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# Combination prediction model of traffic accident using Rough Set Technology approach

Badreldin O. S. Elgabbanni[1], Mohamed Osama Khozium[2], Mahmoud Ali Ahmed[3]
[1,2]Dep. of Engineering-computers, MCC, Umm Al-Qura University, Makkah, Saudi Arabia
[3]Dean of the Faculty of mathematical science, University of Khartoum, Sudan

**Abstract: Accident forecasting is designed to help decision making and planning before loss occur; 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 models, so the result of forecasting will be more precise. Based on the mean relative absolute error it was found that the proposed rough set rough set combination model scored the lowest reading which 0.51% compared to 9.16% for ARMA, 14.41.2% for EXPERT and 8.38% for NEURAL NETWORK.**

**Keywords: Predictive model; Traffic accident; Weighting Coefficient; combination model.**

## 1. INTRODUCTION

Rapidly growing population results in a significant increase in the number of vehicles and traffic accidents. A traffic accident is defined as a random event involving one or more motor vehicles in a collision that results in property damage, injury or death. A traffic accident prediction models enable planners and decisions makers to predict the possibility of accident occurrence it is very important because it can help in identifying number of policemen, hospitals, ambulances cars, street camera due to number of cars and road maintenance. Researchers deal with traffic accident by submitting a lot of pioneer and novel ideas concerning traffic accident[1], like generating rules, causes significant and developing crowd management systems [2].

The paper consists of 5 sections:

Section 1- This introduction which contains research problem and objectives.
Section 2- Literature Review on Prediction Models it comes across topics like rough set technology, time series and regression, ARMA, EXPERT and neural network and discretization.
Section 3- Provides research methodology that describes how the proposed models will be designed.
Section 4- Case study provides experiment about rough set combination for traffic accident prediction In addition to that it contains result validation and analysis.
Section 5- includes conclusion and future work.

## 2. LITERATURE REVIEW

### 2.1 Rough Set Approach

Rough set theory (RS) successfully applied in many areas like medical, industrial etc.. It has been widely used in knowledge discovery, data mining and approximate reasoning[3] when data set is incomplete or imprecise. The main idea is the classification of empirical data by selecting the degree of roughness or precision of data and making subsequent decisions. The philosophy of rough set theory is to let the data speak for itself. Rough set theory is a mathematical tool for dealing with vagueness or uncertainty. The framework can be accurately explained through the use of information systems.

### 2.2 Lower and Upper Approximations

An approximation spaces[4] can be defined as S = (U, R), where U is a finite set of objects Indiscernibility relations are the main concept in rough sets or approximate sets B_indiscernibility relation[5]. can be defined as follows:
xIND(B)y iff InfB(x)=InfB(y). For every subset $X \subseteq U$ the lower approximation $\underline{IND(B)}(X)$ and the upper approximation $\overline{IND(B)}(X)$ define as follows [6].

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$$\underline{IND(B)}(X) = \{x \in U : [x]_B \subseteq X\}, \quad (1)$$

$$\overline{IND(B)}(X) = \{x \in U : [x]_B \cap X \neq \varnothing\} \quad (2)$$

The accuracy of the approximation is measured by[7].

$$\alpha_s = \left|\frac{SX}{\overline{S}X}\right|$$

Where, $0 \le \alpha_s \le 1$

The boundary region[8], where the elementary set contains elements that are members of upper approximation region but not a members of lower approximation region given by set difference $S$X - $\overline{S}$ X, and U - $\overline{S}$ X shows the negative or outside region, where the elementary set contains elements that are members of the universe but not a members of the upper approximation[9] .

### 2.3 Time Series And Regression Model

An important step in analyzing of time series data is to consider the types of data patterns, so that the models most appropriate to those patterns can be utilized[10]. Four types of time series components can be distinguished. They are:

(i) Horizontal when data values fluctuate around a constant value
(ii)Trend when there is long term increase or decrease in the data
(iii) Cyclical when the data exhibit rises and falls that are not of a fixed period.

Time plot (data plotted over time) and seasonal plot (data plotted against individual seasons in which the data were observed) help in visualizing these patterns while exploring the data. A crude yet practical way of decomposing the original data (ignoring cyclical pattern) is to go for a seasonal decomposition either by assuming an additive or multiplicative model[11].

$$Y_t = \begin{cases} T_t.S_t.E & \text{magnitude of TS varies with level of series} \\ \text{else} & T_t + S_t + E_t \end{cases} \quad (3)$$

Where,
$Y_t$ - Original TS data
$T_t$ - Trend component
$S_t$ – Seasonal component t
Et – Error/ Irregular component t

If the magnitude of TS varies with the level of the series then one has to go for a multiplicative model else an additive model. This decomposition may enable one to study the TS components separately or will allow workers to de-trend or to do seasonal adjustments if needed for further analysis[12].

### 2.4 ARMA and ARIMA Models

During the last few decades, various approaches have been developed for time-series forecasting. Among them, ARMA modeling approaches are well-known. ARMA, which is in most cases a combination of Auto Regressive (AR) part and a Moving Average (MA) part, tries to solve two problems. One is the analysis on the stochastic, stationary and seasonal properties of time series, and the other is model selection. ARMA model is based on the premise that the time series used for accident forecasting has been preconditioned by zero-mean- valued stationary random process. Thus for the non-stationary time series it is necessary to make an initial differencing step to remove the non-stationary. The generalized method is called auto- regressive integrated moving average (ARIMA)[12].

In the accident forecasting, some researches have used ARMA to correct the error terms. In their case, a differential equation model is utilized to represent the accident mechanism with time-varying parameters and an ARMA process of white noise is attached to model the equation error. Another example is the combination of a regression model and ARIMA [13]. When regression is applied to time-series data, the error terms are often auto-correlated. In regression with auto- correlated errors, the errors will probably contain information that is not captured by the explanatory variables. ARIMA is used to model this information so that the effect of the explanatory variables on the dependent variable can be more reliably estimated.

The observation values of accident time series are often influenced by the unexpected event error. Outliers occur frequently in practice serious consequences. Considering the impact of outliers in the model, some statistical methods like intervention analysis. Intervention analysis is an extension of ARIMA model allowing study of the change in magnitude and structure of

time-series data. Furthermore, because the non-linear features of a series may behave in a more complicated way than the standard models, it may be advisable for the outlier analysis to be based on more flexible, though less simple and informative, models, such as Functional Auto Regressive (FAR) models [14]. FAR models are mostly direct generalization of linear auto-regression.
Suggested that the FAR-based method is effective both for series following some non-linear models and for linear series generated by ARMA processes.

**2.5 EXPERT Model**

The Time Series Modeler procedure estimates exponential smoothing, univariate Autoregressive Integrated Moving Average (ARIMA), and multivariate ARIMA (or transfer function models) models for time series, and produces forecasts.
Expert Modeler automatically identifies and estimates the best-fitting ARIMA or exponential smoothing model for one or more dependent variable series, thus eliminating the need to identify an appropriate model through trial and error.
Forecasting simply means understanding which variables lead to predict other variables, this means a clear understanding of the timing of lead-lag relations among many variables, understanding the statistical significance of these lead lag relations and learning which variables are the more important ones to watch as signals for predicting the traffic accident. Better forecasting is the key element for better traffic managing decision making [15].

**2.6 EXPONENTIAL Approach.**

Exponential method drives 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 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.

The simple exponential smoothing model N–N (no trend and no seasonality) is given by the formulas [16].

$S_t = a\, x_t + (1-a) S_{t-1}$ , where a $(0 < a < 1)$ (4)

is smoothing factor, St is smoothed statistics Then, two parameters Tt and It are added to reject trend and seasonality respectively, which is provided 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 [17] 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.

**2.7 NEURAL NETWORK Approach**

The neural network approach is motivated by biological neural networks[18]. Roughly speaking, a neural network is a set of connected input/output units, where each connection has a weight associated with it. Neural networks have several properties that make them popular for clustering. First, neural networks are inherently parallel and distributed processing architectures. Second, neural networks learn by adjusting their interconnection weights so as to best fit the data. This allows them to “normalize” or “prototype” the patterns and act as feature (or attribute) extractors for the various clusters. Third, neural networks process numerical vectors and require object patterns to be represented by quantitative features only.
Many clustering tasks handle only numerical data or can transform their data into quantitative features if needed.
The neural network approach to clustering tends to represent each cluster as an exemplar.

An exemplar acts as a “prototype” of the cluster and does not necessarily have to correspond to a particular data example or object.
Self-organizing feature maps (SOMs) are one of the most popular neural network methods for cluster analysis. They are sometimes referred to self-organizing feature maps, after their creator, or as topologically ordered maps.
SOMs’ goal is to represent all points in a high-dimensional source space by points in a low-dimensional (usually 2-D or 3-D) target space, such that the distance and proximity relationships (hence the topology) are preserved as much as possible. The method is particularly useful when a nonlinear mapping is inherent in the problem itself SOMs can also be viewed as a constrained version of k-means clustering, in which the cluster centers tend to lie in a low-dimensional manifold in the feature or attribute space, With SOMs, clustering is performed by having several units competing for the current object. The unit whose weight vector is closest to the current object becomes the winning or active unit. So as to move even closer to the input object, the weights of the winning unit are adjusted, as well as those of its nearest neighbors. SOMs assume that there is some topology or ordering among the input objects and that the units will eventually take on this structure in space. The organization of units is said to form a feature map.

SOMs are believed to resemble processing that can occur in the brain and are useful for visualizing high-dimensional data in 2-D or 3-D space.
The SOM approach has been used successfully for Web document clustering.

The neural network approach to clustering has strong theoretical links with actual brain processing. Further research is required to make it more effective and scalable.
The 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.
Figure 2 provides an example of Multilayer Perceptron (MLP) architecture. An MLP is typically composed of an input layer, one or more hidden layers, and output layer, each consisting of several neurons.

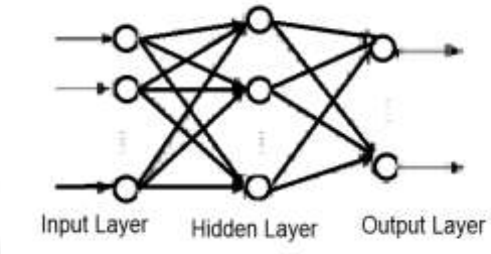


Figure 1: Multilayer Perceptron

A neuron is made up of several protrusions called dendrites and a long-branch called the axon. Millions of neurons are linked together through the dendrites in
a massively parallel manner. The dendrites of neurons meet to form synapses where the message pass, and the neurons receive the pulses via the synapses.

When a neuron receives a set of input pulses, internal processes take place such as activation of neurons, and then the neuron sends out another pulse that is a function of the input pulses. Suppose the inputs $x_1, x_2, \ldots, x_n$ are coming to the neuron and each input xi is multiplied by its corresponding weight wi, then the product wi xi is fed to the neuron. The weight wi represents the biological synaptic strength in a natural neuron. The neuron adds up all the weighted Inputs as follows [19].

$$\text{Net}=\sum_{i=1}^{N} w_i x_i \qquad (5)$$

Where,
$w_i$ is corresponding weight
$x_i$ set of input pulses
Finally, the neuron computes its output as a function of net, i.e.
y = f(net) where f is called the activation or transfer function.

## 3. METHODOLOGY

To achieve the objectives and to contribute to the problem solution the bellowing methodology will be followed.

a- Study previously identified attributes influencing the occurrence of accidents and accident prediction. For this task and through literature preview several articles on accident prediction models was collected and reviewed .
b- Collect and analyze data. This research concerned with National Highway Traffic Safety Administration (NHTSA) records for Washington DC and other states in US.
4. Rough set theory used to generate laws based on the reality of accidents recorded in traffic information system.
c- Identify statistically significant, weighting and prediction using statistical models.
d- Implement RSES2.2 to reduce redundant data, and generate rules from traffic accident database system.
e- Implement RSES2.2 to criticize data and generate weight for attributes.
f- Implement RSES2.2 and SPSS and Excel to estimate expected number of traffic accident using Rough set Technology.
g- Comparing the result with other models results such as neural network, ARMA, and exponential model.

Rough set combination algorithm can be designed as the following flow chart algorithm as shown in Figure 2.

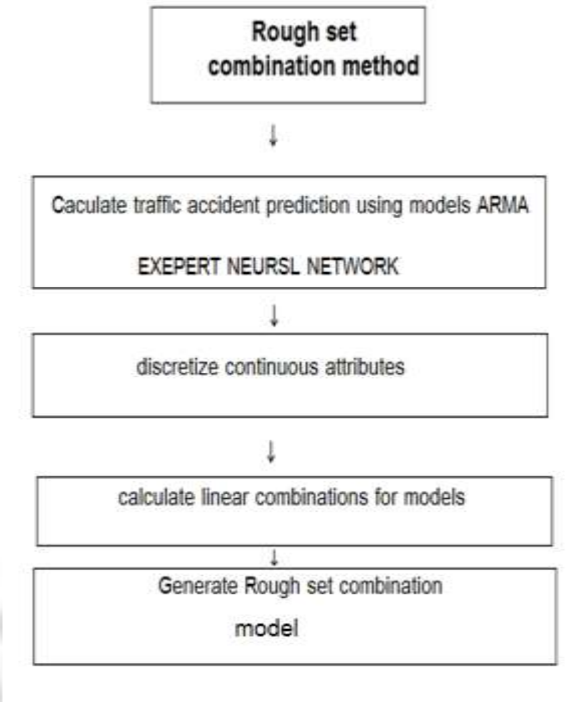

Figure 2: Rough set combination algorithm

## 4. CASE STUDY

The experiment concerned with traffic accident available on National Highway Traffic Safety Administration (NHTSA) for Washington DC in USA from year 1982 to 2008.

Rough set combination model used to predict the number of accidents that may occur in coming years. The following steps are done to establish that purpose:

a- Statistical package SPSS18 is used to calculate traffic accident prediction from National Highway Traffic Safety Administration (NHTSA) records for Washington DC state in US year 1982-2008 as shown in Table 1.

Table 1 Washington DC Raw data

| Year | Traffic Fatalities | Year | Traffic Fatalities | Year | Traffic Fatalities |
|---|---|---|---|---|---|
| 1982 | 1074 | 1992 | 1153 | 2002 | 1177 |
| 1983 | 1046 | 1993 | 1170 | 2003 | 1193 |
| 1984 | 1111 | 1994 | 1214 | 2004 | 1339 |
| 1985 | 1101 | 1995 | 1259 | 2005 | 1270 |
| 1986 | 1230 | 1996 | 1239 | 2006 | 1284 |
| 1987 | 1247 | 1997 | 1225 | 2007 | 1211 |
| 1988 | 1266 | 1998 | 1216 | 2008 | 1043 |
| 1989 | 1088 | 1999 | 1302 | | |
| 1990 | 1177 | 2000 | 1307 | | |
| 1991 | 1113 | 2001 | 1251 | | |

Using spss18 to manipulate predicted data from National Highway Traffic Safety Administration (NHTSA) records for Washington DC state in US year 1982-2008 Using ARMA,EXPERT And NEURAL NETWORK models as shown in Table 2.

Table 2: ARMA, EXPERT and NEURAL Predictions

| Traffic Fatalities | ARMA | EXPERT | NEURAL |
|---|---|---|---|
| 1074 | 1120.259815 | 1118.472565 | 1076.164295 |
| 1046 | 1126.849275 | 1078.699746 | 1046.38311 |
| 1111 | 1133.438735 | 1049.455625 | 1109.036362 |
| 1101 | 1140.028195 | 1104.496149 | 1104.661428 |
| 1230 | 1146.617655 | 1101.369464 | 1233.199445 |
| 1247 | 1153.207114 | 1216.406656 | 1244.664614 |
| 1266 | 1159.796574 | 1243.766974 | 1265.857291 |
| 1088 | 1166.386034 | 1263.650471 | 1086.949144 |
| 1177 | 1172.975494 | 1106.56229 | 1172.457075 |
| 1113 | 1179.564954 | 1169.556324 | 1108.688756 |
| 1153 | 1186.154414 | 1118.976727 | 1153.257395 |
| 1170 | 1192.743874 | 1149.404508 | 1173.647821 |
| 1214 | 1199.333333 | 1167.823521 | 1212.460917 |
| 1259 | 1205.922793 | 1209.120189 | 1260.506898 |
| 1239 | 1212.512253 | 1253.72883 | 1240.149471 |
| 1225 | 1219.101713 | 1240.556505 | 1228.702346 |
| 1216 | 1225.691173 | 1226.643971 | 1210.525351 |
| 1302 | 1232.280633 | 1217.124828 | 1300.760127 |
| 1307 | 1238.870092 | 1293.03061 | 1308.776499 |
| 1251 | 1245.459552 | 1305.523751 | 1248.353431 |
| 1177 | 1252.049012 | 1256.76193 | 1174.955892 |
| 1193 | 1258.638472 | 1185.429036 | 1192.398859 |
| 1339 | 1265.227932 | 1192.19992 | 1347.576097 |
| 1270 | 1271.817392 | 1323.486545 | 1267.796866 |
| 1284 | 1278.406852 | 1275.652321 | 1281.792994 |
| 1211 | 1284.996311 | 1283.117839 | 1207.808952 |
| 1043 | 989.8658101 | 1218.621228 | 1039.112234 |

### 4.1 Continuous Data Discretization

For Rough set combination model (RSES 2.2) is used to discretize attributes with continuous domains into the ones with discrete domains. All such attributes in the source data file will be processed as shown in Table 3.

Table 3; Data Discretization using RSES

| NEURAL_P | ARMA_P | TRAFFIC_F | EXPERT_P |
|---|---|---|---|
| "(-Inf,1108.5)" | "(-Inf,1169.0)" | "(1044.5,1227.5)" | "(1110.0,1133.5)" |
| "(-Inf,1108.5)" | "(-Inf,1169.0)" | "(1044.5,1227.5)" | "(-inf,1089.5)" |
| "(1108.5,1211.0)" | "(-Inf,1169.0)" | "(1044.5,1227.5)" | "(-inf,1089.5)" |
| "(-Inf,1108.5)" | "(-Inf,1169.0)" | "(1044.5,1227.5)" | "(1089.5,1110.0)" |
| "(1211.0,Inf)" | "(-Inf,1169.0)" | "(1227.5,1255.0)" | "(1089.5,1110.0)" |
| "(1211.0,Inf)" | "(-Inf,1169.0)" | "(1227.5,1255.0)" | "(1200.5,1279.0)" |
| "(1211.0,Inf)" | "(-Inf,1169.0)" | "(1255.0,1277.0)" | "(1200.5,1279.0)" |
| "(-Inf,1108.5)" | "(-Inf,1169.0)" | "(1044.5,1227.5)" | "(1200.5,1279.0)" |
| "(1108.5,1211.0)" | "(1169.0,1235.0)" | "(1044.5,1227.5)" | "(1089.5,1110.0)" |
| "(-Inf,1108.5)" | "(1169.0,1235.0)" | "(1044.5,1227.5)" | "(1133.5.1200.5)" |
| "(1108.5,1211.0)" | "(1169.0,1235.0)" | "(1044.5,1227.5)" | "(1110.0,1133.5)" |
| "(1108.5,1211.0)" | "(1169.0,1235.0)" | "(1044.5,1227.5)" | "(1133.5.1200.5)" |
| "(1211.0,Inf)" | "(1169.0,1235.0)" | "(1044.5,1227.5)" | "(1133.5.1200.5)" |
| "(1211.0,Inf)" | "(1169.0,1235.0)" | "(1255.0,1277.0)" | "(1200.5,1279.0)" |
| "(1211.0,Inf)" | "(1169.0,1235.0)" | "(1227.5,1255.0)" | "(1200.5,1279.0)" |
| "(1211.0,Inf)" | "(1169.0,1235.0)" | "(1044.5,1227.5)" | "(1200.5,1279.0)" |
| "(1108.5,1211.0)" | "(1169.0,1235.0)" | "(1044.5,1227.5)" | "(1200.5,1279.0)" |
| "(1211.0,Inf)" | "(1169.0,1235.0)" | "(1277.0,Inf)" | "(1200.5,1279.0)" |
| "(1211.0,Inf)" | "(1235.0,Inf)" | "(1277.0,Inf)" | "(1279.0,Inf)" |

| | | | |
|---|---|---|---|
| "(1211.0,Inf)" | "(1235.0,Inf)" | "(1227.5,1255.0)" | "(1279.0,Inf)" |
| "(1108.5,1211.0)" | "(1235.0,Inf)" | "(1044.5,1227.5)" | "(1200.5,1279.0)" |
| "(1108.5,1211.0)" | "(1235.0,Inf)" | "(1044.5,1227.5)" | "(1133.5.1200.5)" |
| "(1211.0,Inf)" | "(1235.0,Inf)" | "(1277.0,Inf)" | "(1133.5.1200.5)" |
| "(1211.0,Inf)" | "(1235.0,Inf)" | "(1255.0,1277.0)" | "(1279.0,Inf)" |
| "(1211.0,Inf)" | "(1235.0,Inf)" | "(1277.0,Inf)" | "(1200.5,1279.0)" |
| "(1108.5,1211.0)" | "(1235.0,Inf)" | "(1044.5,1227.5)" | "(1279.0,Inf)" |
| "(-Inf,1108.5)" | "(-Inf,1169.0)" | "(-Inf,1044.5)" | "(1200.5,1279.0)" |

Above table will be transferred manually from intervals to constant values as shown in Table 4

Table 4: Final discretization

| EXPERT | Fatal accident | ARMA | NEURAL |
|---|---|---|---|
| 2 | 3 | 1 | 1 |
| 1 | 2 | 1 | 1 |
| 1 | 3 | 1 | 2 |
| 1 | 3 | 1 | 1 |
| 1 | 5 | 1 | 2 |
| 3 | 5 | 1 | 2 |
| 3 | 5 | 1 | 2 |
| 1 | 3 | 2 | 1 |
| 2 | 4 | 2 | 2 |
| 2 | 3 | 2 | 1 |
| 2 | 3 | 2 | 2 |
| 2 | 4 | 2 | 2 |
| 2 | 7 | 2 | 2 |
| 3 | 5 | 2 | 2 |
| 3 | 5 | 2 | 2 |
| 3 | 6 | 2 | 2 |
| 2 | 7 | 2 | 2 |
| 3 | 8 | 2 | 2 |
| 3 | 8 | 2 | 2 |
| 3 | 3 | 2 | 2 |
| 3 | 4 | 3 | 2 |
| 2 | 4 | 3 | 2 |
| 2 | 5 | 3 | 2 |
| 3 | 5 | 3 | 2 |
| 3 | 8 | 3 | 2 |
| 3 | 7 | 3 | 2 |
| 3 | 2 | 1 | 1 |

### 4.2 Rough Set Combination Model

To generate rough set combination model, RSES 2.2 software package is used to calculate the weighs of the models EXPERT, ARMA and NEURAL NETWORK then the Rough Set Combination Model(RSCM)can be illustrated as:

RSCM=ABS(EXPERT*0.022-ARMA*0.012+NUERAL*0.99) (6)

Where,

EXPERT is the value predicted by EXPERT model
ARMA is the value predicted by ARAMA model
NEURAL is the value predicted by NEURAL NETWORK model
The results generated by rough set combination model (RST_C) shown in Table 5

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Table 5: Models Predictions

| YEAR | F_acc | ARMA | NEURAL | EXPERT | RST_C |
|---|---|---|---|---|---|
| 1982 | 1074 | 1120.259815 | 1076.164295 | 1118.472565 | 1076.565931 |
| 1983 | 1046 | 1126.849275 | 1046.38311 | 1078.699746 | 1046.128482 |
| 1984 | 1111 | 1133.438735 | 1109.036362 | 1049.455625 | 1107.432758 |
| 1985 | 1101 | 1140.028195 | 1104.661428 | 1104.496149 | 1104.233391 |
| 1986 | 1230 | 1146.617655 | 1233.199445 | 1101.369464 | 1231.338167 |
| 1987 | 1247 | 1153.207114 | 1244.664614 | 1216.406656 | 1245.140429 |
| 1988 | 1266 | 1159.796574 | 1265.857291 | 1243.766974 | 1266.644032 |
| 1989 | 1088 | 1166.386034 | 1086.949144 | 1263.650471 | 1089.883331 |
| 1990 | 1177 | 1172.975494 | 1172.457075 | 1106.56229 | 1171.001168 |
| 1991 | 1113 | 1179.564954 | 1108.688756 | 1169.556324 | 1109.177329 |
| 1992 | 1153 | 1186.154414 | 1153.257395 | 1118.976727 | 1152.108456 |
| 1993 | 1170 | 1192.743874 | 1173.647821 | 1149.404508 | 1172.885315 |
| 1994 | 1214 | 1199.333333 | 1212.460917 | 1167.823521 | 1211.636425 |
| 1995 | 1259 | 1205.922793 | 1260.506898 | 1209.120189 | 1260.0314 |
| 1996 | 1239 | 1212.512253 | 1240.149471 | 1253.72883 | 1240.779863 |
| 1997 | 1225 | 1219.101713 | 1228.702346 | 1240.556505 | 1229.078345 |
| 1998 | 1216 | 1225.691173 | 1210.525351 | 1226.643971 | 1210.697971 |
| 1999 | 1302 | 1232.280633 | 1300.760127 | 1217.124828 | 1299.741904 |
| 2000 | 1307 | 1238.870092 | 1308.776499 | 1293.03061 | 1309.268966 |
| 2001 | 1251 | 1245.459552 | 1248.353431 | 1305.523751 | 1249.645905 |
| 2002 | 1177 | 1252.049012 | 1174.955892 | 1256.76193 | 1175.830507 |
| 2003 | 1193 | 1258.638472 | 1192.398859 | 1185.429036 | 1191.450648 |
| 2004 | 1339 | 1265.227932 | 1347.576097 | 1192.19992 | 1345.145999 |
| 2005 | 1270 | 1271.817392 | 1267.796866 | 1323.486545 | 1268.973792 |
| 2006 | 1284 | 1278.406852 | 1281.792994 | 1275.652321 | 1281.698533 |
| 2007 | 1211 | 1284.996311 | 1207.808952 | 1283.117839 | 1208.539499 |
| 2008 | 1043 | 989.8658101 | 1039.112234 | 1218.621228 | 1043.652389 |

**4.3 Result and Discussion**

Error Calculation:

The statistical equations of RMSE, MRE, MSE, MAPE and MAE can be summarized as shown in Table 7.

Table 7: Error Calculation Formula

| Measure | Definition |
|---|---|
| Mean Error | $\mathrm{ME}=\frac{1}{n}\sum_{i=1}^{n} e_i$ |
| Mean Absolute Error | $\mathrm{MAE}=\frac{1}{n}\sum_{i=1}^{n}\lvert e_i\rvert$ |
| Mean squared Error | $\mathrm{MSE}=\frac{1}{n}\sum_{i=1}^{n} e_i^2$ |
| Mean percentage Error | $\mathrm{MPE}=\frac{1}{n}\sum_{i=1}^{n} PE_i$ |
| Mean absolute percentage Error | $\mathrm{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\lvert PE_i\rvert$ |

And to calculate Mean Absolute Percentage Error (MAPE) and Mean Relative Error (MRE)

$$\mathrm{MAPE}=\frac{1}{n}\sum_{i=1}^{n}(\lvert Yd_i - Y_i\rvert)/Y_i * 100 \quad (7)$$

$$\mathrm{MRE}=\mathrm{MAX}\,(\lvert Yd_i - Y_i\rvert)/Y_i * 100 \quad (8)$$

Where, N is the number of samples

$Yd_i$ is observed value for ith sample

$Y_i$ is predicted value for ith sample

Table 6: Absolute Error of Models

| YEAR | COMBINATI_ON | NEURAL NETWORK | EXPERT | ARMA |
|---|---|---|---|---|
| 1982 | 2.5659 | 2.1643 | 44.473 | 46.26 |
| 1983 | 0.1285 | 0.3831 | 32.7 | 80.849 |
| 1984 | 3.5672 | 1.9636 | 61.544 | 22.439 |
| 1985 | 3.2334 | 3.6614 | 3.4961 | 39.028 |
| 1986 | 1.3382 | 3.1994 | 128.63 | 83.382 |
| 1987 | 1.8596 | 2.3354 | 30.593 | 93.793 |
| 1988 | 0.644 | 0.1427 | 22.233 | 106.2 |
| 1989 | 1.8833 | 1.0509 | 175.65 | 78.386 |
| 1990 | 5.9988 | 4.5429 | 70.438 | 4.0245 |
| 1991 | 3.8227 | 4.3112 | 56.556 | 66.565 |
| 1992 | 0.8915 | 0.2574 | 34.023 | 33.154 |
| 1993 | 2.8853 | 3.6478 | 20.595 | 22.744 |
| 1994 | 2.3636 | 1.5391 | 46.176 | 14.667 |
| 1995 | 1.0314 | 1.5069 | 49.88 | 53.077 |
| 1996 | 1.7799 | 1.1495 | 14.729 | 26.488 |
| 1997 | 4.0783 | 3.7023 | 15.557 | 5.8983 |
| 1998 | 5.302 | 5.4746 | 10.644 | 9.6912 |
| 1999 | 2.2581 | 1.2399 | 84.875 | 69.719 |
| 2000 | 2.269 | 1.7765 | 13.969 | 68.13 |
| 2001 | 1.3541 | 2.6466 | 54.524 | 5.5404 |
| 2002 | 1.1695 | 2.0441 | 79.762 | 75.049 |
| 2003 | 1.5494 | 0.6011 | 7.571 | 65.638 |
| 2004 | 6.146 | 8.5761 | 146.8 | 73.772 |
| 2005 | 1.0262 | 2.2031 | 53.487 | 1.8174 |
| 2006 | 2.3015 | 2.207 | 8.3477 | 5.5931 |
| 2007 | 2.4605 | 3.191 | 72.118 | 73.996 |
| 2008 | 0.6524 | 3.8878 | 175.62 | 53.134 |

Error calculation showed that RST COMBINATION result is more perfect than ARMA and EXPERT and for a little bit less than NEURAL NETWORK model see Figure 3.
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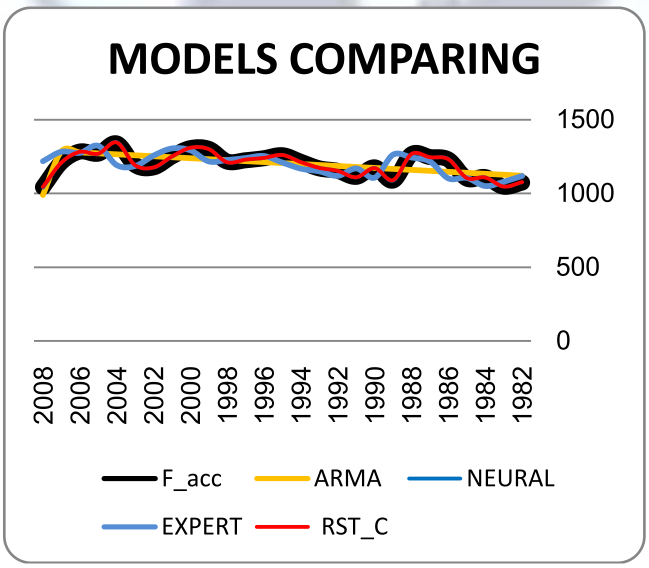


Figure 3: models comparing

The statistical values of RMSE, MRE, MSE and MAE of the models are given in Table 8.

Table 8: Error Measurement

| Model | MRE | MAE | MSE | RMSE |
|---|---|---|---|---|
| ARMA | 9.16% | 47.37184646 | 3224.158 | 47.37185 |
| EXPERT | 14.41% | 56.11085873 | 5478.746 | 56.11086 |
| NEURAL | 8.38% | 2.570590389 | 9.850176 | 2.57059 |
| RST_C | .51% | 2.391121808 | 8.137928 | 2.391122 |

## 5. CONCLUSION AND FUTURE WORK

The results of traffic accidents prediction, show that the performance of the proposed **RST** COMBINATION is more precise and accurate compared to other models like ARMA, EXPERT and NEURAL NETWORK.

For future work other models and/or discretization methods may be used so as to generate more precise weight coefficient and then accurate prediction.

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