50.34	42.49	47.09	45.67
2007	30	47.09	61.77	70.11	55.98	57.97	56.98

Table 5. THE VALUES AND THE ACCURACY OF THE FORCASTING.

Method / year	Error Percent	
	ANN	Rough set
2001	0.1565	0.1423
2002	0.1155	0.0523
2003	0.3041	0.2711
2004	0.1767	0.1423
2005	0.1745	0.1656
2006	0.1409	0.1267
2007	0.2797	0.2698

4 CONCLUSIONS

The development of Traffic accident prediction system can influence the Development of society and the wealthy economic. To avoid Traffic accident losses in the future we should have forecasted accurately. Lots of the methods for forecasting have remarkable result, but the rough set combination method can select the distillate and abandon the draffy of these methods, and the accuracy of it is more perfect than the others.

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