Multi-Step Approach to Improving Accuracy of Incident Duration Estimation: Case Study of Istanbul

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Abstract: Unexpected events, such as crashes, disabled vehicles and spilled loads cause traffic congestion or increase the level of existing congestion on roads. Traffic incident management requires the estimation of incident duration from the beginning to the final stage of the event, in order to identify the most suitable strategies for decreasing their impact. Accordingly, the adverse effects of an incident can be minimised by efficiently managing the process between the time the incident occurred and the traffic returning to normal operating conditions. The purpose of this paper is to present a methodology and improve the accuracy of the model by using a multi-step approach to estimate the duration of an incident. For this purpose, incident duration data was obtained for Istanbul Transit Europe Motorways (TEM). Using the incident data and implementing the multi-step approach, Kalman Filtering and linear regression analysis in stepwise, were used for the incident duration estimation model.

Keywords: incident duration; Kalman Filter; linear regression; multi-step approach; traffic incident

1 INTRODUCTION

One of the major problems encountered in the operation of highways in large urban areas is traffic congestion. Traffic congestion often occurs in segments where demand is greater than capacity and emerges in two different ways, recurring and non-recurring. For recurring congestion, which regularly occurs in peak hour traffic every day, travellers would be able to plan their journey according to expected congestion; even so, non-recurring congestion originated by traffic incidents (accidents, vehicle breakdowns, debris, for example), results in unexpected congestion on the carriageway. Therefore, road users cannot take this congestion into account when planning a journey unless they have been told about the incident before they start travelling.

Within the scope of this study, an incident duration estimation model was established using Kalman Filtering and linear regression analysis and the incident data that occurred on the Istanbul TEM. In the second section, studies in the literature regarding traffic incident duration estimation were investigated. Details of the data are given in the third section. In the following section, methodology and the methods used in the study are discussed. The established forecasting model and corresponding results are evaluated in the fifth section. In the last section, results of the study are presented and recommendations are made.

2 LITERATURE REVIEW

Taking into account studies regarding incident duration estimation, in general, the process of a traffic incident is examined in four time intervals, partitioned with five time points [1, 2]. These points are, chronologically: incident occurrence, incident notification, response unit arrival, incident clearance, and normal operation. The first three time intervals between these points are expressed as the total incident duration [3-5], and all four time intervals are expressed as the total delay caused by the incident [1, 2].

As seen in Fig. 1, the stages of the incident are detection time, response time, clearance time and, recovery time [1, 2]. Due to the difficulty in defining the precise starting time of an incident, in some research the time interval between incident notification and incident clearance is called modified incident duration [6, 7].

Incident delay and incident duration can vary, depending on factors such as environmental conditions and the nature of the incident. By determining these characteristics, incident duration can be estimated using statistical forecasting methods. Accuracy of incident duration estimations depends on the quality of the collected data, incident characteristics and the estimation methods. The quality of the data declines due to an insufficient number of data and its being collected from only one source. On the other hand, different incident characteristics and environmental components can be used to estimate the incident duration, such as the type of incident (crash, debris, breakdown etc.), time, location, number of vehicles involved in the incident, category of vehicle, number of lanes affected by the incident, injury and death toll, the number of heavy vehicles involved in the incident, cargo spilled, weather conditions and damage to road equipment. In addition to the nature of the incident, traffic demand data for the segment of road on which the incident occurred should be known at the time of the incident to establish a model for incident delay, including recovery time [8-10].

Also the estimation method used for incident duration could have a significant effect on the accuracy of the estimated incident duration. In previous research studies, various statistical methods and data mining techniques have been used, including the classification tree method [1], artificial neural networks [4, 6], linear regression [5, 8], hazard based analysis model [2, 10, 11], cyclic subspace regression [12], support vector regression [13], partial least squares regression [7, 14], time series method [15], fuzzy logic model [16] and Bayesian Networks approaches [17-19].

Garib et al. [8], analysed 277 incidents and six different incident characteristics for estimating incident duration in the USA. Accordingly, they performed regression analysis with lognormal distribution and found the estimating accuracy of the incident duration to be 81%. Özbay & Noyan made the other USA study [17]. They used the Bayesian Network method and 650 incident data for estimating the incidents' clearance time. By using seven model inputs and 10 test datasets generated by dividing the

whole dataset, estimating the accuracy of incident duration was 81%, following 10 iterations.

Chung [3], established a Hazard Based incident duration estimation model by analysing 4869 incidents in South Korea. The average error of estimation was found to be 18 minutes and the Mean Absolute Percentage Error (MAPE) was calculated to a reasonable value of 47%.

Lopes et al. [6] analysed 10 762 incidents that occurred in Portugal between 2008 and 2011. They estimated the clearance time of incidents using Artificial Neural Networks. As a result, after testing the model with 244 incidents that occurred in 2011, the model estimated 72% with an error of less than 10 minutes and 92% with an error of less than 20 minutes.
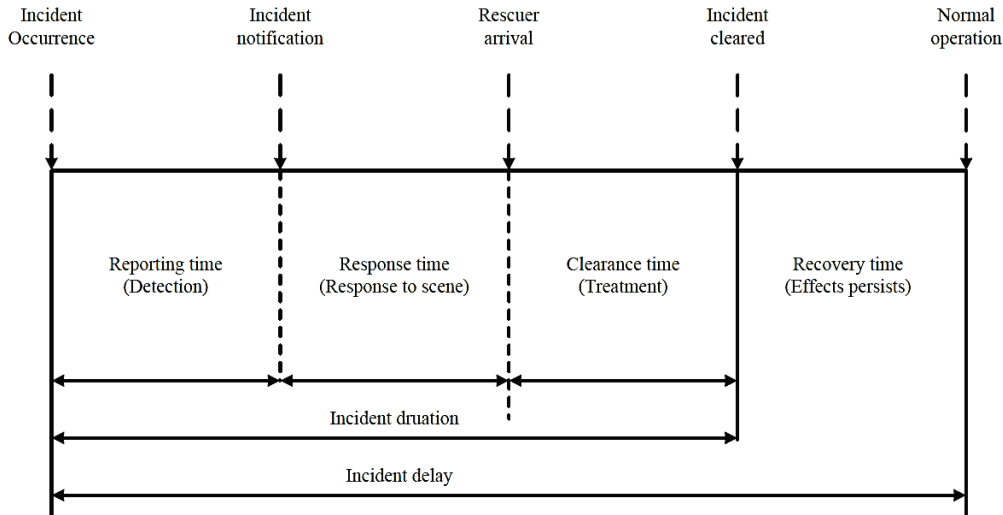

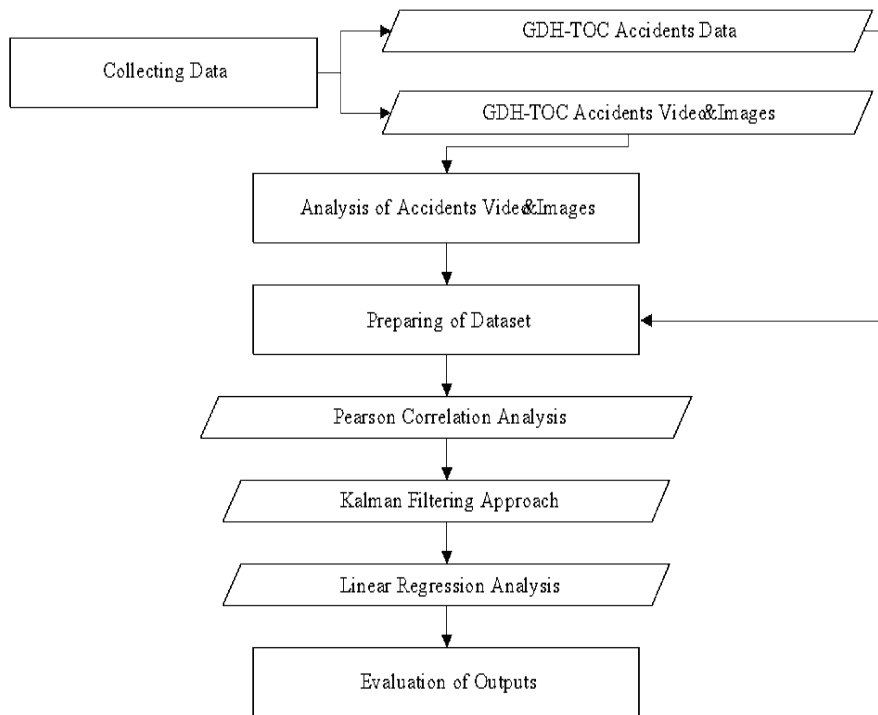**Figure 1** Traffic incident time intervals and points

Figure 2 Study flow chart

Wang et al. [7], established four models, using four different regression types. For estimating incident duration, they used 1853 incidents that occurred in Netherlands. The models acquired the best accuracy of prediction to be 83,6%, 92,7%, and 88,2% at error for 20 minutes, for stopped vehicle, lost-load and accident, respectively.

According to above-mentioned studies, in literature, traffic incident duration is generally estimated in a single step. However, a multi-step approach, whose estimated duration in the first step is used as input to the subsequent

step, is expected to increase accuracy. On the other hand, Kalman Filtering is used in many fields in the literature including traffic incident detection in traffic incident management studies but estimation of incident duration [20]. Thus, in this study, the multi-step approach, whose estimated duration in the Kalman Filtering Analysis is used as input to the Multi Linear Regression Analysis is proposed.

3 METHODOLOGY

The multi-step approach was used for the estimation of the incident duration. The study flow chart is given in Fig 2. As seen in Fig. 2, the necessary data was obtained from the General Directorate of Highways Traffic Operation Centre (GDH-TOC) and analysed the video streaming and the images to collect the incident characteristic data [21]. A data cleaning process was applied to exclude outliers from the data set. Pearson Correlation was conducted to investigate a relationship between the incident characteristics. Kalman filter estimation was run for each significant variable to calculate the initial incident duration. Linear regression conducted using the initial incident duration as an independent variable, was the output of the Kalman Filtering Analysis, while the incident duration is the dependent variable.

Kalman Filtering is a theory developed by Rudolf Kalman in 1960. It is primarily used in weather forecasting. Kalman filtering makes predictions based on present and previous data. For instance a ship travelling between destinations A and B finds its way with the help of GPS. If the GPS stops working, the Kalman filtering approach can be used to calculate a route based on the previous routing data [22].

The Kalman filter is an efficient recursive computational method to predict or estimate the state of a process. It is based on a set of mathematical equations that try to minimize the mean squared error and it works on a so-called prediction-correction approach [23]. In the first step of the Kalman Filtering Analysis, Eq. (1) and Eq. (2) are used for making predictions.

$$x_k = A \cdot x_{k-1} + B \cdot u_k + w_{k-1} \qquad (1)$$
$$Z_k = H \cdot x_k + v_k \qquad (2)$$
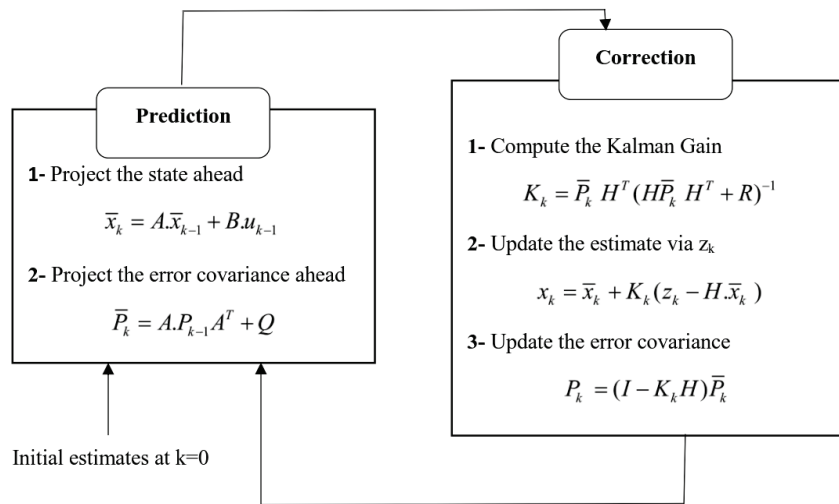
Each x_k can be evaluated by using linear stochastic equation. Any estimated incident duration (x_k) is a combination of its previous value estimated plus a control signal u_k and noise. Z_k is a measured value that consists of a linear combination of x_k and v_k. The notation used in Kalman Filtering is illustrated in Tab. 1.

Table 1 Notation used in Kalman Filter

Notation	Description
k	Time interval
x_k	Current estimation
x_{k-1}	Previous estimation
u_k	Control input vector
w_{k-1}	Process noise vector
Z_k	Measured value
v_k	Measurement noise vector
A	State transition matrix
B	Control input matrix
H	Output matrix
$\underline{x}_k$	Estimation at time k
$\underline{x}_{k-1}$	Previous estimation
$\underline{P}_k$	Covariance before measurement
Q	Covariance matrix
R	Measurement noise covariance

The second step of the Kalman Filtering Analysis is the iteration (prediction-correction mechanism). The filter estimates the process state at a given value and then obtains feedback in the form of (noise) measurements. The main equations in Kalman Filtering and the working process are presented in Fig. 3. As seen in Fig. 3, Kalman filter iteration equations are divided into two groups, as follows: prediction and correction. The prediction equations are responsible for projecting forward the current state and error covariance estimates to obtain the a priori estimates for the next step. The correction equations are used for integrating new measurements into a previous estimate to obtain an improved a posteriori estimate [23].

Prediction

1- Project the state ahead

$$\overline{x}_k = A.\overline{x}_{k-1} + B.u_{k-1}$$

2- Project the error covariance ahead

$$\overline{P}_k = A.P_{k-1}A^T + Q$$

Correction

1- Compute the Kalman Gain

$$K_k = \overline{P}_k H^T (H\overline{P}_k H^T + R)^{-1}$$

2- Update the estimate via z_k

$$x_k = \overline{x}_k + K_k(z_k - H.\overline{x}_k)$$

3- Update the error covariance

$$P_k = (I - K_k H)\overline{P}_k$$

Initial estimates at k=0

The output at k will be the input for k+1.
Figure 3 Kalman Filtering steps

4 DATA DESCRIPTION

Within the scope of this study, data from the GDH-TOC was used for incidents that occurred on the Istanbul TEM for the 12 months between October 1, 2013 and September 30, 2014, including recorded streaming and images [21]. Data includes the following information about the incidents: date, time, vehicle type, number of vehicles, location, severity, detection time, response time, clearance time and response units. Recorded streaming and images were examined to gather new characteristics about the incidents. Characteristics that were gathered by analysing

the recorded streaming and images included, accident type, number of lanes, lane blockage, lane(s) that accident occurred, number of heavy vehicles, road condition (wet or dry), cargo spillage, liquid spillage and damage to road equipment.

For reliability, short time incidents of less than five minutes that did not have an effect on traffic flow and incident data that had uncertain characteristics were excluded from the data set. Consequently, the total of 2517 incident data was reduced to 1151, the number of incident data that was used in this study.

As can be seen from the distribution of incident duration presented in Fig. 4, the mean duration is 30,34 minutes and approximately 92% of these incidents were under 60 minutes. Also, standard deviation is 24,86 minutes with an extreme right-skewed distribution and the maximum duration was 260 minutes. There were 12 incidents that had a duration of more than 120 minutes and the duration was 14 minutes for more than 60 incidents.

In the study, 15 different variables regarding incidents that could possibly have affected the incident duration were taken into consideration. The effect of each variable on incident duration was established by correlation analysis using the Pearson coefficient and is presented in Tab. 2. According to Tab. 2, five of the 15 variables, including what part of the week, season, number of vehicles, number of heavy vehicles and the road condition are insignificant for incident duration, so these variables were not used for the estimation.
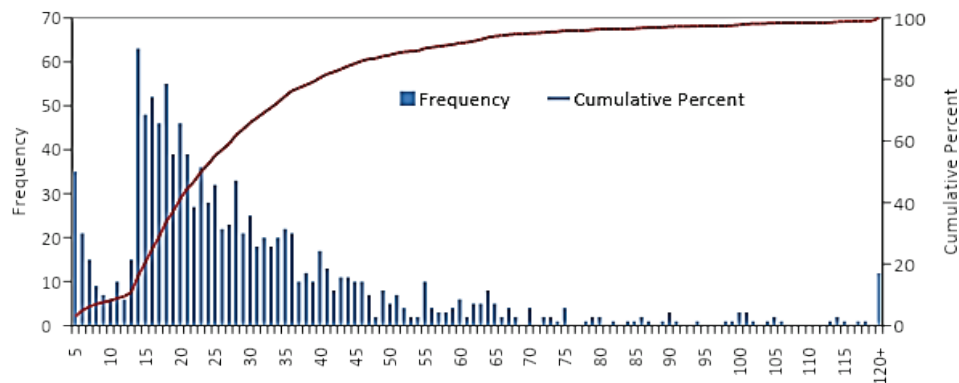

Figure 4 Incident duration distribution

Table 2 Results of Pearson Correlation analysis

Accidents Characteristics	Coefficient	P-Value
Part of Week	0,024	0,412
Season	-0,037	0,205
Part of Day	**0,084**	**0,004***
Location	**-0,113**	**0,000***
Severity	**0,259**	**0,000***
Type	**0,243**	**0,000***
Number of Lanes	**-0,124**	**0,000***
Lane	**-0,079**	**0,008***
Lane Blockage	**0,088**	**0,003***
Number of Vehicles	0,025	0,389
Number of Heavy Vehicles	0,050	0,089**
Road Condition (Dry/Wet)	0,039	0,181
Cargo Spill	**0,284**	**0,000***
Liquid Spill	**0,389**	**0,000***
Damage Equipment	**0,290**	**0,000***

* Significant at 95% confidence level; ** Significant at 90% confidence level; Coefficients which are statistically significant at 95% level or greater are in bold.

5 ANALYSIS RESULTS

The Kalman Filtering approach is applied with respect to different incident characteristics and new incident durations, that were found, are presented in Tab. 3.

On the TEM, the highway that is analysed in this study, heavy vehicles are prohibited from using it during peak periods. Therefore, accident data is separated according to different times of the day, based on the time of the accident. The heavy vehicle restriction periods are 06:00-10:00 AM and 04:00-10:00 PM Abd are called Morning and Evening restriction periods, respectively. The other periods, during which there are no heavy vehicle restrictions, are 10:00 AM - 04:00 PM, called Intraday and 10:00 pm - 06:00 am, called Night period. At night and during the morning

period, incident duration is above 35 minutes; by contrast, it is less than 30 minutes for the intraday and the evening period.

When data was analysed with respect to types of accident, maximum incident duration was for those involving overturned vehicles. On the other hand, incident duration was less than 30 minutes for rear-end and sideswipe accidents. Accidents are divided into four parts, based on the location of the incident. The part including FSM Bridge and its tollbooths was named FSM; similarly, the remaining parts of the TEM highway were named TEM. But the response time to the accidents at bridges, viaducts and tollbooths are quite different. For this reason Bridges-Viaducts and Tollbooths were classified separately. FSM Bridge was found to be the location with the lowest incident duration. This section can be reopened to traffic flow 24 minutes after the occurrence of an accident. Also, incident duration is less than half an hour for other accidents that happened on bridges and viaducts, except the FSM Bridge. Bridges and viaducts are critical points on the highway and have frequent traffic controls, so incident duration is low at these segments.

Based on the number of lanes at the sections where an accident occurs, incident duration at segments with 5 and 5+ lanes is found to be approximately 25 minutes. Frontage roads with 2 lanes that run parallel to the main road have the highest incident duration, which is about 42 minutes. On the other hand, accidents that occurred in the right lane occupied the incident site for longer than either the left or middle lane.

The blockage percentages of the lanes were calculated by dividing the number of blocked lanes at the incident location by the total number of lanes. Based on these

percentages, the data is divided into five parts; none (0%), few (0-33%), medium (33-67%), many (67-100%), all (100%). According to the blockage percentages of the lanes, incident duration is highest for 'none'. For the other accidents, incident duration increased gradually, with increasing blockage percentages. On the other hand, incident duration of injury-fatal accidents is more than PDO accidents.

Table 3 Results of Kalman Filtering approach with respect to different accident characteristics

Accident Characteristics		Incident Duration	Size
Accident Type	Rear-end	28,38	692
	Sideswipe	27,66	369
	Collision With Barrier	54,34	44
	Run-off-road	48,19	37
	Overturn	86,32	9
Part of Day	Morning (06:00-10:00)	35,25	118
	Intraday (10:00-16:00)	27,01	577
	Evening (16:00-22:00)	29,90	271
	Night (22:00-06:00)	37,84	185
Location	TEM	38,00	399
	FSM	23,93	521
	Bridges-Viaducts	29,68	212
	Tollbooths	48,67	19
Lane	Right	36,92	248
	Middle	27,17	532
	Left	30,35	371
Number of Lanes	2	42,11	28
	3	33,80	250
	4	30,97	572
	5	23,32	92
	5+	25,59	209
Lane Blockage	None	50,84	22
	Few	27,69	636
	Medium	31,31	375
	Lot	34,73	83
	All	42,03	35
Accident Severity	PDO	28,07	1025
	Fatal-Injury	48,49	126
Cargo Spill	No	29,60	1134
	Yes	89,93	17
Liquid Spill	No	29,45	1043
	Yes	82,65	108
Damage to Road Equipment	No	27,78	1018
	Yes	50,25	133

Accident data was also analysed according to factors such as the spilling of cargo, spilling of liquids (for example fuel and oil) and the existence of any damage to road equipment. According to this evaluation, spilling of cargo, spilling of liquid and the existence of damage to road equipment, increased the incident duration dramatically.

By using the Kalman Filtering approach with respect to different accident characteristics, incident duration is estimated for each incident data. A scatter graph of the actual and estimated value of each incident is shown in Fig 5. As seen in Fig. 5, the Kalman Filtering approach underestimated incident duration and the accuracy of the estimation needs to be improved.

For the evaluation of the model accuracy, mean absolute percentage error (*MAPE*), root mean square error (*RMSE*), standard deviation and average value of estimated values were calculated.

The *RMSE* basically provides an estimate of error variance. The normal variance measures the distance from the mean of a data set. However, *RMSE* measures the variance from 0, which should be an ideal error for any prediction. The *RMSE* can be computed by taking the sum of the squares of the errors (difference between the predicted and actual values), computing the average and then taking the square root (Eq. (3)) [20].

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}\left(predicted\ \ value(t) - actual\ \ value(t)\right)^2}{N}} \quad (3)$$

The mean absolute percentage error (*MAPE*) is a summary measure widely used for evaluating the accuracy of prediction results, and it is expressed as follows (Eq. (4)):

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{\left(actual\ \ value(t) - predicted\ \ value(t)\right)}{actual\ \ value(t)}\right| \quad (4)$$

The lower the *MAPE* value, the more accurate the prediction model is. Listed in Tab. 4 is a scale rating for evaluating the accuracy of a model based on the *MAPE* method, as developed by Lewis [3].

Table 4 Scale of evaluation of prediction accuracy

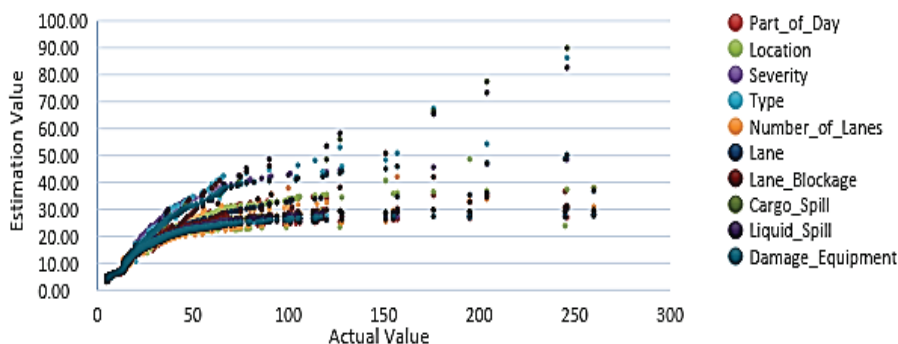| MAPE	Assessment
Less than 10%	Highly accurate prediction
11% to 20%	Good prediction
21% to 50%	Reasonable prediction
51% or more	Inaccurate prediction

Figure 5 The scatter graph of the actual value and the estimated values with Kalman Filtering

As presented in Tab. 5, results of the Kalman Filtering approach for the different accident characteristics are almost the same. RMSE is about 24 minutes and MAPE is approximately 37%.

As seen in Tab. 5, for all the methods that implemented the Kalman Filtering approach, RMSE values are higher than average values and if the duration is more than 25 minutes the error of the models and accuracy of the models is unsatisfactory for incident management, as shown in Fig. 5. Therefore, to increase the model's accuracy, linear regression analysis has been applied to estimate the incident duration, using the Kalman Filtering estimation results. Actual incident duration values were selected as a dependent value while the Kalman Filtering estimated values were selected as independent values. Results of the linear regression analysis are illustrated in Tab. 6.

Table 5 Evaluating accuracy of Kalman Filtering approach

Method		RMSE (min)	MAPE (%)	Standard Deviation (min)	Average (min)
Kalman Filtering Approach	Part of Day	24,47	37,55	6,43	16,19
	Location	23,87	37,19	6,84	16,41
	Severity	23,99	36,10	7,45	16,71
	Type	23,40	36,88	7,72	16,57
	Number of Lanes	24,53	37,66	6,31	16,13
	Lane	24,54	37,55	6,28	16,13
	Lane Blockage	24,43	37,52	6,60	16,20
	Cargo Spill	23,87	37,54	6,95	16,18
	Liquid Spill	23,85	37,45	7,03	16,23
	Damage Equipment	23,78	36,71	7,25	16,54

Table 6 Results of Linear Regression Analysis

	Coefficients	P-value
Constant	**-19,73**	**0,00***
Part of Day (X_1)	-0,22	0,41
Location (X_2)	**2,70**	**0,00***
Severity (X_3)	**-0,63**	**0,00***
Type (X_4)	0,27	0,10**
Number of Lanes (X_5)	**-0,98**	**0,01***
Lane (X_6)	-0,01	0,97
Lane Blockage (X_7)	**-0,48**	**0,02***
Cargo Spill (X_8)	**1,80**	**0,00***
Liquid Spill (X_9)	0,20	0,56
Damage Equipment (X_{10})	**0,41**	**0,02***

* Significant at 95% confidence level; ** Significant at 90% confidence level; Coefficients which are statistically significant at 95% level or greater are in bold.

The scatter graph of the actual and the estimated values calculated with a multi-step approach are depicted in Fig. 6.

Results of the multi-step approach are given in Tab. 7. If the results are compared with the Kalman Filtering estimation method (Tab. 5), a significant improvement can be seen in the mean of the MAPE (9,40%) and the RMSE (11,71 min).

Table 7 Evaluating accuracy of Multi-Step Approach

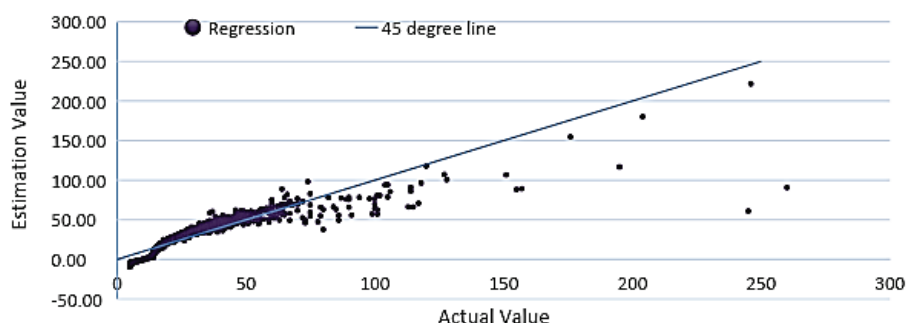| Method	RMSE (min)	MAPE (%)	Standard Deviation (min)	Average (min)
Actual Value	-	-	24,84	30,34
Multi-step Approach	11,71	9,40	21,91	30,34

Figure 6 The scatter graph of the actual value and the estimated values with Multi-Step Approach

6 CONCLUSIONS AND RECOMMENDATIONS

Throughout this study, data on traffic accidents that occurred in Istanbul have been evaluated. By using incident data and the multi-step approach to implementing the step wise Kalman Filtering and linear regression analysis, the incident duration estimation model has been established. The RMSE value of the incident duration for Kalman Filtering is approximately 24 minutes, but it is 12 minutes for the multi-step approach. Therefore, the accuracy of the multi-step approach is two times higher than the estimation of the incident duration using Kalman Filtering. In conclusion, the offered model can be considered as a useful tool to estimate incident duration for Istanbul.

It is possible to increase the accuracy of the estimations by adding new parameters, such as the number of fatalities and injuries, the location of the closest response unit and weather conditions.

Even so, in order to provide effective incident management, studies relating to incident duration estimation should be improved. It is possible to determine those aspects that will be affected by an accident and imply new strategies for incident management, which will result in a decrease in the negative impact of these incidents.

Acknowledgements

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