Hindawi
Journal of Advanced Transportation
Volume 2023, Article ID 3402853, 13 pages
https://doi.org/10.1155/2023/3402853

Research Article

A Data-Driven Approach to Estimate Incident-Induced Delays Using Incomplete Probe Vehicle Data: Application to Safety Service Patrol Program Evaluation

Minsoo Oh and Jing Dong-O'Brien

Department of Civil Construction and Environmental Engineering, Iowa State University, Ames, IA 50011, USA

Correspondence should be addressed to Jing Dong-O'Brien; jingdong@iastate.edu

Received 22 March 2023; Revised 27 June 2023; Accepted 28 June 2023; Published 10 July 2023

Academic Editor: Mei Chen

This paper presents a data-driven approach to estimate incident-induced delays (IIDs) using probe vehicle data while accounting for missing data. The proposed approach is applied to evaluate the effectiveness of a safety service patrol (SSP) program. Existing data-driven methods for IID estimation usually rely on complete data sets. The proposed approach employs a random forest-based classification model and an interpolation method to estimate IIDs when real-time data are completely or partially missing during the incident-impacted time period. It also identifies reference profiles from the closest spatial-temporal road segments to improve data availability. The case study shows that the SSP program in the Quad Cities area of Iowa reduces IIDs associated with various incidents by 15%–91%. This data-driven evaluation framework can be applied to other traffic incident management programs, allowing more accurate and objective evaluations of their effectiveness.

1. Introduction

Incidents, such as collisions and stalled vehicles, can significantly affect the traffic flow, causing significant travel delays, especially during peak hours and in urban areas with high traffic volumes. These disruptions are stochastic in nature as they occur infrequently and are not part of the expected traffic flow patterns. The delays caused by incidents can lead to secondary crashes, additional fuel consumption, and increased air pollution. Therefore, rapid incident detection, response, and cleanup are crucial to mitigate the negative impact of incidents. Consequently, transportation agencies have implemented various traffic incident management programs to better manage road incidents [1, 2].

One of the key performance measures to evaluate the effectiveness of traffic incident management programs is the reduction in incident-induced delay (IID). IID is the additional travel time caused by incidents and is a means of quantifying the impact of incidents on the traffic flow. Therefore, accurately quantifying IIDs is critical to evaluating traffic incident management programs. Various methods have been proposed to estimate IID in the literature, including the deterministic queueing theory [3–6], simulation [7, 8], and statistical analysis [1, 9–14]. The method of the deterministic queueing theory estimates the IID by assuming constant traffic demand and reduced capacity caused by the incident. This method is widely used in the literature because of its simplicity and minimal data requirements. However, the deterministic queueing model does not account for traffic dynamics [3–6]. Simulation-based methods include macroscopic simulation [7] and microscopic simulation runs [8] with and without incident to estimate IID. Developing and calibrating simulation models are usually costly and time consuming [9]. To address the shortcomings of the methods mentioned above, data-driven approaches have been proposed using travel-time data [1, 9–14]. Data-driven IID calculation methods use traffic data from various sources to estimate the impact of incidents on the traffic flow. For example, Habtemichael et al. calculated the IID based on travel time differences between an incident profile and a reference profile representing the normal traffic condition [1]. The core of this method is to identify the reference profiles for each incident. When field data are available and accurate, this method provides reliable IID estimates. Furthermore, Park et al. quantified the impact of nonrecurring congestion using probe vehicle data. Their approach captures the dynamics of traffic evolution and can detect the incident-impacted area accurately using real-time speed data collected from probe vehicles [14]. These data-driven approaches provide a more accurate and objective assessment of IID, which can help transportation agencies better understand the impact of incidents and make informed decisions to minimize delays. In addition, the IID calculation can also be used to assess the performance of traffic incident management systems and identify areas for improvement. However, existing data-driven approaches rely on real-time traffic data, which can be partially or entirely missing at the time of an incident, making the data-driven approach impossible to determine the IID.

Consequently, this paper proposed a data-driven approach to estimate incident-induced delays using incomplete data from the probe vehicle. The proposed method avoids the following weaknesses identified in the literature. First, the typical IID calculation is based on a reference profile from the same location on a different day, which requires continuous field data collection during the incident duration and the reference period. However, due to the frequent missing data, an accurate IID calculation is problematic for some incidents. Therefore, this study proposed a methodology to find a reference profile of the road segments that are the most proximate in terms of spatial-temporal range to the incident but not affected by the incident. The method can mitigate the impact of missing data by finding a reference profile of road segments with similar traffic patterns. Second, this study accounts for short and long periods of missing data. In particular, simple interpolation is used to fill in missing data for a short period. For incidents with a long period of missing data, the IID occurrence classification model is developed using incident information and applied to incidents without real-time speed data. The proposed data-driven IID estimation method is applied to evaluate the benefits of implementing a safety service patrol (SSP) program in the Quad Cities area of Iowa. The new evaluation framework addresses the deficiencies in existing evaluation methods and provides a reliable IID estimation. Existing studies focused on finding the reference profile and calculating IIDs but usually ignored missing data issues. Therefore, this study proposes an integrated IID estimation procedure that accounts for missing data obtained from probe vehicles. The data-driven IID savings estimation approach is applicable to evaluating other incident management programs, such as removal laws and dispatch collection.

2. Data Description

In this study, three types of data are used for the calculation, estimation, and evaluation of the IID of the SSP program, namely, speed data from probe vehicles, estimated traffic volume from annual average daily traffic (AADT), and incident data from advanced traffic management system (ATMS) event logs. It is possible to use other data sources for analysis as long as speed (or travel time), volume, and incident information are collected.

2.1. Speed Data. The speed data used in this study were collected by INRIX, a real-time traffic information platform that provides traffic speed and travel time data. INRIX is a crowd-sourced traffic data set that uses connected vehicles and smartphones to collect real-time traffic data. In addition, INRIX provides historical speed data derived from multiple sources, including GPS probes and physical sensors. The GPS probe vehicles include trucks, taxis, buses, and passenger cars equipped with onboard GPS devices and transmitting capability. The data set includes travel time and average speed in each segment of the road with a data collection frequency of one minute, as well as the following confidence score: 10 (historical), 20 (combination of real and historical), and 30 (real). In this study, only real-time speed data (i.e., data with a confidence score of 30) are used to calculate IID because when an incident occurred, the traffic condition is likely different from the normal condition represented in the historical data. However, there were cases where real-time speed data were missing due to communication failures or the probe vehicle was not traveling through the incident location at that time [15].

2.2. Traffic Volume. Traffic volume is needed to estimate the number of vehicles impacted by the incident. To provide an accurate IID calculation, volume data collected on impacted roadway segments during the incident are preferred. However, due to the limited coverage of roadway sensors and the random occurrence of incidents in the road network, continuous traffic counts were not available in many incident locations. Therefore, in this study, the adjusted hourly traffic volume based on AADT is used. AADT is collected from the Iowa DOT roadway asset management system (RAMS). The adjusted traffic volume applies the hourly factors based on the month, day of week, and time of day, as shown in the following equation [16]:

$$\text{modified traffic flow (vph)} = \text{AADT} \times \text{monthly factor} \times \text{hourly factor}. \quad (1)$$

2.3. Incident Data. The incident data are collected from the Iowa DOT ATMS, which records detailed information of various types of traffic events. For each event, ATMS recorded information including received time, cleared time, location, lane blockage, event type, severity (injuries, fatalities, etc.), and types of vehicle involved. In this study, the following types of events are considered as nonrecurrent incidents: crashes (involving one, two, three, or more vehicles), debris, earlier crashes, emergency vehicles, slow traffic (i.e., slow-moving vehicles on the road), stalled vehicle, towing operation, and vehicle fire. The analysis period is from 2019 to 2021. During the analysis period, a total of 5,217 incidents were recorded, with stalled vehicles, crashes, and debris being the most frequent type of incident.

3. Methodology

As illustrated in Figure 1, the IID estimation framework consists of four modules, namely, data preprocessing, incident classification, IID calculation, and IID estimation. The data preprocessing module includes data cleaning and spatial and temporal alignment of speed, traffic volume, and incident data. The incident classification module classifies incidents based on the availability of real-time speed data. The IID calculation module computes incident-induced delays based on the travel time difference under normal traffic conditions and under incident conditions, provided that real-time speed data are available or can be interpolated. Lastly, the IID occurrence classification model uses the random forest method to estimate the occurrence of IID in the cases where real-time speed data are missing.

3.1. Spatial and Temporal Alignments. The INRIX speed data and the RAMS traffic volume data use different segmentation systems. INRIX utilizes the extreme definition (XD) segmentation system, which includes functional road class (FRC) 1 (i.e., highways and major intersections)–3 (i.e., major road), and usually breaks at intersections and interchanges [17]. The RAMS segmentation system comprises FRCS 1–4 (i.e., neighborhood streets) and has different breakpoints from the XD segments. RAMS collects traffic, roadway geometrics, pavement condition, and business data associated with public roads in the state [18]. In addition, incident locations are recorded by coordinates, road name, and direction. Therefore, to calculate the IID, incident information, speed, and traffic volume data were linked using the geographic information system (GIS). In addition, since the traffic impact of an incident could propagate upstream and downstream of the incident location, speed data from five upstream segments, one downstream segment, and the incident segment were included in the analysis. The spatial range was determined based on the most severe incident within the scope of this study. The upstream roadway segments within 3 miles (4.8 km) and the downstream segments within 1 mile (1.6 km) of the incident segment were determined as the maximum range affected by an incident. Furthermore, to account for the latency in the reported incident time and to monitor traffic conditions before and after an incident, the data collection period starts 30 minutes before the reported time and ends 30 minutes after the incident cleared time. In other words, the temporal range was set based on incident reported time and cleared time by adding 30 minutes before and 30 minutes after incident clearance.

In addition, some data cleaning efforts were conducted to prepare the data set for subsequent analysis. For example, cases in which the incident clearance time exceeds one day (i.e., 24 hours) were excluded from the analysis. These incidents are mainly stalled vehicles left at the roadside for a long period of time, which usually have minimal impact on delay. Speeds based on historical data or partial real-time data are excluded, as real-time speed data can reflect the impact of an incident on traffic conditions. As a result, a combined data set is created that includes speed, volume, and incident information for analysis. The spatial-temporal aligned data set provides a basis for quantifying incident-induced delay. Figure 2 shows the traffic impact of an incident in the time-space diagram. The spatial unit is one roadway segment. The temporal unit is one minute (i.e., the INRIX data collection frequency). The incident was a two-vehicle crash that occurred near Exit 4 on I-280 (MM 10) in Quad Cities around 8:40 am on December 11, 2019. The incident was cleared at 12:40 pm. Therefore, the incident clearance time was 240 minutes, including a two-lane blockage for about 2 minutes. The incident impacted five roadway segments upstream (approximately 3 miles). It took 255 minutes for the traffic to recover. This example also shows that some real-time speed data are missing.

3.2. Incident Classification Based on the Availability of Real-Time Data. Based on the availability of real-time speed data, incidents are classified into three categories: (1) speed data are available throughout the period and on all highway segments, (2) speed data are missing for a short period, and (3) speed data are missing completely or for a long period. In this study, about 63% of the incidents have real-time speed data available for the entire duration. Short period speed data missing is defined as a case where real-time speed data are missing in one or more segments for less than 15 minutes. For a short period of missing data, the speeds were filled using a moving average interpolation method. The interpolation method calculates the average speed between the previous two time intervals and the next two available time intervals on the same roadway segment. The 15-minute threshold was determined on the basis of the accuracy of the speed estimation. When the missing data are less than 15 minutes, the mean absolute percentage error (MAPE) of the interpolation method is within 10%, as shown in Figure 3. For cases with long periods of missing data (i.e., exceeding 15 minutes), the average IID calculated from a similar case is used. In the incident data set, 15.5% of the cases have missing speed data for a short period and 21.5% of the data set has missing speed data for a long period.

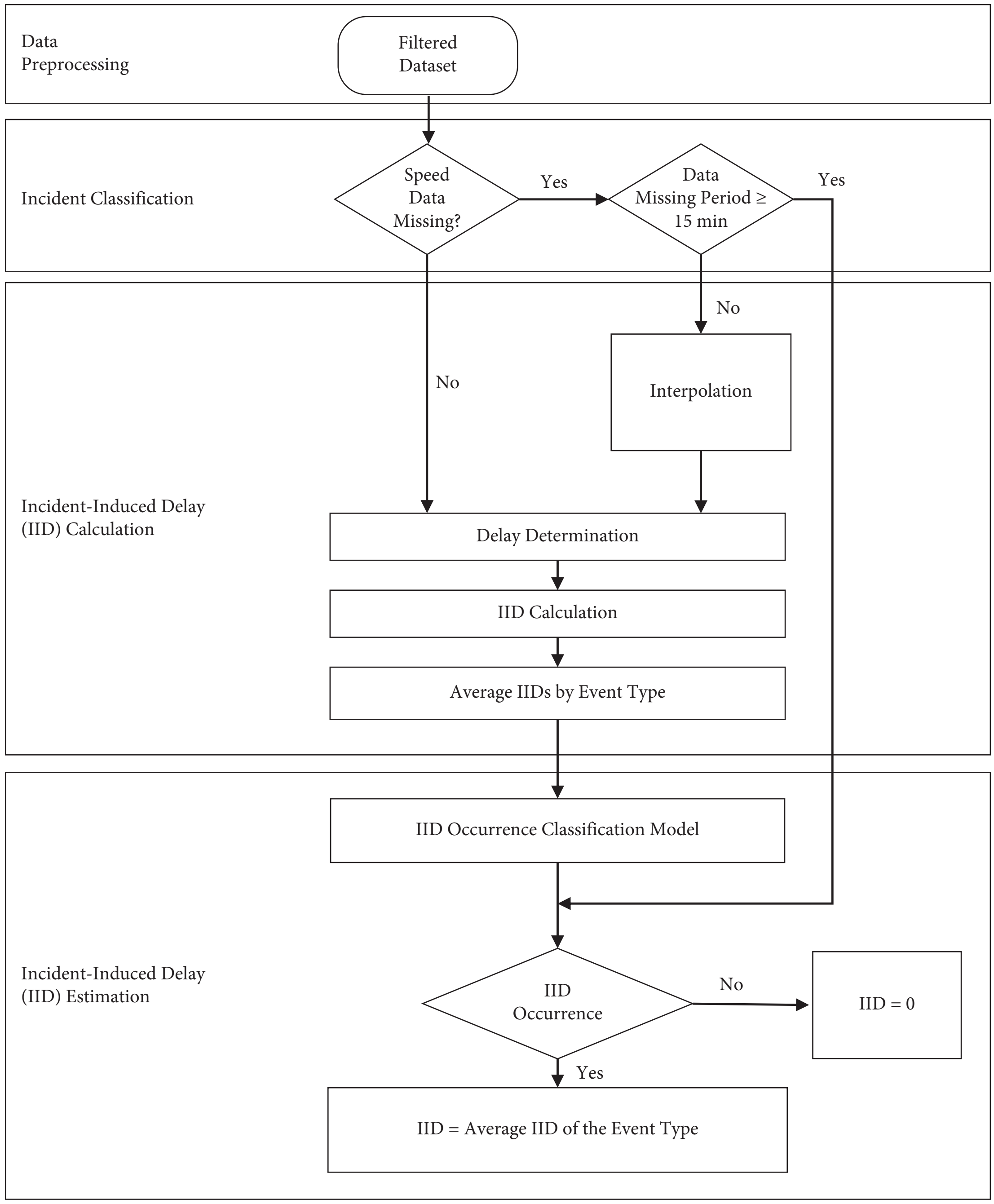

Figure 1: Incident-induced delay estimation framework.

3.3. Calculation of Incident-Induced Delay. The IID calculation module determines the delay caused by an incident based on real-time or partially interpolated speed data. The delay determination threshold was set at 80% of the normal speed, which is defined as the 85 percentile speeds. In addition, the procedure for determining the threshold was derived from the Federal Highway Association (FHWA) method of calculating congested hours [19].

If a delay has occurred due to an incident, the IID of the incident is calculated using equation (2). The travel time of one cell is calculated based on the length of the road segment and the speed. The average speed under normal traffic conditions is then used to determine the normal travel time for each segment and the time interval. The normal traffic condition is found from the road segments that are the most proximate in terms of spatial-temporal ranges to the incident but outside the incident-impacted range. The proposed IID calculation process accounts for nonrecurrent delays, as it can detect segments with slower travel speeds compared to the normal speed of road segments with recurring delays during peak hours. The difference between the travel time affected by the incident and the average travel time under normal traffic conditions is considered the IID per vehicle. Finally, the delay in the vehicle by different

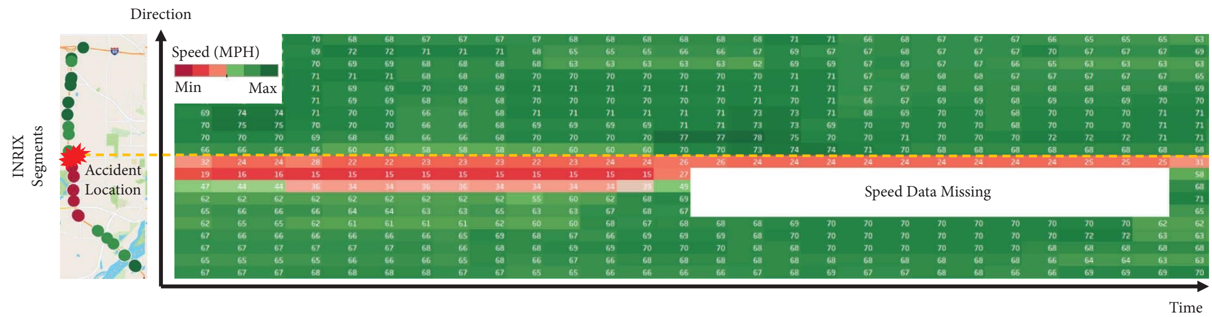

FIGURE 2: Spatial-temporal speed profile of an example incident (I-280 MM 10).

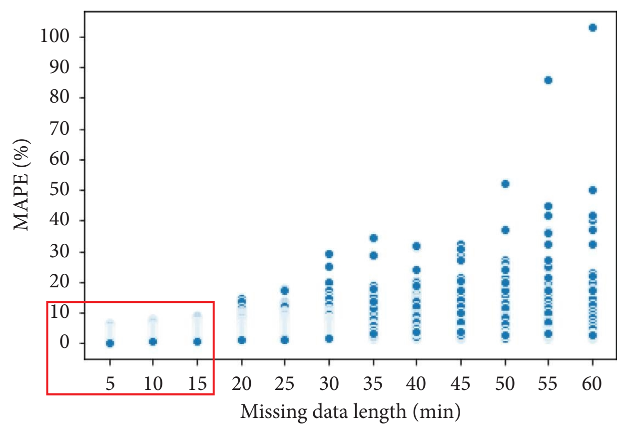

FIGURE 3: Accuracy of the interpolation method with varying lengths of missing data.

classes of vehicles is calculated by applying the traffic volume based on AADT.

An example of determining whether IID occurs within an incident impact range is shown in Figure 4. Figure 4(a) shows the speed profile around the location and time of the accident. In this case, the accident affected one segment downstream and up to five segments upstream. Figure 4(b) shows the occurrence of delays on the speed profile by applying the proposed IID determination method. Based on the normal-condition speed threshold, each cell is classified as normal or delay occurrence. The normal speed profile in the analysis area is calculated using the speeds in the cells of normal condition at each time interval. Figure 4(c) shows both the normal speed profile and the incident-impacted speed profile. The results confirmed that the proposed method can distinguish the spatiotemporal range of delays caused by the accident. The average travel time calculated in the surrounding area, defined as normal conditions, can effectively reflect the traffic characteristics of the corresponding time of day. During peak hours, this approach can calculate the additional delay caused by incidents by comparing it with the normal travel time observed during peak hours.

$$\mathrm{IID}_{\mathrm{PC\,and\,Truck}} = \left(\sum_{i=1}^{\mathrm{LSN}} \sum_{j=1}^{\mathrm{LM}_i} \left(\left(\mathrm{CTT}_{ij} - \mathrm{NTT}_{ij} \right) \right) \times N_{ij-\mathrm{PC\,and\,Truck}} \right), \quad (2)$$

where i is the segment number (LSN: last delayed segment number). j is the time (LM: last delayed minute). CTT is the cell travel time. NTT is the average travel time in normal traffic condition. N is the number of vehicles in one cell

3.4. IID Occurrence Classification Model. To deal with cases where real-time speed data are missing entirely or for a long period of time, an IID occurrence classification model is developed. The IID occurrence classification model uses the characteristics of incidents to predict whether an additional delay is caused by an incident or not. Various classification methods were tested, including artificial neural networks (ANNs), support vector classifier (SVC), Naïve Bayes (NB), K-nearest neighbors (KNNs), and random forest (RF). The RF method was selected because it provides the highest classification accuracy.

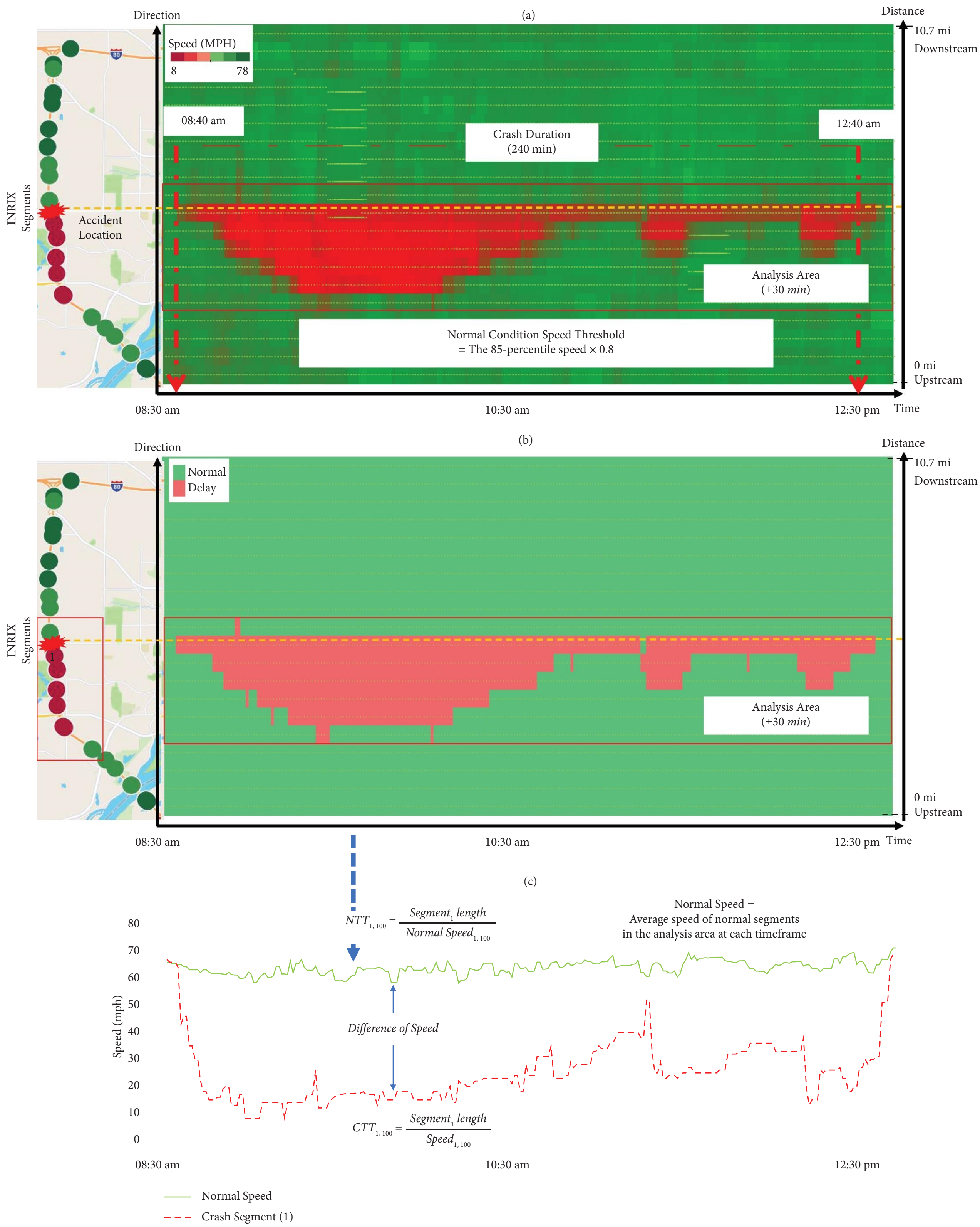

Figure 4: Calculation of IID for an example incident (I-280 MM 10). (a) Segment speed time-space diagram. (b) Delay occurrence determination diagram. (c) Speed profile comparison.

ANN is a machine learning algorithm inspired by the structure and function of the human brain. ANN models are made up of layers of interconnected nodes that perform mathematical operations on input data to generate output predictions. ANNs have been widely used in various fields, including anomaly detection [20], incident detection [21], and incident duration prediction [22]. The advantages of ANNs include their ability to handle nonlinear relationships in data, their flexibility in modeling complex systems, and their ability to learn from large data sets. However, ANNs can be computationally expensive and require a large amount of data to train [20–22].

SVC is a supervised learning algorithm that is commonly used in classification tasks. SVC finds a hyperplane that optimally separates the different classes of data points in a high-dimensional space. SVC has been used in applications such as classification of crash severity [23, 24] and detection of transport modes [25]. The strengths of SVC include its ability to handle high-dimensional data, its effectiveness in dealing with nonlinearly separable data, and its relatively low computational cost. However, SVC can be sensitive to the choice of kernel function and hyperparameters [26].

NB is a probabilistic classifier based on the Bayes theorem. By assuming conditional independence among different features, the NB calculates the probability of belonging to each class, given the input features. NB has been used in applications such as text categorization [27], traffic risk management [28], and incident detection [29]. The advantages of NB include simplicity, the ability to handle high-dimensional data, and the fast computational time for training and prediction. However, NB can be sensitive to the assumption of independence among features, which may not hold in some data sets [20, 28].

KNN is an instance-based learning algorithm commonly used for classification and regression. KNN finds the k-nearest neighbors of a new data point in a feature space and then assigns the data point to the class that is the most common among its k-nearest neighbors. KNN has been used in applications such as vehicle classification [30], incident classification [31], and anomaly detection [32]. The advantages of KNN include simplicity, ability to handle nonlinear relationships in data, and dealing with noisy data. However, KNN can be sensitive to the choice of distance metric and the number of classes [32].

Lastly, RF is a model generated by gathering many decision trees and is a technique for separating data based on specific features. Using the principle of majority rule, the most frequent value among the prediction values made by several decision trees is the final prediction value, called the ensemble. The advantages of RF are threefold: first, the RF consists of multiple decision trees, which can inherently manage missing values without requiring extensive preprocessing. Second, each decision tree in the forest is trained independently on a random subset of data. This parallelization leads to a reduced training time, especially when dealing with large data sets. Third, RF can reduce the risk of overfitting by averaging the output of multiple decision trees [33, 34].

Four metrics, namely, precision, recall, $F1$ score, and accuracy, were compared across the classification models mentioned above. The precision metric is the proportion of what the classification model classifies as true to actually be true. Recall is the proportion of what the model predicts as true out of what is actually true. Precision and recall are complementary to each other. Higher values of both metrics indicate a better model. The $F1$ score is the harmonic mean of precision and recall [35]. In addition, the false alarm rate (FAR), the detection rate (DR), and the overall accuracy of the model (classification rate, CR) are used to obtain the performance of the model. FAR is the ratio of false negative cases among the number of cases without delays. DR is the accuracy to detect IID occurrences between IID cases, which is the same as the recall of with delay occurrence cases. Lastly, CR describes the proportion of correctly classified cases out of the total number of cases evaluated using the established classification for IID occurrences and is also used for model selection [36].

For incidents with adequate real-time speed data, the IID calculation method is applied, as discussed in Section 3.3. Each incident is classified as a "delay" or a "no delay." A total of 5,217 incidents are included in the data set, of which 2,025 (38.8%) incidents cause additional delay and 3,192 (61.2%) incidents cause no delay. The data set is divided into training and testing sets, with 3,901 (75%) and 1,316 (25%) incidents in each subset with an equal proportion of cases in which delay occurred and cases in which it did not, respectively. The training and testing sets have an equal proportion of cases in which a delay occurred and cases in which it did not. The training set is used to train each classification model using supervised learning, with the aim of maximizing the accuracy of each model by comparing various classification factors. The number of hidden layers and the learning rate are adjusted with a maximum of 1,000 iterations to find the optimized ANN model. For the selection of the SVC model, four kernels (linear, polynomial, sigmoid, and radial basis function) are considered as the changeable factors. The KNN model selection process is conducted to find the optimal number of neighbors, and the number of estimators for RF to achieve the best performance is determined through iterations.

Table 1 compares the performance metrics of different classification models, and Figure 5 shows the classification performance of each model. Based on the data set provided, the RF classifier had the highest CR of 0.758, indicating a relatively high proportion of instances that were correctly classified. Furthermore, RF had a relatively low FAR of 0.165 and a moderate DR of 0.640, indicating that it was able to minimize the number of false positive predictions while maintaining a reasonable proportion of true positive predictions. However, the ANN and NB classifiers showed high DRs of 0.706 and 0.640, respectively, and also high FARs of 0.338 and 0.426, indicating that they may have been too sensitive to positive instances and produced too many false positive predictions. The SVM and KNN classifiers showed the opposite trend, with low FARs but also low DRs.

Two key elements of a random forest classification model are the selection of the classification features and the number of estimators. First, the importance based on the impurity of each feature among the explanatory variables of the incident data sets was calculated and applied to the classification model when the importance was 0.01 or greater. This method, called Gini importance, prioritizes features that affect the ability of a classifier. The method of calculating importance is described by Menze et al. [34]. Ten

Table 1: Comparison of performance metrics of different classification models.

Methods	Delay occurrence	Precision	Recall	*F*1 score	Accuracy (CR)	Delay occurrence classification (cases)		Model specification
						No	Yes	
ANN	No delay	0.78	0.66	0.71	0.68	529[1]	270[2]	Hidden layers: 1,000, learning rate: 0.01, max iteration: 1,000
	Delay	0.57	0.71	0.63		152[3]	365[4]	
SVC	No delay	0.68	0.92	0.78	0.69	735	64	Kernel: "Radial basis function (RBF)"
	Delay	0.72	0.32	0.45		349	168	
NB	No delay	0.71	0.57	0.64	0.60	459	340	—
	Delay	0.49	0.64	0.56		186	331	
KNN	No delay	0.70	0.88	0.78	0.70	707	92	Number of neighbors: 95
	Delay	0.70	0.41	0.52		303	214	
RF	No delay	0.78	0.83	0.81	0.76	667	132	Number of estimators: 800
	Delay	0.71	0.64	0.68		186	331	

[1]True negative (TN), [2]false positive (FP), [3]false negative (FN), and [4]true positive (TP).

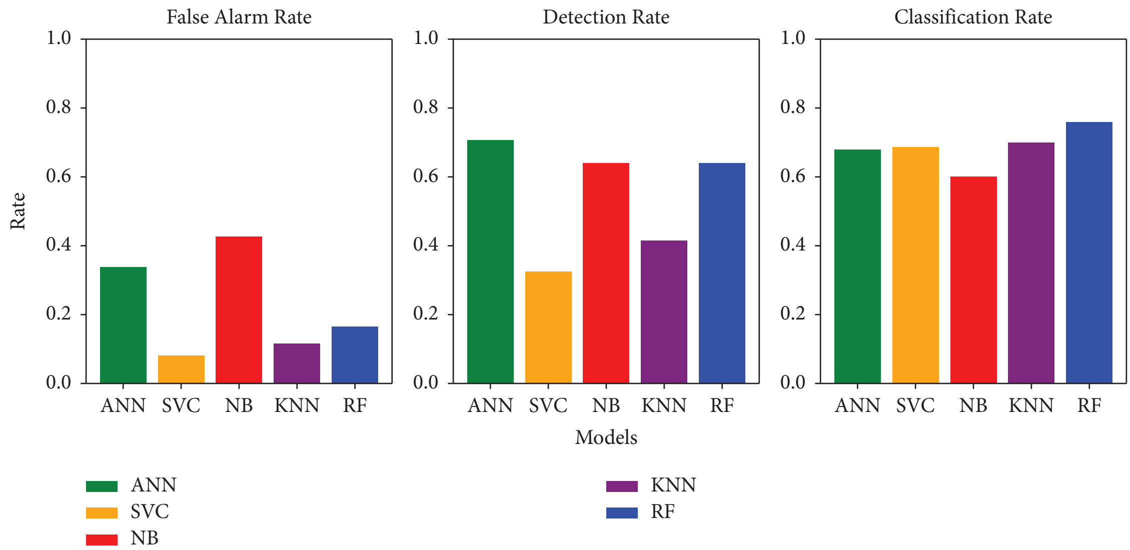

Figure 5: Comparison of the performance of classification models.

Table 2: The selected random forest features.

Numbers	Feature variables	Types	Descriptions	Importance
1	Traffic volume by passenger cars	Numeric	Number of vehicles	0.30
2	Incident clearance hour	Numeric	Hours	0.28
3	Truck traffic volume	Numeric	Number of vehicles	0.27
4	Lane blockage hour	Numeric	Hours	0.03
5	The number of incidents that involved vehicles	Numeric	Number of vehicles	0.03
6	Event type (stalled vehicle)	Factor	1: yes, 0: no	0.02
7	Safety service patrol application indicator	Factor	1: yes, 0: no	0.01
8	Event type (1 vehicle crash)	Factor	1: yes, 0: no	0.01
9	Event type (2 vehicles crash)	Factor	1: yes, 0: no	0.01
10	Event type (debris)	Factor	1: yes, 0: no	0.01

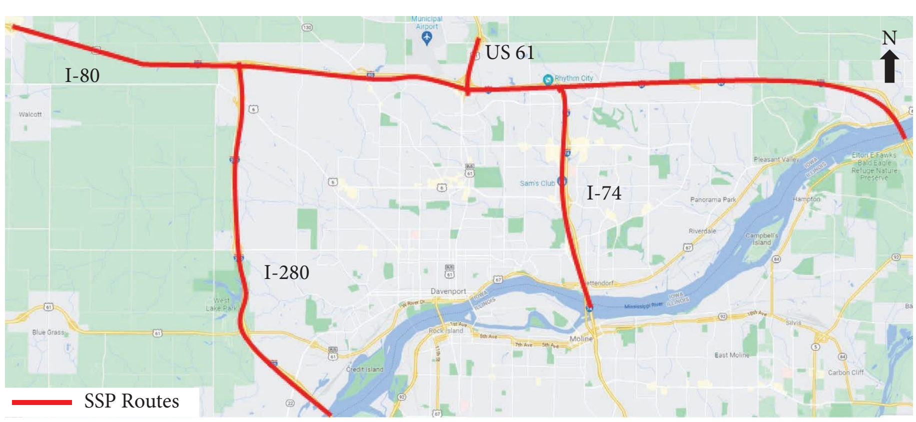

Figure 6: Routes of the safety service patrol program in the Quad Cities area of Iowa.

characteristics were selected and presented in Table 2. The importance of traffic volume and incident clearance hour was found to be greater than other features. Second, setting an appropriate number of estimators helps increase the accuracy of the RF classification model. Therefore, a sensitivity analysis was performed with respect to the number of estimators.

Finally, the IID occurrence classification model is applied to incidents without real-time speed data to determine whether a delay occurred or not. If a delay occurs, the

Table 3: Incident-induced delays by incident types.

Incident types	Entire incident dataset (1/1/2019–12/31/2021)				Before SSP (1/1/2019–9/8/2019)				After SSP (9/9/2019–3/15/2020)			
	All counts	Delay occurrence			All counts (M_B^{**})	Delay occurrence			All count (M_A^{**})	Delay occurrence		
		Counts	%*	Average IIDs (veh-h)		Counts	%	Average IIDs (veh-h)		Counts	%***	Average IIDs*** (veh-h)
1 vehicle crash	229	162	70.7	54.83	78 (6)	57	73.1	89.11	14 (5)	9	64.3% [8.8%]	17.11 [72.00]
2 vehicles crash	116	96	82.8	111.84	24 (3)	23	95.8	157.69	12 (1)	11	91.7% [4.1%]	123.12 [34.57]
3+ vehicles crash	16	13	81.3	129.02	6 (2)	5	83.3	93.81	0 (0)	0	—	—
Debris	198	38	19.2	2.25	14 (2)	4	28.6	6.73	11 (2)	1	9.1% [19.5%]	0.01 [6.72]
Earlier crash	78	66	84.6	56.15	25 (1)	20	80.0	79.33	4 (0)	1	25.0% [55.0%]	7.07 [72.26]
Emergency vehicle	43	26	60.5	25.59	8 (3)	5	62.5	56.34	1 (0)	0	—	—
Slow traffic	42	34	81.0	432.77	7 (0)	7	100.0	118.80	4 (0)	4	100.0% [0%]	46.12 [72.68]
Stalled vehicles	4,446	1,556	35.0	11.15	418 (85)	260	62.2	18.60	606 (156)	221	36.5% [25.7%]	15.85 [2.75]
Towing operation	24	16	66.7	76.95	6 (0)	6	100.0	159.43	0 (0)	0	—	—
Vehicle fire	25	18	72.0	165.97	3 (1)	3	100.0	126.89	1 (0)	1	100.0% [0%]	57.37 [69.52]
Total	5,217	2,025	38.8	30.36	589 (103)	390	66.2	46.35	653 (164)	248	38.0% [28.2%]	21.21 [25.14]

*Delay occurrence % = delay occurrence counts/all counts. **$M_{A,B}$: the number of incidents whose speed data are unavailable during the after (A) and before (B) SSP. ***(program benefit) = before value − after value.

Table 4: The program delay savings.

Types (unit: veh-hour)	Passenger car				Truck			
	Shoulder block		Lane(s) block		Shoulder block		Lane(s) block	
	Before SSP	After SSP	Before SSP	After SSP	Before SSP	After SSP	Before SSP	After SSP
The number of cases	341	593	248	60	341	593	248	60
Sum of delay	7,519.36	3,534.03	6,751.59	804.20	2,028.00	647.81	1,777.25	274.32
Average delay	22.05	5.96	27.22	13.40	5.95	1.09	7.17	4.57
Average delay savings	16.09		13.82		4.86		2.60	
Sum of delay saving	9,541.37		829.20		2,881.98		156.00	
Annual delay savings	18,723.66		1,627.19		5,655.50		306.13	
Total annual delay saving	20,305.85				5,961.63			

average IID associated with the same type of incident is utilized.

4. Case Study: Evaluation of the Safety Service Patrol Program

The proposed IID estimation approach is applied to assess the benefits of deploying a safety service patrol program in the Quad Cities area, Iowa. SSP programs have been implemented in many states to reduce incident clearance times and mitigate the impact of incidents on highways [37, 38]. This area is classified as municipal interstates in Iowa, so expansion factors and the hourly distribution of daily traffic for municipal interstates were used to calculate the adjusted AADT in each segment [16].

4.1. Safety Service Patrol Program. In Iowa, the Iowa Department of Transportation operates a safety service patrol program, called Highway Helper, in several metropolitan areas. Through the program, Highway Helper trucks patrol roads, assist vehicles in accidents or inoperable conditions, and remove debris [39]. The SSP program was introduced to the Quad Cities area in September 2019. The roads covered by the program include I-74, I-80, I-280, and US 61 (see Figure 6), with patrol services provided from 5 am to 9 pm on weekdays. To assess the benefits of the program, the data set is divided into two subsets, i.e., before and after the SSP is in operation to determine the delay savings. The period before the SSP program is from 01/01/2019 to 09/08/2019. Since the operation of the SSP program was impacted by COVID-19 from March 16, 2020, the after period is set from 09/09/2019 to 03/15/2020. The benefit of the SSP program is evaluated based on savings in IID.

4.2. IID Comparison. The average IIDs for each type of event were calculated and summarized in Table 3. IIDs are averaged over the entire incident data set, before and after the SSP program is deployed. Note that after the SSP period, it was only extended to March 15, 2020, to exclude the impact of COVID-19. In general, the IID occurrence rate of vehicle crash-related incidents was higher than the IID for debris or stalled vehicles. In particular, the average IID for one vehicle crashes was 54.83 veh-h, which is about five times higher than the average IID for stalled vehicles, that is, 11.15 veh-h. Among all types of incidents, the IID occurrence rate for debris was the lowest at 19.2%, and the average IID was also the minimum at 2.25 veh-h.

Based on the before and after comparison, the SSP program significantly reduces both the IID occurrence rate and the average IID. The number of incidents collected during the pre-SSP period was 589, of which 103 cases (i.e., 17%) were with no sufficient real-time speed data. During the period after SSP, a total of 653 incidents were collected with the program. Speed data were insufficient for 164 incidents (i.e., 25%). In addition, two secondary crashes were detected in the data set. Through the missing-speed data processing approach, 267 incidents (21% of the total) can be incorporated for program-saving quantification. When comparing crash-type events before and after the SSP program, it was found that the average IIDs after the SSP program had decreased from a minimum of 21.9% (2 vehicle crashes) to a maximum of 91.1% (earlier crashes) than the average IIDs before the application of the program. It was also confirmed that the delay occurrence rates of incidents had a statistically significant difference. Furthermore, although the average decrease in IIDs for the stalled vehicle type in the program application period was only 14.8%, the probability of the occurrence of IIDs was at a level of 60% before the program application period.

4.3. SSP Benefit Evaluation. To estimate the benefit of the SSP program, incidents are classified into shoulder blocks and lane(s) blocks. Among the 653 incidents that occurred during the "after SSP" period, there are 60 cases of lane(s) blockage and 593 cases of shoulder blockage. In all types of vehicles and blockage, delay savings were ensured with the program's help, and the greatest delay savings benefit was obtained for the shoulder block of passenger cars. The delay savings calculated for the period after the introduction of the program were converted into annual delay savings, and the delay savings of 20,306 veh h and 5,962 veh-h are for passenger cars and trucks, respectively (Table 4).

5. Conclusion

This paper presents a data-driven approach to estimate incident-induced delays using probe vehicle data, accounting for missing data. When the speed data are missing for a period of less than 15 minutes, it can be reliably interpolated on the basis of the moving average. In the case of a long period of missing data, a classification model is developed to estimate the occurrence of a delay and the average IID for each type of incident is used when a delay is expected to occur. The proposed IID estimation method is applied to evaluate the benefits of a safety service patrol program deployed in the Quad Cities area in Iowa. The results of the analysis showed that when SSP helped in the incident clearance process, the average IIDs were lower than those of the same types of incidents before the introduction of SSP. This shows that the SSP is an effective method for traffic incident management.

The significance of this study can be summarized as follows. First, the proposed IID estimation approach takes advantage of real-time traffic data while mitigating the impact of missing data. Through this data-driven approach, it is possible to measure the performance of the SSP program with greater accuracy. Second, the IID was calculated based on speed data collected in segments around an incident location and in proximity time intervals that are not affected by the incident, which can reduce the likelihood of missing speed data when finding a reference profile. Third, the proposed IID estimation approach can be applied to evaluate the performance of other traffic incident management programs, in addition to SSP.

However, there are limitations to the present study. First, this study did not include weather information, which can have a significant impact on the occurrence and impact of the incident. If weather information is included, the accuracy of the IID classification model may improve. Second, in future research, an IID measurement model can be developed. In this study, the average IID was used according to incident characteristics after determining the occurrence of the IID using the classification model. However, a more accurate program benefit analysis would be possible when developing an estimation model based on a larger data set.

Data Availability

The data used are provided by the 3rd party data provider INRIX.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was funded by the Iowa Department of Transportation.

References

[1] F. G. Habtemichael, M. Cetin, and K. A. Anuar, "Incident-induced delays on freeways: quantification method by grouping similar traffic patterns," *Transportation Research Record*, vol. 2484, no. 1, pp. 60–69, 2015.

[2] M. F. Coelho, J. M. Bandeira, and M. C. Coelho, "Impact of road traffic incidents on pollutant emissions," in *Proceedings of the IEEE Forum on Integrated and Sustainable Transportation Systems*, pp. 312–316, Vienna, Austria, June 2011.

[3] J. M. Morales, "Analytical procedures for estimating freeway traffic congestion," *Public Roads*, vol. 50, no. 2, pp. 55–61, 1986.

[4] H. Al-Deek, A. Garib, and A. E. Radwan, *New Method for Estimating Freeway Incident Congestion*, Transportation Research Record, Washington, DC, USA, 1995.

[5] A. Guin, C. Porter, B. Smith, and C. Holmes, "Benefits analysis for incident management program integrated with intelligent transportation systems operations: case study," *Transportation Research Record*, vol. 2000, no. 1, pp. 78–87, 2007.

[6] L. E. Dougald and M. J. Demetsky, "Assessing return on investment of freeway safety service patrol programs," *Transportation Research Record*, vol. 2047, no. 1, pp. 19–27, 2008.

[7] P. A. Hawkins, "Evaluation of the southwest freeway motorist assistance program in houston," Final Report, No. TX-94/1922-1F, Texas Transportation Institute, Texas, TX, USA, 1993.

[8] G. L. Chang, D. Shrestha, and J. Y. Point-Du-Jour, *Performance Evaluation of Chart: An Incident Management Program: in 1997*, State Highway Administration of Maryland, Maryland, MD, USA, 2000.

[9] M. Snelder, T. Bakri, and B. Van Arem, "Delays caused by incidents: data-driven approach," *Transportation Research Record*, vol. 2333, no. 1, pp. 1–8, 2013.

[10] Y. Chung, "Quantification of nonrecurrent congestion delay caused by freeway accidents and analysis of causal factors," *Transportation Research Record*, vol. 2229, no. 1, pp. 8–18, 2011.

[11] M. Mauch, S. Ahn, K. Chung, and A. Skabardonis, "Baseline evaluation of the freeway service patrol (FSP) I-710 big-rig demonstration program," Institute of Transportation Studies, University of California at Berkeley, Berkeley, CA, USA, UCB-ITS-WP-2005-3, 2005.

[12] R. Dowling, A. Skabardonis, M. Carroll, and Z. Wang, "Methodology for measuring recurrent and nonrecurrent traffic congestion," *Transportation Research Record*, vol. 1867, no. 1, pp. 60–68, 2004.

[13] Y. Chung and W. W. Recker, "A methodological approach for estimating temporal and spatial extent of delays caused by freeway accidents," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 3, pp. 1454–1461, 2012.

[14] H. Park, A. Haghani, and M. Hamedi, "Quantifying non-recurring congestion impact on secondary incidents using probe vehicle data," in *Proceedings of the 54th Annual Transportation Research Forum*, Annapolis, Maryland, March 2013.

[15] A. Sharma, V. Ahsani, and S. Rawat, *Evaluation of Opportunities and Challenges of Using INRIX Data for Real-Time Performance Monitoring and Historical Trend Assessment*, Nebraska Department of Roads, Lincoln, NV, USA, 2017.

[16] Iowa, "Automatic Traffic Recorders 2011 – 2021, Office of Systems Planning," 2022, https://iowadot.gov/maps/Data/AUTOMATIC-TRAFFIC-RECORDER-REPORTS.

[17] K. Barichello and S. Knickerbocker, *Using INRIX Data in Iowa*, Iowa Department of Transportation, Iowa, MA, USA, 2017.

[18] Iowa Department of Transportation, *Iowa DOT Analytics*, Iowa Department of Transportation, Iowa, MA, USA, 2022.

[19] Operations Performance Measurement Program, "The Urban Congestion Report (UCR): Documentation and Definitions, Office of Operations," 2014, https://ops.fhwa.dot.gov/perf_measurement/ucr/documentation.htm.

[20] M. M. Saritas and A. Yasar, "Performance analysis of ANN and Naive Bayes classification algorithm for data classification," *International journal of intelligent systems and applications in engineering*, vol. 7, no. 2, pp. 88–91, 2019.

[21] Y. K. Ki, N. W. Heo, J. W. Choi, G. H. G. Ahn, and K. S. S. Park, "An incident detection algorithm using artificial neural networks and traffic information," in *Proceedings of the 2018 Cybernetics & Informatics (K&I)*, pp. 1–5, IEEE, Lazy pod Makytou, Slovakia, January 2018.

[22] L. Guan, W. Liu, X. Yin, and L. Zhang, "Traffic incident duration prediction based on artificial neural network," in *2010 International Conference on Intelligent Computation Technology and Automation*, vol. 3, pp. 1076–1079, IEEE, 2010.

[23] C. Chen, G. Zhang, Z. Qian, R. A. Tarefder, and Z. Tian, "Investigating driver injury severity patterns in rollover crashes using support vector machine models," *Accident Analysis & Prevention*, vol. 90, pp. 128–139, 2016.

[24] Z. Li, P. Liu, W. Wang, and C. Xu, "Using support vector machine models for crash injury severity analysis," *Accident Analysis & Prevention*, vol. 45, pp. 478–486, 2012.

[25] S. Chen, H. Luo, F. Zhao, W. Yuan, and M. Jiang, "Transportation mode recognition algorithm based on multiple support vector machine classifiers," in *Proceedings of the 2017 the 5th International Conference on Enterprise Systems (ES)*, pp. 253–259, IEEE, New York, NY, USA, September 2017.

[26] K. S. Durgesh and B. Lekha, "Data classification using support vector machine," *Journal of Theoretical and Applied Information Technology*, vol. 12, no. 1, pp. 1–7, 2010.

[27] P. Chandrasekar and K. Qian, "The impact of data preprocessing on the performance of a naive Bayes classifier," in *2016 IEEE 40th annual computer software and applications conference (COMPSAC)*, vol. 2, pp. 618-619, IEEE, 2016.

[28] H. Chen, S. Hu, R. Hua, and X. Zhao, "Improved naive Bayes classification algorithm for traffic risk management," *EURASIP Journal on Applied Signal Processing*, vol. 2021, no. 1, pp. 30–12, 2021.

[29] S. Kang, B. Kwon, C. Kwon, S. Park, and I. Yun, "Development of incident detection algorithm using naive Bayes classification," *The Journal of The Korea Institute of Intelligent Transport Systems*, vol. 17, no. 6, pp. 25–39, 2018.

[30] S. S. Sarikan, A. M. Ozbayoglu, and O. Zilci, "Automated vehicle classification with image processing and computational intelligence," *Procedia Computer Science*, vol. 114, pp. 515–522, 2017.

[31] J. Xiao, "SVM and KNN ensemble learning for traffic incident detection," *Physica A: Statistical Mechanics and Its Applications*, vol. 517, pp. 29–35, 2019.

[32] J. Tang, L. Zheng, C. Han et al., "Statistical and machine-learning methods for clearance time prediction of road incidents: a methodology review," *Analytic Methods in Accident Research*, vol. 27, Article ID 100123, 2020.

[33] X. Zhou, P. Lu, Z. Zheng, D. Tolliver, and A. Keramati, "Accident prediction accuracy assessment for highway-rail grade crossings using random forest algorithm compared with decision tree," *Reliability Engineering & System Safety*, vol. 200, Article ID 106931, 2020.

[34] B. H. Menze, B. M. Kelm, R. Masuch et al., "A comparison of random forest and its Gini importance with standard chemometric methods for the feature selection and classification of spectral data," *BMC Bioinformatics*, vol. 10, no. 1, pp. 213–216, 2009.

[35] K. Kang and H. Ryu, "Predicting types of occupational accidents at construction sites in Korea using random forest model," *Safety Science*, vol. 120, pp. 226–236, 2019.

[36] M. S. Sheikh, J. Liang, and W. Wang, "An improved automatic traffic incident detection technique using a vehicle to infrastructure communication," *Journal of Advanced Transportation*, vol. 2020, Article ID 9139074, 14 pages, 2020.

[37] A. Marquess, P. Desai, G. Havinoviski, and C. Heise, *Safety Service Patrol Priorities and Best Practices, FHWA-HOP-16-047. Federal Highway Administration*, Office of Operations, Washington, DC, USA, 2017.

[38] N. Islam, E. K. Adanu, A. M. Hainen, S. Burdette, R. Smith, and S. Jones, "Evaluating the impact of freeway service patrol on incident clearance times: a spatial transferability test," *Journal of Advanced Transportation*, vol. 2022, Article ID 272747, 10 pages, 2022.

[39] Z. Khalilzadeh, *Benefit-cost Analysis of the*, Iowa Department of Transportation's safety service patrol program, Iowa, MA, USA, 2020.