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Highly Accurate Emergency Vehicle Management for Multiple Path Using Support Vector Machine Based Predictor

Cyriac Jose, K S Vijula Grace, C Asha Beaula

***Abstract:** Emergency vehicle management (EVM) plays an important role in different lifesaving field such as medicine, fire and safety, and defense etc. The transportation time of the EV mainly depends upon various parameter such as traffic density (TD), weather condition (WC), road condition, conjunction etc. Before selecting a route, it is necessary to confirm that the selected route can reach the destination with minimum time without any destruction of the carrier. A highly accurate emergency vehicle management for multiple path using support vector machine (MP-EVM-SVM) with objective function which is modelled mathematically is proposed in this work. Objective function is modelled based on various parameters such as distance, traffic density, slope, road type, road width etc. MP-EVM-SVM system can be used in the real-time applications such as transportation time estimation and optimum path selection from various path. MP-EVM-SVM can predict the best path which can reach the destination with less time in smooth manner. Proposed algorithm gives 97% of accuracy which is high when compared to the conventional path prediction techniques.*

***Index Terms:** Adaptive Neuro Inference System (ANFIS), Emergency Vehicle Management (EVM), Support Vector Machine (SVM), Traffic Density (TD).*

I. INTRODUCTION

Emergency vehicle management plays an important role in our everyday life. The delay in the EV can cost valuable lives. The transportation time of the emergency vehicle is directly proportional to the various parameters which are traffic density and road conditions. Emergency vehicle path routing in disaster conditions is more important and can save more lives [1].

Minimization of emergency response time is a key concentration in attempts to enhance emergency transport frameworks. Fast reaction to an emergency circumstance can anticipate or limit unfavorable results, for example, fatalities or the loss of property.

In the event that then again, normal vehicles are told ahead of time of the course emergency vehicles will take, both conventional and emergency vehicles can diminish a danger of the crash. Dynamic routing for emergency vehicle can be used to rapidly change the path of EV with varying traffic conditions. Empowering emergency vehicles to announce their course adaptable and continuously to alarm conventional vehicles can enhance activity stream and diminish the number of mishaps including customary and emergency vehicles [2].

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Proficient routing under indeterminate traffic conditions can enhance the execution of insightful transportation frameworks. Wherein ongoing movement data is accessible emergency dispatch centers. This exploration plans to create and improve a continuous emergency reaction framework that utilization constant travel time data to help the dispatchers of crisis vehicles in allotting the vehicles to ideal course. To this end, this paper proposes a numerical model for a basic decision-making process progressively real-time route dispatching. The model is specified as a constrained shortest-path problem issue that can assist the dispatcher with making choices. EV path routing can be effectively perform by using optimization techniques. Best solution can be estimated by using ant colony optimization technique using proper objective functions [3].

Path planning can be applied in autonomous vehicle using artificial intelligence techniques. Radial basis function neural network is previously proposed to plan motion and path [4]. The sample points are randomly selected in the drivable region, and a gradient descent method is used to train the RBF network. Other machine learning algorithms also can be used in the path planning algorithms to predict and plan the path accurately. In Conventional method, routing problem can be solved on huge scale systems hubs and connections, calculation times are restrictively high when we apply the customary Dijkstra's shortest path calculation. In addition, actual link travel times are determined by traffic congestion and road conditions. Hence the data (network) used in computing the shortest paths has to be updated periodically [4]. To beat this computational issue, we utilize a progressive methodology point by point in area Since in a calamity circumstance, any hub can be a potential cause or a goal, a quick heuristic that can give great estimation results in a restricted measure of time is liked to correct techniques.

In this work, a new technique for EV management using SVM is proposed to predict the accurate path. A mathematically modelled fitness function is introduced in this work to predict the transition time more accurately. MP-EVM-SVM uses various linear and nonlinear traffic parameters which is used to model the objective function for prediction. Proposed system has advantage in accuracy and flexibility when compared to the conventional technique. The major contributions of this paper are as follows.

1) path identifier: By using support vector machine which is trained by objective function. The best path among various path can be determined.

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2) Classification Model: Identification of the best path is done by using Multiple classification. Maximum voting concept is used to select best decision among three classifiers.

3) Validation: The experiment is done using real-time database which is collected from various area with different traffic and environmental conditions. The structure of this paper is given as follows. In Section II, various works which are proposed previously is explained. Detailed explanation of proposed method and its supporting algorithms also explained in Section III with its architecture. Section IV provides the experimental analysis which is carried out for different data from real-time database. Section V concludes this paper.

II. RELATED WORK

Jading Zhao et al. [6] introduced a solution for dynamic path prediction for emergency vehicle. Shortest travel time and the minimum degree of traffic congestion is considered as main goal. A polyline-shaped speed function is constructed and based on the historical data of the road such as traffic density average speed etc. are considered. Clustering algorithm based on shuffled frog leaping is used to predict the shortest path. Generally, optimization may take more time to converge. It may increase the response time to the uses to select proper path. Shankar et al. [7] proposed congestion avoidance and path planning and reservation is proposed by adaptive neuro inference system ANFIS. System is trained by using human decision that is based on the historical results which are collected from particular path. Rules are developed for low high medium based on Mamdani fuzzy models. The accuracy of the system is not good because fuzzy cant train for large number of parameters. Takwa et al. [8] implemented and validated PSO optimization technique to determine the optimized path of an EV. Ambulance is considered as EV and open vehicle routing is introduced to perform the path routing. Cluster- first route-second algorithm is proposed to improve the prediction accuracy. Combination of optimization and clustering may reduce the computation time and it may reduce the performance of algorithm.

Elalouf et al. [9] proposes an exact pseudo-polynomial algorithm and an ε-approximation algorithm to solve the optimum path problem in EV. It is a graph-based theory which can determine the path of EV with less computational cost. The main disadvantage of this technique is, it is not applicable in the complex traffic environment conditions. +

Chia et al. [10] proposed a new emergency vehicle dispatching system to reduce the emergency response time. This can be useful to the emergency vehicles such as ambulance, military\y vehicle, fire force vehicles etc. similarly lane reservation scheme also used to avoid the crash risk. No intelligence technique or optimization technique is proposed in this work. The main disadvantage of this work is it not applicable for the real-time path selection process.

Peng Zhan et al. [11] introduced a historical data clustering-based path prediction algorithm. log fuzzy C-means clustering algorithm (LFCM) is used to cluster the data. Realtime historical data collected from various path and it is used to predict the traffic. Large amount of data will take more time to clustering process. The existing literatures reveal that Optimization, graph and clustering based path selection and planning algorithms where implemented. Performance of the system is affecting in terms of accuracy or computation time. In some techniques, computation is more and it cannot apply in the real-time environment. Similarly graph theory-based algorithms are not much efficient in complex traffic conditions. Therefore, in this work, a novel technique by using support vector machine with objective function which is modelled mathematically is proposed to estimate the path prediction. Training can be done while installing the system in the real-time environment. Once trained testing can be perform rapidly based on the availability of real-time data.

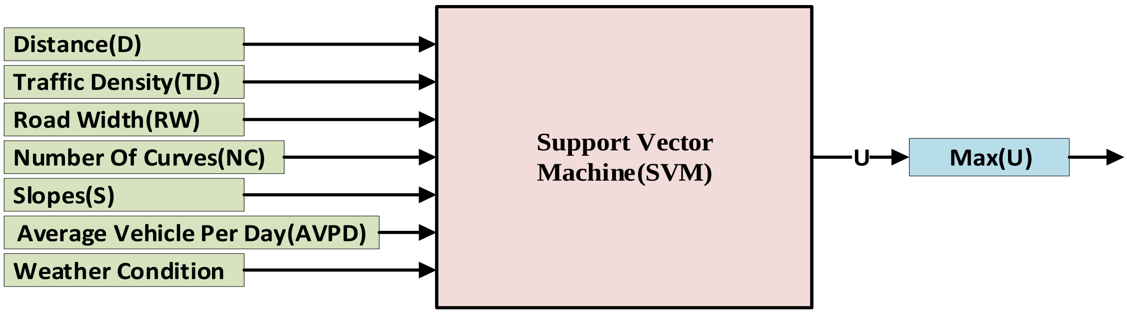

Fig 1. Schematic Representation of predictor with parameters

III. MULTIPLE PATH PREDICTION USING SUPPORT VECTOR MACHINE (MP-EVM-SVM)

The accurate decision for path of an emergency vehicle about the route is provided by the proposed methodology. It is important for the EV to reach the destination point with minimal time to save the life. For finding an efficient route it is important for considering the parameters that affect the speed of the emergency vehicle. The transportation time of the emergency vehicle is directly proportional to the various parameters. Which are depends on traffic density, road conditions, and weather conditions etc. The efficiency of the algorithm is depending mainly based on the effectiveness of the classifier. The performance of the system can be improved by using an effective prediction algorithm.

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A. *Parameters Considered*

Proposed methodology uses SVM classifier to find the minimal time route. The parameters which considered for finding the minimal time route are given below. Fig.1 Schematic Representation of predictor with parameters.

1) Distance(D)
2) Traffic density (TD)
3) Road width (RW)
4) Number of Curves (NC)
5) Slope up and down (SU & SD)
6) Average vehicle per day (AVPD)
7) Weather condition (WC)

a) Distance

To reach the given destination point we have the different route with different distance. Distance is an important parameter that affects the time of emergency vehicle to reach the destination. The fitness value is inversely proportional to distance. To reach the given destination point, generally more path can be available with different distance. Eq (1) shows how the distance is affecting the transportation time of an emergency vehicle.

$$f_n \propto \frac{1}{D_n} \qquad (1)$$

b) Traffic Density (TD)

TD is one of the time varying parameter which effects the time of the EV to reach the destination from source. TD is the number of vehicles possessing a given length of the roadway in a traffic path. It is represented as a vehicle/mile or vehicle/kilometer. Traffic density is inversely proportional to the transportation time of EV such as ambulance fire and safety vehicle and military vehicles etc.

Fig. 2 shows the graphical representation of traffic density

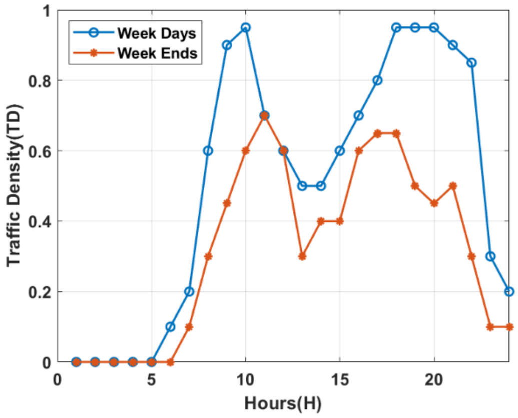

Fig 2. Normalized traffic density of a route for week days and week ends

with respect to the time in hours. It shows how the traffic density of a route changing for normal days and weekends. Fitness value is best for lesser value of traffic density as shown in Eq. (2).

$$f_n \propto \frac{1}{TD_n} \qquad (2)$$

c) Road Width (RW)

The effect of road width limits the speed of the emergency vehicle. If the width of the road is high, EV can moves with constant speed without more variation in the velocity. Fitness function for RW is Directly proportional to road width as shown in eq (3).

$$f_n \propto RW_n \qquad (3)$$

d) Number of Curves

Curvature is a roadway element which is a major factor that limits vehicle speeds. Speed of an EV will be less at the curvature sections of a route. Number of curvatures limits the speed of the vehicle. As shown Eq. (4) Fitness function is inversely proportional to number curves in the road.

$$f_n \propto \frac{1}{NC_n} \qquad (4)$$

e) Up and Downslope the road

In down slope increases the speed of vehicle as shown in Eq. (5). Similarly, for the upslope speed of the vehicle is limits as shown in Eq. (5).

$$f_n \propto ASD_n + \frac{1}{ASU_n} \qquad (5)$$

f) Average Vehicles per Day

Average vehicle per day is an important factor that affects the speed of the vehicle. Fitness function is inversely proportional to the average vehicle per day as Eq (6).

$$f_n \propto \frac{1}{AVpD_n} \qquad (6)$$

g) Weather Condition (WC)

Extreme weather conditions can have any kind of effect in typical driving. Weather conditions may completely stope the EV due to the destruction of road on block in the road. In some cases, Weather conditions slow down the vehicle and it makes high traffic density resulting very less speed of vehicles. As shown in Eq. (7) fitness is inversely proportional to the weather conditions.

$$f_n \propto \frac{1}{WC_n} \qquad (7)$$

h) Road Type

Road type is an important factor that limit the speed of the vehicle. Generally, speed limit of one-way road will be high when compared to the bidirectional road, Road type is a positive factor and it is directly proportional to the fitness value as shown in Eq (8).

$$f_n \propto RT_n \qquad (8)$$

B. *Block Diagram*

Fig 3. shows the block diagram of the proposed methodology. First Training database is normalized between 0 to 1 range to get uniformity of all parameters. The fitness function is computed for all paths of routes in a given source to destination. Each route has corresponding fitness value which depends on all parameters in the given route and cascaded all routes parameters and corresponding fitness value. Then route information and corresponding fitness value are given to the SVM for training. Here, route information is given as input and fitness value as output to the SVM. For testing, purpose collects information of all routes for given source to destination. Input data will be pre-processed and

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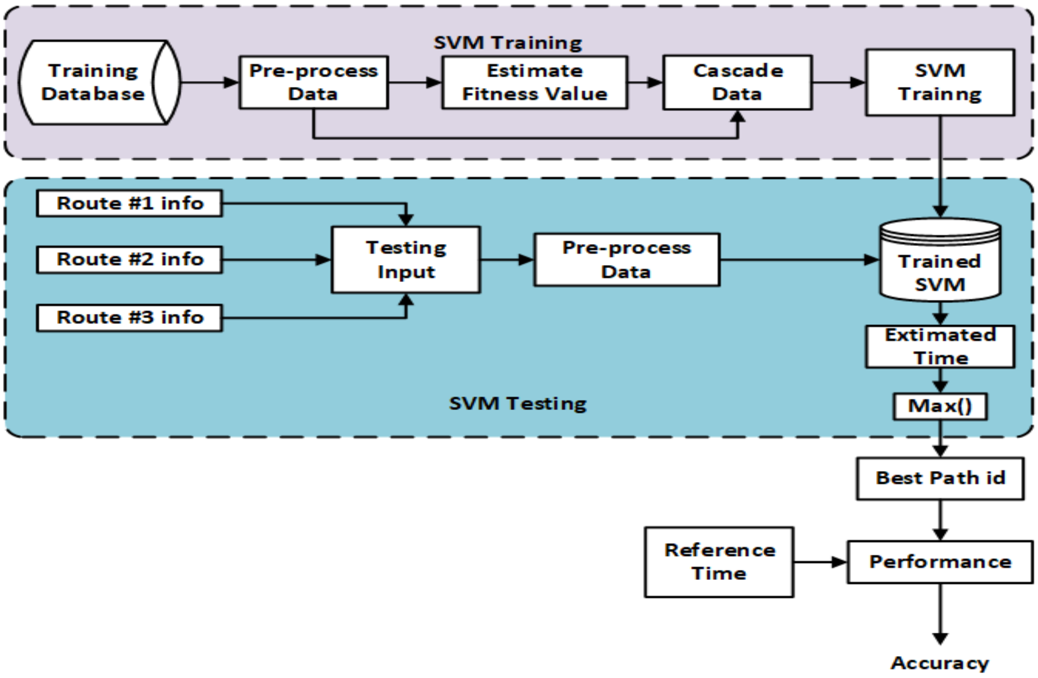

Fig 3. Block Diagram for the proposed system (MP-EVM-SVM).

feed to the support vector machine for the prediction.

C. *Mathematical Model*

A nonlinear Mathematical model is developed to solve the problem. The main objective of mathematical modelling is to develop a cost function that depends on different parameters of distinct routes. Schematic representation of emergency vehicle from source to destination with parameters are shown in Figure 4. From source to the destination have different routes, but main objective is to select the best fit route from different traffic conditions, road conditions and also different environmental factors. Mathematically modelled path can be shown in Fig. 4.

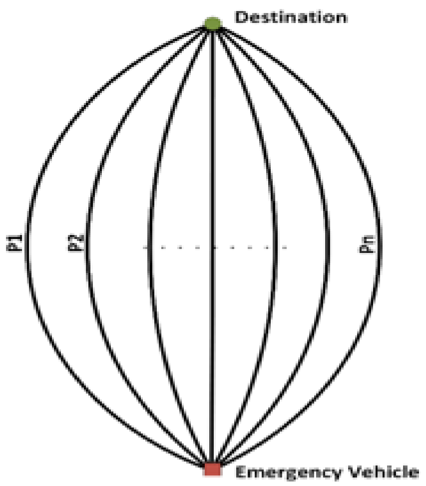

Fig 4. Mathematical modelling

From the above figure it is shown that $P_1, P_2, P_3, \ldots\ldots, P_n$ is different path in given source to destination. Here n is the number of the path in given source to destination.

$$P_1 = \{D_1, TD_1, RW_1, NC_1, SU_1, SD_1, AVPD_1, WC_1\}$$
$$P_2 = \{D_2, TD_2, RW_2, NC_2, SU_2, SD_2, AVPD_2, WC_2\}$$
$$P_3 = \{D_3, TD_3, RW_3, NC_3, SU_3, SD_3, AVPD_3, WC_3\}$$
.
.
$$P_n = \{D_n, TD_n, RW_n, NC_n, SU_n, SD_n, AVPD_n, WC_n\}$$

Here

$D_1, D_2, D_3, \ldots, D_n$ is the distance for the source to the destination of path $1,2,3, \ldots, n$.

$TD_1, TD_2, TD_3, \ldots, TD_n$ is the traffic density of path $1,2,3, \ldots, n$.

$NC_1, NC_2, NC_3, \ldots, NC_n$ is the Number of curves of path $1,2,3, \ldots, n$.

$SU_1, SU_2, SU_3, \ldots, SU_n$ is the Angle of upslope of path $1,2,3, \ldots, n$.

$SD_1, SD_2, SU_3, \ldots, SU_n$ is the Angle of downslope of path $1,2,3, \ldots, n$.

$AVPD_1, AVPD_2, AVPD_3, \ldots, AVPD_n$ is Average vehicle per day of path $1,2,3, \ldots, n$.

$WC_1, WC_2, WC_3, \ldots, WC_n$ is the weather condition of path $1,2,3, \ldots\ldots, n$.

D. *Fitness Function*

The fitness function is important to combine all parameters which affect the speed of the vehicle in a given source to destination. By combining all Eq. (1) to (2) we can find the fitness value by using given Eq. (9)

$$f_n = \frac{1}{D_n} + \frac{1}{TD_n} + RW_n + \frac{1}{NC_n} + SD_n + \frac{1}{SU_n} + \frac{1}{AVpD_n} + WC_n + RT_n \qquad (9)$$

$f_n -$ Fitness function of n^{th} route,

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D_n– Distance of n^{th} route,
TD_n–Traffic density of n^{th} route,
RW_n–Road width of n^{th} route,
NC_n–Number of curves in n^{th} route,
SD_n–Angle of downslope of n^{th} route,
SU_n– Angle of upslope of n^{th} route,
$AVpD_n$–Average vehicle per day of n^{th}route,
WC_n–Weather condition of n^{th}route,
RT_n–Road type (one way or two way)

E. SVM Prediction

SVM is used to predict the minimal time of emergency vehicle to reach the destination point. In classification or regression challenges Support Vector Machine" (SVM) is a supervised machine learning algorithm can be used. Support Vector Machines rely upon the possibility of decision planes that characterize decision limits. A decision plane is one that disengages between a course of action of items having particular class participation. They investigate the substantial measure of information to distinguish designs from them.

Table I . Performance of path selection for various route using different techniques

Route	Path	Parameters										Method			
		D	Slope		# of Slopes		NC	TD	RW	AVPD	WC				
			UP	Down	UP	DWN						ANFIS [7]	SFLA-KC [6]	MP-EVM-SVM	Correct Path
Route #1	Path #1	105	0.279	0.320	4	3	3	0.709	0.525	0.951	1	Path #4	Path #2	Path #1	Path #1
	Path #2	100	0.735	0.824	4	3	3	0.548	0.566	0.971	1				
	Path #3	100	0.615	0.637	4	3	11	0.824	0.725	0.774	0				
	Path #4	104	1.448	1.740	4	3	3	0.743	0.718	0.723	0				
Route #2	Path #1	104	0.942	0.931	4	3	3	0.579	0.985	0.979	0	Path #2	Path #2	Path #1	Path #1
	Path #2	101	1.307	1.567	4	3	4	0.839	0.879	0.872	0				
	Path #3	103	0.726	0.960	3	2	5	0.975	0.517	0.719	0				
Route #3	Path #1	105	0.520	0.602	4	3	3	0.967	0.565	0.784	0	Path #3	Path #4	Path #4	Path #4
	Path #2	101	0.687	0.502	4	3	2	0.845	0.874	0.725	0				
	Path #3	103	0.505	0.375	3	2	4	0.502	0.887	0.909	1				
	Path #4	107	0.200	0.319	4	3	4	0.935	0.790	0.775	0				
Route #4	Path #1	104	0.942	0.931	4	3	4	0.579	0.985	0.979	0	Path #1	Path #1	Path #4	Path #4
	Path #2	101	1.307	1.567	4	3	4	0.839	0.879	0.872	0				
	Path #3	100	0.726	0.960	3	2	3	0.975	0.517	0.719	0				
	Path #4	102	0.806	0.791	3	2	4	0.828	0.581	0.559	0				
Route #5	Path #1	104	0.806	0.791	3	2	3	0.828	0.581	0.559	0	Path #1	Path #3	Path #2	Path #3
	Path #2	100	0.764	1.016	4	3	3	0.774	0.569	0.575	0				
	Path #3	104	0.525	0.671	4	3	5	0.676	0.915	0.793	1				

SVM produces parallel partitions by creating two parallel lines. For every class of information in a high-dimensional space and uses all traits. It isolates the space in a solitary go to produce the level and direct partitions. Partition the 2 classifications by a reasonable hole that ought to be as wide as could be expected under the circumstances. Do this apportioning by a plane called hyperplane. An SVM makes hyperplanes that have the longest edge in a high-dimensional space to isolate given information into classes. The edge between the 2 classes speaks to the longest separation between nearest information purposes of those classes. The bigger the edge, the lower is the speculation mistake of the classifier. The calculation of SVM, think about two cases:

Separable case – Infinite limits are conceivable to isolate the information into two classes.

Non-Separable case – Two classes are not isolated but rather cover with one another.

a) The separable case

In the separable case, interminable limits are conceivable. The limit that gives the largest separation to the closest perception is known as the ideal hyperplane. The ideal hyperplane guarantees the fit and strength of the model. To locate the ideal hyperplane, utilize the accompanying condition.

$$a.x + b = 0 \qquad (10)$$

Here, $a.x$ is the scalar product of a and x. This equation must satisfy the following two conditions:

It should separate the two classes A and B very well so that the function defined by:

$f(x) = a.x + b$ is positive if and only if $x \in A$

$f(x) \leq 0$ if and only if $x \in B$

It exists as far away as possible from all the observations (robustness of the model). Given that the separation from a perception x to the hyperplane is $|a.x + b|/\|a\|$. The width of the space between observations is $2/\|a\|$. It is called a margin and it should be largest. Hyperplane relies upon help focuses called the nearest focuses. Speculation limit of SVM increments as the quantity of help focuses on diminishes.

b) The non-Separable Case

In the event that two classes are not flawlessly isolated but rather cover. By estimating the separation isolating it from the limit of the edge in favor of its class. This distance is then normalized by dividing it by the half-margin $1/\|a\|$, giving a term i, called the slack variable. An error in the model is an observation for which $\xi > 1$. The sum of all the ξ_i represents the set of classification errors. The quantity δ is a parameter that penalizes errors. It controls the adaptation of the model to the errors. As this increases and sensitivity to errors rise, adaptation also increases.

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In SVMs, the way toward rebuilding information is known as change and do it with the assistance of a capacity. Allude this capacity as the change work and spoken to by the image (Φ). Actually, the change capacities delineate speck result of information focuses to a higher dimensional place.

IV. RESULT AND DISCUSSION

As explained in the previous sections MP-EVM-SVM uses SVM as core classifier which is very effective and highly accurate classifier among the existing classifiers. The accuracy of the classifier is directly proportional to the

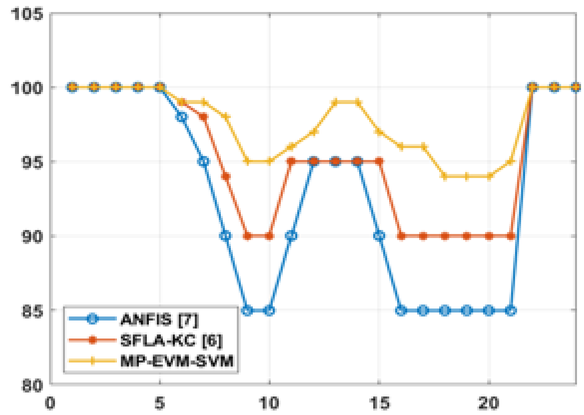

Fig 5. The graphical user interface for the proposed method

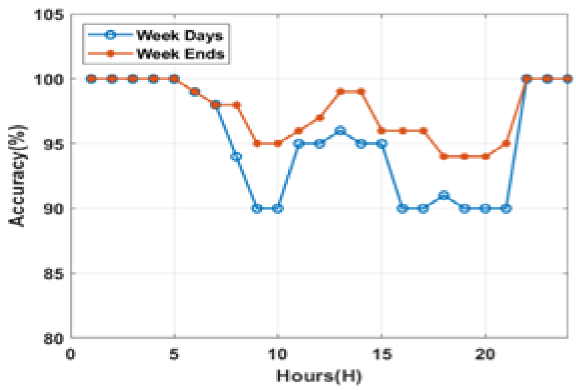

Fig 6. Performance of accuracy in week days and week end

amount of training data used. Increases in the sample collection increases the accuracy of the decision. The following section explains the data collection and result analysis as explained below:

A. Dataset

Dataset used in MP-EVM-SVM is real-time data which is collected from transportation system of one the particular route for 100 days with traffic congestion of each day and corresponding weather conditions. The static parameters of road condition such as a number of curves, road width, an angle of up and down slopes of particular routes can also collected for training and testing process. Similarly, data for multiple route also collected to determine the accuracy of the trained model.

B. Result Analysis

The proposed method is implemented in MATLAB. 100 days real-time traffic data and their corresponding cost function is used to train the SVM. The proposed method is compared with the different existing method such as **ANFIS [7]** and **SFLA-KC [6].** From the analysis, it is shown that a noteworthy favorable position of SVMs is that while **SFLA-KC [6]** can experience the ill effects of different time duration when compared to the MP-EVM-SVM. **ANFIS [7]** technique is giving lesser performance when compared to the **SFLA-KC [6]** and MP-EVM-SVM. The quality of the proposed algorithm is evaluated by using accuracy performance. Accuracy of the EV is measured for particular interval to estimate the overall performance. It is done in a particular route by different EV such as using ambulance. By the combination of mathematical model which is used to train the SVM, MP-EVM-SVM can predict the path more accurately when compared to the other techniques.

C. Accuracy Assessment

To validate the MP-EVM-SVM, it is necessary to compare the real-time data and the predicted value. **Fig. 5.** Shows the performance of the model with respective to the time in hours. It shows that the performance of proposed method is stable in various traffic density conditions. The accuracy of the system is directly proportional to the traffic density of the route. From figure 5 it is clear that at 9-10

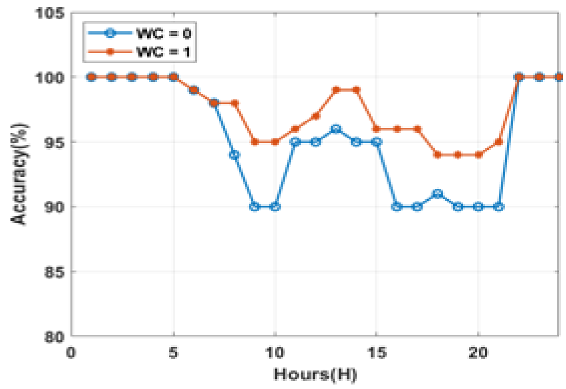

Fig 7. Performance of accuracy while weather condition 0 and 1

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ANFIS [7] giving an accuracy of 85% and SFLA-KC [6] gives 90% but MP-EVM-SVM gives maximum accuracy of 95%. It is clear that ANFIS [7] giving 10% less accuracy percentage and ANN giving 5% less accuracy when compared to MP-EVM-SVM. It is shown that only a small percentage of changes in

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Table II. Performance of path selection for a route in different days

		Parameters										Method			
Days	Path	D	Slope		# of Slopes		NC	TD	RW	AVPD	WC	ANFIS [7]	SFLA-KC [6]	MP-EVM-SVM	Correct Path
			UP	Down	UP	Down									
Sun	Path #1	105.2	0.279	0.320	4	3	3	0.309	0.525	0.551	1	Path #1	Path #2	Path #4	Path #4
	Path #2	100.9	0.735	0.824	4	3	3	0.548	0.566	0.471	1				
	Path #3	100.3	0.615	0.637	4	3	11	0.624	0.725	0.174	0				
	Path #4	104.6	1.448	1.740	4	3	3	0.143	0.718	0.323	0				
Mon	Path #1	105.2	0.279	0.320	4	3	3	0.901	0.525	0.951	1	Path #4	Path #2	Path #1	Path #1
	Path #2	100.9	0.735	0.824	4	3	3	0.548	0.566	0.971	1				
	Path #3	100.3	0.615	0.637	4	3	11	0.824	0.725	0.774	0				
	Path #4	104.6	1.448	1.740	4	3	3	0.743	0.718	0.723	0				
Tues	Path #1	105.2	0.279	0.320	4	3	3	0.687	0.525	0.821	1	Path #1	Path #2	Path #2	Path #2
	Path #2	100.9	0.735	0.824	4	3	3	0.321	0.566	0.321	1				
	Path #3	100.3	0.615	0.637	4	3	11	0.432	0.725	0.436	0				
	Path #4	104.6	1.448	1.740	4	3	3	0.871	0.718	0.490	0				
wed	Path #1	105.2	0.279	0.320	4	3	3	0.209	0.525	0.851	1	Path #1	Path #1	Path #3	Path #3
	Path #2	100.9	0.735	0.824	4	3	3	0.567	0.566	0.844	1				
	Path #3	100.3	0.615	0.637	4	3	11	0.121	0.725	0.787	0				
	Path #4	104.6	1.448	1.740	4	3	3	0.998	0.718	0.521	0				
the	Path #1	105.2	0.279	0.320	4	3	3	0.569	0.525	0.121	1	Path #2	Path #2	Path #1	Path #1
	Path #2	100.9	0.735	0.824	4	3	3	0.766	0.566	0.233	1				
	Path #3	100.3	0.615	0.637	4	3	11	0.544	0.725	0.668	0				
	Path #4	104.6	1.448	1.740	4	3	3	0.822	0.551	0.456	0				
Fri	Path #1	105.2	0.279	0.320	4	3	3	0.219	0.525	0.443	1	Path #1	Path #1	Path #2	Path #1
	Path #2	100.9	0.735	0.824	4	3	3	0.661	0.566	0.234	1				
	Path #3	100.3	0.615	0.637	4	3	11	0.432	0.725	0.900	0				
	Path #4	104.6	1.448	1.740	4	3	3	0.821	0.718	0.554	0				
Sat	Path #1	105.2	0.279	0.320	4	3	3	0.829	0.525	0.544	1	Path #3	Path #1	Path #1	Path #1
	Path #2	100.9	0.735	0.824	4	3	3	0.988	0.566	0.921	1				
	Path #3	100.3	0.615	0.637	4	3	11	0.543	0.725	0.776	0				

accuracy of MP-EVM-SVM in real-time data. Similarly, variation in the accuracy can be measured in peak hour such as 16-20 hours from figure 5. **Fig. 6.** shows the performance of MP-EVM-SVM at week days and weekends. Generally, in week days the performance of the system is less because nonlinear variation in the traffic density. From figure it is clear that the accuracy of the system is reduces when compared to the normal hour on various paths. From table I it is very clear that MP-EVM-SVM took more best number of decision while conventional techniques fail. Similarly, Table II. Shows the performance of proposed techniques for different days with different algorithms. Similar kind of variation can be observed in Fig. 7. Due to the complex nonlinearity in the traffic density at bad weather conditions. Table I. shows the performance of various algorithms

V. CONCLUSION

In this work, Efficient implementation of path planning for the Emergency vehicle MP-EVM-SVM is implemented and tested. MP-EVM-SVM shows high performance in terms of accuracy when compared to the conventional predictors such as ANFIS [7] and SFLA-KC [6]. Proposed work uses support vector machine as core predictor to predict the cost value which is used to predict the accurate path along with linear and nonlinear route parameters. Data collected from different routes for multiple days including different weather conditions. MP-EVM-SVM model is analyzed with different cases such as for various routs with respective to each days of weeks. From analytical results of all cases concludes that MP-EVM-SVM technique is stable and highly accurate when compared to the conventional techniques. Due to the moderate complexity of the algorithm, it can be used in the real-time environment to perform the prediction process. In future work, hardware implementation with hybrid predictor will be used to increase the computational accuracy of the system in real-time environment.

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