PREDICTING THE DURATION OF NON-RECURRING ROAD INCIDENTS BY CLUSTER-SPECIFIC MODELS

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Abstract— In metropolitan areas, about 50% of traffic delays are caused by non-recurring traffic incidents. Hence, accurate prediction of the duration of such events is critical for traffic management authorities. In this paper, we study the predictability of the duration of traffic incidents by considering various external factors. As incident data is typically sparse, training a large number of models (for instance, model for each road) is not possible. On the other hand, training one model for the entire network may not be a suitable solution, as such a model will be too generalized and consequently unsuitable for many relatively rare scenarios. Therefore, we propose to solve this issue by first grouping incidents through common latent similarities among them and then training data-driven predictors for each group. In our numerical analysis we consider incident data from Singapore and the Netherlands. Our results show that by training cluster-specific models we can reduce the prediction error by 19.41% for incidents in Singapore and by 17.8% for incidents in the Netherlands.

I. INTRODUCTION

Non-recurrent road-incidents such as accidents, vehicle breakdowns can seriously disrupt the normal traffic flow. Due to the non-recurring nature of such events, it is almost impossible to predict exactly when and where these events will occur. Various external factors such as weather conditions, types of roads, lanes affected, time of the day can help to group various incidents with similar impact together, for the purpose of investigating the impact of traffic incidents. In this paper, we propose data-driven regression models to obtain the relationship between these factors and the duration of different incidents. The time duration associated with a traffic incident can be divided into four components: (1) reporting time (r_t): the time between the occurrence and the reporting of the incident, (2) response time (s_t): the time from reporting of the incident to arrival of the response team, (3) clearance time (c_t): the time required by the response team to clear the road, and (4) recovery time (v_t): the time taken by the traffic condition to restore back to normal [1][2]. The incident duration T that we consider here is the sum of all of these stages,

$$T = r_t + s_t + c_t + v_t. \qquad (1)$$

In the following, we will briefly discuss related research works in this area.

A. Literature Review

As accurate prediction of incident duration is critical for traffic management, this topic has garnered considerable attention in the area of urban transportation. In the recent years, different techniques such as Artificial Neural Networks [3] and Decision Trees [4] have been applied for this purpose. For instance, Valenti *et al.* applied various machine learning methods for predicting the duration of traffic incidents [5]. They observed that Support Vector Regression/ Relevance Vector Machines (SVR/RVM) [6] perform well for predicting long durations and Artificial Neural Networks (ANN) [3] are mostly suitable for short durations. In our work, we consider several modelling techniques separately for accidents and vehicle breakdowns in Singapore as well as incidents in the Netherlands in order to predict the duration of incidents. Pereira *et al.* considered a similar approach for traffic incidents in Singapore [7]; however, they did not analyze the prediction performance of these models individually for accidents and breakdowns. Moreover, they did not include certain external factors like weather conditions. Similarly, Lopes et al. also applied ANN in a sequential model containing four neural networks with incremental inputs [8]. However, the scenario was highly homogeneous because they focused on only a single highway in Portugal. Wu et al. considered 1853 incidents for a five-month interval (May-Sept, 2015) from Utrecht, a central city in the Netherlands and applied support vector regression technique to predict the incidents duration [6]. However, they did not include the information about blockage of lanes or carriageways in the feature-set and considered only three types of incidents, whereas we took five types of incidents into consideration for the Netherlands. Although Qing *et al.* studied the impact of various external factors in predicting the duration of the incidents [1], they did not compare the performance of different predictors nor did they analyze the distribution of prediction errors. Moreover, they did not validate their prediction model for different cities. In summary, there exist certain research gaps in the previous literature, which we aim to improve in our work.

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B. Our Contributions

Let us now briefly summarize our main contributions in relation with the prior literature:

1) In our work, we take several additional important incident characteristics into consideration, such as type of blocked lanes or carriageways, weather information, whether shoulder lane is affected or not, which have not been considered in previous studies.

2) We observe that the traffic incidents can be naturally grouped into multiple clusters. By training cluster-specific classifiers, we obtain substantially more reliable predictions of the duration of traffic incidents,

3) Last but not least, a comparative analysis is demonstrated for two different countries i.e., Singapore and the Netherlands, allowing us to evaluate the performance and validity of our proposed predictive model for different datasets.

The remainder of this paper is organized as follows. In the next section, we describe our dataset. In Section III, we briefly discuss the prediction problem, whereas we analyze the performance of various predictors in Section IV. We perform clustering on the incidents data to design cluster-specific prediction models in Section V. Finally, Section VI provides concluding remarks and ideas for future research.

II. DESCRIPTION AND ANALYSIS OF THE DATA

The dataset for Singapore considered in this study primarily comprises two types of data: (1) historical records of incidents, and (2) weather information. The data about the traffic incidents in Singapore were provided by the Land Transport Authority (LTA), whereas weather information was obtained from the National Environmental Agency (NEA) of Singapore.

The historical record of traffic incidents contains the following information: Type of incident (vehicle breakdown or accident), position (road-segment id, latitude & longitude), time (start-time and end-time in terms of month, date, hour and minute), number of lanes affected and their types, name of the expressway, and direction along which the incident happened. The lanes are numbered from right to left as lane 1, 2, 3 and so on. Therefore, the type of lane is represented by this serial number according to its position. Singapore's entire road network has 11 expressways, which are divided into 2156 road segments for analysis. We consider the records of incidents for four months (Aug–Nov 2014) on those expressways. There were in total 8507 vehicle breakdowns and 2246 accidents recorded in this period. Among them, few incidents occurred for very long durations (more than 90 min). Hence we discard those outliers and finally consider 8399 breakdowns and 2052 accidents for our analysis. The weather data contain the rain intensity information for the island of Singapore. These images have a time resolution of 5 minutes [9] and each pixel corresponds to an area of about 100×100 meters.

In this study, we consider the following nine features for each traffic incident i: day of week ($w_i \in \{0, 1\}$, where 0 represents weekend and 1 represents week-day), time of day ($t_i \in \{0, 1\}$, where 0 represents off-peak and 1 represents peak-hour), total number of lanes ($n_i \in \{1, 2, 3, 4, 5\}$), shoulder affected or not ($s_i \in \{0, 1\}$, where 0 represents not affected and 1 represents affected), number of lanes affected ($l_i \in \{0, 1, 2\}$), the type of affected lane ($a_i \in \{0, 1, 2, 3, 4, 5, 6, 7\}$, where 0 represents no lane affected and 1, 2, 3, ... represent the serial number of the affected lane according to its position from right to left), expressway ($e_i \in \{0, 1, 2, ..., 11\}$), direction ($d_i \in \{0, 1\}$, where 0 represents upstream and 1 represents downstream), and rainfall effect ($r_i \in \{0, 1\}$, where 0 represents no rainfall and 1 represents strong rainfall).

Our main goal is to find the relationship function f to predict incident duration T_i:

$$T_i = f(w_i, t_i, n_i, s_i, l_i, a_i, e_i, d_i, r_i). \tag{2}$$

Furthermore, we consider the incidents data of the Netherlands in order to have a comparative discussion with Singapore. The National Data Warehouse for Traffic Information (NDW) [10] provided the real time traffic data from the entire network of the Netherlands. The incident information in the historical records for the Netherlands are not identical to the ones from Singapore, due to vast area of the Netherlands and varieties in the types of incidents. We have the following information: Type of incident, position (primary point & secondary point, latitude & longitude), time (start-time and end-time in terms of month, date, hour and minute), the type of affected lane (left lane, middle lane, right lane, and rush-hour lane), the type of affected carriageway (main carriageway, entry slip-road, exit slip-road, parallel carriageway, and connecting carriageway), the type of management, the length of the abnormal traffic situation (in meters) developed due to the incident, and the direction along which the incident happened. We considered the records of incidents for five months (Aug–Dec 2015).

In the dataset of the Netherlands, for a traffic incident j, we have the following eight features: day of week ($w_j \in \{0, 1\}$, where 0 represents weekend and 1 represents week-day), time of day ($t_j \in \{0, 1\}$, where 0 represents off-peak and 1 represents peak-hour), type of management ($m_j \in \{1, 2, 3\}$, where 1 represents carriageway-closure, 2 represents lane-closure and 3 represents road-closed), the type of affected carriageway ($c_j \in \{0, 1, 2, 3, 4, 5\}$, where 0 represents no carriageway affected, and 1, 2, ... 5 represent previously mentioned types of carriageways), the type of affected lane ($l_j \in \{0, 1, 2, 3, 4\}$, where 0 represents no lane affected, and 1,... 4 represent different types of lanes mentioned earlier), length of the developed queue ($q_j \in \{1, 2, 3, 4\}$, where each number represents a range of length, for example, 1 represents < 2000 m, 2 represents $2000 - 4000$ m, 3 represents $4000 - 6000$ m and 4 represents > 6000 m), direction ($d_j \in \{0, 1\}$, where 0 represents upstream and 1 represents downstream), and type of the incident ($i_j \in \{1, 2, 3, 4, 5, 6\}$, where 1, 2, ... 6 represent accident, congestion, vehicle breakdown,

general obstruction, abnormal traffic, and poor environmental condition respectively).

Our main goal is to find the relationship function g to predict incident duration T_j:

$$T_j = g(w_j, t_j, m_j, c_j, l_j, q_j, d_j, i_j). \tag{3}$$

III. PREDICTION METHODS

In this study, we consider various regression methods to model the relationship between traffic factors and traffic incident duration. These methods include Classification And Regression Tree (CART) [11], Multi-Layer Perceptron (MLP) [12], Support Vector Regression (SVR) [6], Treebagger and LSBoost [13].

For each of these methods, we select the optimal parameters for each regression method by 10-fold cross validation. For Treebagger and LSBoost, we find that an ensemble of five trees provided the best results, whereas the MLP architecture with three hidden layers provided optimal results. In the case of SVR, we found that the ν-SVR method with radial basis function as kernel, cost parameter set to 10, and $\gamma = 1$ provided the best result.

As performance measures, we calculate the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) for all of the methods:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} e_i^2}{N}}, \tag{4}$$

$$\text{MAE} = \frac{\sum_{i=1}^{N} |e_i|}{N}, \tag{5}$$

where N is total number of incidents and e_i is the error between the actual and predicted duration d_i and $\hat{d}_i$ respectively:

$$e_i = d_i - \hat{d}_i. \tag{6}$$

IV. PERFORMANCE OF VARIOUS REGRESSION METHODS IN PREDICTION

In this section, we analyze the performance of various predictors in predicting the duration of non-recurring road-incidents in the network of Singapore and the Netherlands.

At first, the RMSE and MAE values obtained for the five methods are shown in Table I and II for vehicle breakdowns and accidents respectively in Singapore. For the purpose of benchmarking, we also consider a dummy predictor that always outputs the average incident duration.

TABLE I: Prediction error (in min) for vehicle breakdowns in Singapore.

	Dummy classifier	CART	MLP	SVR	Treebagger	LSBoost
RMSE	20.76	13.268	13.231	12.61	13.12	13.1
MAE	16.89	10.946	10.97	10.481	10.84	10.86

TABLE II: Prediction error (in min) for accidents in Singapore.

	Dummy classifier	CART	MLP	SVR	Treebagger	LSBoost
RMSE	27.8	23.442	23.215	23.6	23.11	23.898
MAE	23.65	19.466	19.095	20.1	19.05	19.816

From the tables we can conclude that it is generally more difficult to predict the duration of accidents than breakdowns.

We show the distributions of the absolute error for vehicle breakdowns and traffic accidents in Fig. 1 and Fig. 2 respectively. All curves in Fig. 1 follow a similar pattern.
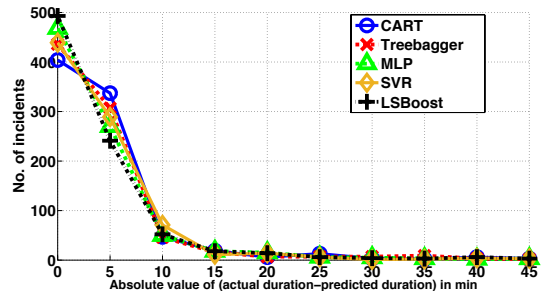

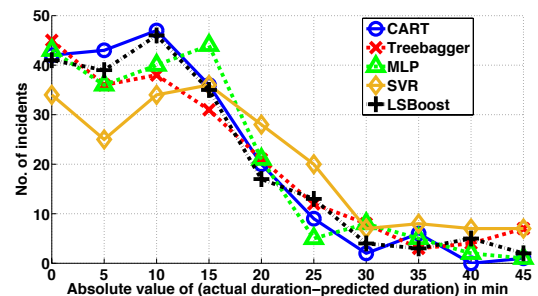Fig. 1: Absolute error distribution for vehicle breakdowns in Singapore.

Fig. 2: Absolute error distribution for accidents in Singapore.

Moreover, the maximum error in prediction is found to be less than 50 min. For most of the breakdowns, the prediction error is less than 20 min. However, the error distributions for accidents (see Fig. 2) are more fluctuative, probably due to the smaller number of accidents compared to breakdowns. For some accidents, the prediction error is larger than 90 min (not shown in Fig. 2). The high value of RMSE and MAE in Table II are clearly reflected in Fig. 2.

Let us now analyze incidents data from the Netherlands in a similar way. However, as the records of incidents in this case are not limited to vehicle breakdowns and accidents only (in fact, there are six types of incidents in this case), we incorporate the type of the incident as a separate feature. We have, in total, 5917 incidents, which have the duration in the range of $0 - 150$ min. The RMSE and MAE values obtained for the Netherlands are mentioned in Table III. From

TABLE III: Prediction error (in min) for incidents in the Netherlands.

	Dummy classifier	CART	MLP	SVR	Treebagger	LSBoost
RMSE	19.7	16.56	16.86	16.94	17.2	17.3
MAE	17.5	13.57	13.12	13.81	14.21	13.89

the tables we can conclude that the error values are almost identical for all the methods. We show the distributions of traffic incidents in Fig. 3. The error distributions for incidents
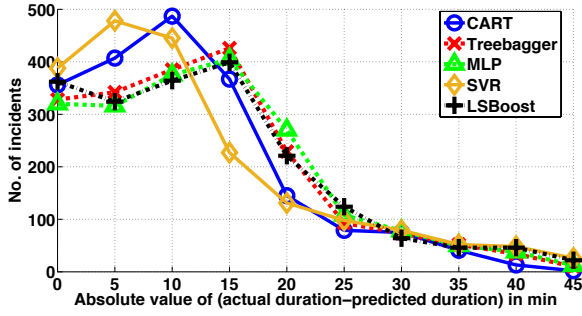
Fig. 3: Absolute error distribution for incidents in the Netherlands.

of the Netherlands are a bit fluctuative compared to the distributions of vehicle breakdowns (see Fig. 1), however similar to those of accidents (see Fig. 2) in Singapore.

V. PREDICTION BY CLUSTER-SPECIFIC CLASSIFIERS

In this section, we investigate whether there are certain latent relationships between different features of traffic incidents. We apply the K-means clustering and affinity propagation methods to group different incidents together, and then design cluster-specific prediction models.

K-means is a commonly used method for cluster analysis [14]. Let $(x_1, x_2, ...x_n)$ be a set of observations. The K-means clustering method partitions these n observations into $K(\leq n)$ sets $S = \{S_1, S_2, ...S_k\}$ in such a way that the intra-cluster distance W defined as:

$$W = \sum_{i=1}^{K} \sum_{x \in S_i} ||x - C_i||^2, \tag{7}$$

attains a minimum, where C_i is the cluster center or mean of set S_i.

Affinity propagation is a clustering algorithm that takes similarity between pairs of input data points to find out the potential cluster centers among them [15]. Let $(x_1, x_2, ...x_n)$ be a set of data points, and s be a function quantifying the similarity between any two points, i.e. $s(x_i, x_j) > s(x_i, x_k)$ iff x_i is more similar to x_j than to x_k. The algorithm proceeds by alternating two message passing steps, to update two matrices [15]:

1) The "responsibility" matrix R has values $r(i, k)$ that quantify how well-suited x_k is to serve as the exemplar for x_i, relative to other candidate exemplars for x_i.
2) The "availability" matrix A contains values $a(i, k)$ represents how appropriate it would be for x_i to pick x_k as its exemplar, taking into account other points' preference for x_k as an exemplar.

The algorithm then performs the following updates iteratively:

1) First, responsibility updates are sent as:
   $r(i, k) \leftarrow s(i, k) - \max_{k' \neq k} \{a(i, k') + s(i, k')\}$
2) Then, availability is updated as:
   $a(i, k) \leftarrow \min \left(0, r(k, k) + \sum_{i' \notin \{i, k\}} \max(0, r(i', k))\right)$
   for $i \neq k$ and $a(k, k) \leftarrow \sum_{i' \neq k} \max(0, r(i', k))$.

Unlike other clustering algorithms such as K-means, affinity propagation does not require the number of clusters to be determined or estimated before running the algorithm.

To determine the optimum number of clusters, we verify how the intra-cluster distance W varies with the number of clusters K for K-means method, as shown in Fig. 4. The curve for traffic accidents (not shown here) is similar to that of vehicle breakdowns.
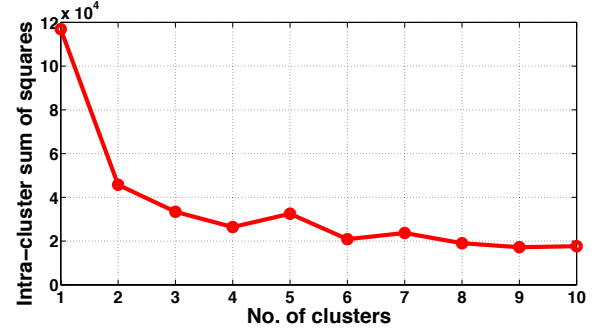

Fig. 4: Intra-cluster distance W for different values of K for K-means method (vehicle breakdowns in Singapore).

From Fig. 4, we can see that the largest drop in W occurs at $K = 2$, while for larger values of K, the reduction in W is not so prominent. Therefore, we set $K = 2$, and hence consider 2 clusters. To visualize these two clusters obtained by K-means method, we apply Principal Component Analysis (PCA) [16] to the 9-dimensional feature set. The two principal components for breakdowns and accidents are listed in Table IV and Table V. In Fig. 5 and Fig. 6 we show

TABLE IV: Two Principal Components (PC) of the 9-dimensional feature-set for vehicle breakdowns in Singapore.

	day of week	time of day	no. of lanes	shoulder	number of lanes affected	type of affected lane	express-way	direction	rainfall
PC1	0.03	0.03	0.06	**-0.57**	**0.59**	**0.57**	-0.001	0.01	-0.02
PC2	**0.67**	**0.66**	0.02	0.02	-0.01	-0.02	0.12	-0.06	0.32

TABLE V: Two Principal Components (PC) of the 9-dimensional feature-set for traffic accidents in Singapore.

	day of week	time of day	no. of lanes	shoulder	number of lanes affected	type of affected lane	express-way	direction	rainfall
PC1	0.02	0.01	0.3	**-0.56**	**0.57**	**0.53**	0.001	0.03	-0.02
PC2	**0.67**	**0.7**	0.06	0.02	-0.03	-0.01	0.02	-0.07	0.21

the two clusters along the two main principal components for breakdowns and accidents respectively. The clusters are indicated by two different colours.

In Fig. 5, the breakdowns are clustered along the first principal component. Therefore, the features contributing the most to this component, such as, number of affected lanes, type of those lanes and whether the shoulder is affected or not (See Table IV), are the determining factors. The left cluster contains the incidents with no lane affected. However, other incidents are clustered according to the condition of shoulder and the type of affected lane. When right-most lanes (lane
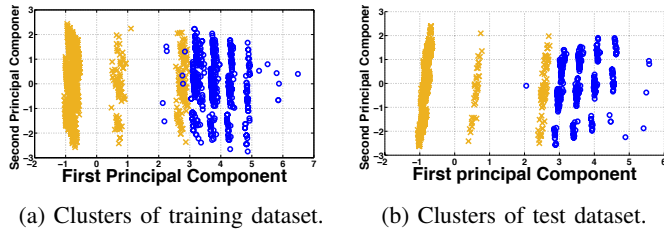
(a) Clusters of training dataset.　　(b) Clusters of test dataset.

Fig. 5: Clusters of vehicle breakdowns in Singapore along two principal dimensions obtained by K-means method.

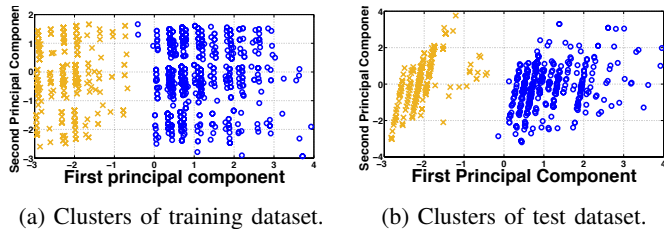(a) Clusters of training dataset.　　(b) Clusters of test dataset.

Fig. 6: Clusters of traffic accidents in Singapore along two principal dimensions obtained by K-means method.

1 or 2) are affected, the incidents are in the left cluster if shoulder is blocked, and in the right cluster if it is not. However, the conditions are reverse in case of left lanes (lane 4 or 5) i.e., the incidents are in the right cluster if shoulder is blocked and vice-versa.

Next we concentrate on the cluster diagrams of the accidents from Singapore (see Fig. 6). Like vehicle breakdowns, we find in Table V that the three above-mentioned features contribute the most to the first principal dimension for accidents also. Clustering mostly depends on the shoulder in this case. If the shoulder is not affected, the incident is assigned to the right cluster. However, if the shoulder is blocked, it depends on the type of the closed lane which cluster the incident belongs to. The incident is grouped in the left cluster if no lane is affected. On the contrary, the right cluster comprises of those accidents where lane 3, 4 or 5 is closed.

From the discussions about the cluster diagrams of the incidents in Singapore, we come to the conclusion that the condition of the shoulder is the most important factor in the prediction of duration of the incidents.

We further utilize these clusters to train individual prediction models. As all of the prediction methods perform almost equally well, we limit ourselves to the CART method. We apply 3-fold cross-validation. From the training data, we determine the clusters and learn a CART model for each cluster. In the test phase, we assign each test data-point to the nearest cluster. By applying the CART model of the nearest cluster, we generate a prediction of the incident duration. This procedure is repeated for each of the three training and test datasets.

The RMSE and mean of absolute errors obtained by K-means clustering are shown in Table VI and Table VII. The RMSE and MAE values without clustering are 16.21 min and 12.18 min respectively, averaged across all incidents.

By contrast, for cluster-specific regression, the values drop to 13.18 min and 10.2 min respectively. To improve the results obtained by clustering of the incidents further, we apply the affinity propagation technique. We follow the same steps as K-means clustering. The cluster diagrams are similar to Fig. 5 and Fig. 6, however the RMSE and mean of absolute error obtained by affinity propagation are mentioned in Table VI and Table VII and we can see that prediction improves further by affinity propagation.

Therefore, as can be seen from Table VI and Table VII, clustering clearly helps to reduce the prediction error. The overall RMSE and MAE have improved for the cluster-specific models, both for accidents and breakdowns. As we group incidents of similar nature together on the basis of external factors, the regression models are able to capture the impact of input features more effectively.

TABLE VI: RMSE and MAE (in min) for duration prediction with and without clustering for vehicle breakdowns in Singapore.

	Without clustering	K-means clustering	Affinity propagation
RMSE	13.27	12.04	**9.02**
MAE	10.48	7.12	**6.5**

TABLE VII: RMSE and MAE (in min) for duration prediction with and without clustering for accidents in Singapore.

|	Without clustering	K-means clustering	Affinity propagation
RMSE	23.5	20.8	**18.97**
MAE	19.5	16.3	**14.5**

Now we apply a similar clustering analysis to the traffic incident data from the Netherlands. From similar curves as in Fig. 4 (not shown here), we observed that the optimal value of K is again 2, and hence we consider 2 clusters of incidents in our analysis. To visualize these two clusters, we apply Principal Component Analysis (PCA) to the 8-dimensional feature set. The two principal components for the incidents are summarized in Table VIII. We observe from Table VIII

TABLE VIII: Two Principal Components (PC) of the 8-dimensional Feature-set for incidents in the Netherlands.

	day of week	time of day	type of management	affected carriageway	affected lane	length of the queue	direction	type of incident
PC1	-0.03	0.04	**-0.35**	-0.03	**0.48**	**0.52**	**0.52**	0.33
PC2	0.15	**0.83**	-0.31	0.12	0.01	-0.23	-0.21	0.27

that the features contributing the most to the first principal component are the management type, length of the developed queue, type of affected lane and direction. In Fig. 7 we show the two clusters along the two main principal components for the incidents. The clusters are shown by different colours.

In Fig. 7, the incidents are in left cluster if left lane is blocked and the queue-length is small. On the other hand, right cluster consists of those incidents where right lane or rush-hour lane is affected and the queue-length is high. As a whole, clustering of incidents of the Netherlands depends on several factors.
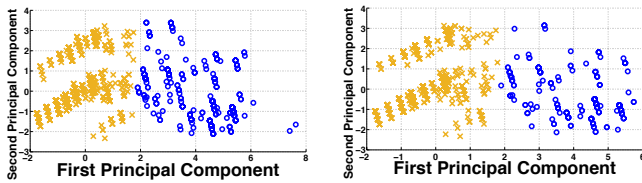
(a) Clusters of training dataset.　　(b) Clusters of test dataset.

Fig. 7: Clusters of incidents in the Netherlands along two principal dimensions obtained by K-means method.

We further utilize these clusters to train individual prediction models. The RMSE and MAE values without clustering are 16.57 min and 12.13 min respectively, averaged across all incidents. By contrast, for cluster-specific regression by K-means method, the values drop to 13.57 min and 10.3 min respectively. To improve the results obtained by clustering of the incidents further, we apply affinity propagation technique. The same steps are applied as K-means clustering. The RMSE and MAE values obtained by K-means clustering and affinity propagation method are mentioned in Table IX.

TABLE IX: RMSE and MAE (in min) for duration prediction with and without clustering for incidents in the Netherlands.

	Without clustering	K-means clustering	Affinity propagation
RMSE	16.57	13.09	**12.13**
MAE	13.57	11.42	**10.3**

In general, the percentage of incidents having prediction errors less than 15 minutes improves from 80% to 90% with clustering. Finally, the comparative analysis of the results (obtained by CART method) averaged across all incidents for Singapore and the Netherlands is presented in Table X.

TABLE X: RMSE and MAE (in min) for duration prediction of incidents in Singapore and the Netherlands.

	Singapore		The Netherlands	
	without clustering	with clustering	without clustering	with clustering
RMSE	16.21	**13.18**	16.57	**12.13**
MAE	12.18	**10.2**	13.57	**10.3**

To summarize, we obtain competitive results for predicting traffic incidents duration compared to the state-of-the-art. We achieve this by properly choosing the features (external factors), and training cluster-specific prediction models.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, we aimed to predict the duration of traffic incidents and investigated how to reduce the uncertainty of prediction models. To this end, we considered traffic incidents data from Singapore and the Netherlands. Our results show that the prediction performance of the data-driven methods can be substantively improved by finding common latent features between different incidents first. This can be achieved by clustering the incidents into different groups and then training models for each individual group. In future work, we plan to analyze larger datasets in order to obtain more reliable and detailed results. Moreover, we will apply Bayesian SVR method to anticipate large variations in prediction performance in real-time. Thus, we will be able to anticipate the uncertainty associated with the prediction error values.

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