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A supervised learning approach to calibrating annual average daily traffic against highway roadworks: the impact of demographic and weather conditions

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ABSTRACT
Annual average daily traffic (AADT) is an essential parameter to evaluate the level of mobility in large urban corridors often affected by highway roadworks. However, very little is known about AADT calibration methods that can project the impact of highway roadworks. This study draws upon 13,152 data points collected from the M8 motorway in Scotland, U.K., to propose a machine-learning-driven schematic calibration methodology that can extract the impact of highway roadworks from existing AADT measurements. The robustness of the proposed model is rigorously tested and validated. As the first of its kind, this study provides practical equation models that can extract the impact of roadworks under different demographic and weather conditions from the given AADT. This study should assist governmental transportation agencies in estimating the potential impact of highway roadworks from the very beginning procedures of developing transportation management plans, which is hidden from a single figure of historical AADT.

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KEYWORDS
Annual average daily traffic (AADT); highway roadworks; schematic calibration; machine learning; demographic profile; weather conditions

Introduction
Annual average daily traffic (AADT) is defined as the average number of daily traffic flows at a certain location over an entire year (Sfyridis and Agnolucci 2020). It is well-known that AADT plays a pivotal role in providing essential information to present a wide picture of traffic flows, evaluate traffic patterns, and predict the level-of-service of roads in the future (Eom et al. 2006; Sfyridis and Agnolucci 2020; Wang, Gan, and Alluri 2013; Gastaldi, Gecchele, and Rossi 2014; Xia et al. 1999; Gastaldi et al. 2013; Ha and Oh 2014; Khan et al. 2019; Jessberger et al. 2016). As a way to collect AADT data, the permanent traffic count method is intended to collect 24-hour basis traffic volume during 365 days a year, using automatic traffic counters (Sfyridis and Agnolucci 2020; Department for Transport 2020). Portable devices are also used to collect traffic data 1–5 times over a year, as the short-term traffic count method (Ha and Oh 2014).
Especially, AADT is an essential parameter to project the level of traffic flows in large urban corridors because highway roadworks adjacent to major cities often cause severe level of the mobility disruption (Bae, Choi, and Oh 2017). In this sense, it is crucial for transportation agencies to maintain tolerable levels of mobility disruption and minimize the inconvenience to the traveling public during construction. To respond to these needs, for example, the ‘Work Zone Safety and Mobility Rule’ currently enforces governmental transportation agencies to develop and implement a transportation management plan (TMP) for all federally funded U.S. highway projects (Scriba and Seplow, 2006; Bae, Choi, and Oh 2017). A TMP describes a set of coordinated transportation management strategies and lays out how the strategies will be used to manage potential impacts of highway roadworks on the degree of roadway congestion at and around the planned project location (Federal Highway Administration 2017). Hence, it would be important to know about AADT trends affected by highway roadworks to increase confidence in future TMP decisions.

Given the significance of evaluating traffic flows, many previous research efforts on estimating AADT were made, mainly using linear regression, spatial clustering, and machine learning techniques (Sfyridis and Agnolucci 2020; Department for Transport 2020; Shamo, Asa, and Membah 2015; Tsapakis and Schneider IV 2015; Phillips and Blake 2007). However, most previous studies are underpinned by those technical methods to estimate AADT values themselves. To the best of the author’s knowledge through a thorough literature review, very little is known about the AADT calibration methodology that can project the impact of highway roadworks from existing AADT values. Especially when it comes to the technical aspects, the use of artificial neural networks (ANN) for AADT estimates has been paid attention by some researchers (Sharma et al. 2001, 1999, 2000; Gastaldi, Gecchele, and Rossi 2014; Fu, Andrew Kelly, and Peter Clinch 2017). Despite those research efforts, there is still very little known about schematically evaluating the impact of highway roadworks within given AADT values, and how an ANN-based learning model can capture different trend patterns on existing AADT under different roadwork types. In addition, those previous studies failed to overcome the ‘black-box’ nature of ANN. In other words, any practical model that can be used in AADT calibration practices has not yet been introduced. Therefore, it would be valuable to know how to extract the impact of highway roadworks from existing AADT schematically, but effectively and efficiently, from the very beginning of TMP procedures.

**Research objectives and methods**

Bridging the knowledge gaps delineated above, this study endeavors to assist governmental transportation agencies and decision makers in calibrating existing AADT data against highway roadworks in line with secondary indicators, allowing them to use the proposed models easily, and helping them gain advanced knowledge of different patterns on AADT under different roadwork types, demographic and weather conditions. To achieve these end goals, this study aims to propose a new schematic calibration methodology that can extract the impact of highway roadworks under different demographic and weather conditions from existing AADT measurements on the macro level. More specifically, this study centers on developing a supervised learning model to predict AADT affected by highway roadworks and creating practical equation models that calibrate AADT data against roadwork types in junction with the identified calibration indicators.
(i.e. population, rainfall, snowfall). The main objectives of this study are achieved through a six-step methodology that includes the proposed two-stage modeling framework:

1. A total of 13,152 data points were collected from the M8 motorway in and around two major cities and three towns in Scotland, U.K., over the past three years.
2. Roadworks and secondary calibration indicators (i.e. demographic and weather conditions) were mapped with AADT on a weekly basis (e.g. weekdays, weekends, holidays) to improve the learning performance of the model.
3. A supervised machine learning model using feedforward neural networks was developed to predict AADT by designated highway roadwork classification (Stage I).
4. Based on the results in Stage I, practical equation models were created to calibrate existing AADT estimates against roadworks under different demographic and weather conditions, overcoming the ‘black-box’ nature of neural networks and thus providing decision-makers with easy-to-use models (Stage II).
5. The practical applicability of the equation models was demonstrated based on what-if roadwork scenarios under certain demographic and weather conditions (Stage II).
6. The robustness of the developed model was validated by demonstrating whether the applied datasets were randomly created and measuring forecast accuracy using two different relative error measurement methods.

**Research assumptions and limitations**

The following assumptions and limitations of this study, which would be considered in future work, include:

- It is assumed that the collected datasets of AADT estimates are sufficiently reliable to calibrate AADT against highway roadwork types. This assumption was made because this study underscores a calibration modeling framework, not improving the accuracy and reliability of AADT values themselves.
- It is assumed that an AADT value is represented as a single figure of traffic flow, which already includes some influencing factors, such as economic growth, non-recurrent events, and the occurrence of traffic accidents.
- It is assumed that demographic and weather conditions are key external indicators affecting traffic flows at the macro level. The demographic profile used in this study is defined as population size per year, which projects all inhabitants of a place showing increases or decreases of an area over time. Meanwhile, weather conditions are represented by rainfall and snowfall conditions, which could affect traffic flows based on drivers’ behaviors with their reduced driving speed.
- The scope of this study was focused on the macro level of calibration, based on the designated highway roadwork classification. In other words, a micro-level calibration method for certain roadwork sites will be considered in future work, considering travel times and traffic speeds in and around roadwork sites, and actual roadwork durations.
- Given the proportion of roadwork data, the proposed schematic calibration models were confined to certain highway roadworks defined by Transport Scotland, such as major, minor, and standard roadworks (Transport Scotland 2020).
Data collection and classification

In the United Kingdom (U.K.), AADT is known as annual average daily flow (AADF), which is used hereafter. AADF values have been collected based on around 10,000 manual counts over a 12-hour period per year, while employing around 190 automatic traffic counters (Department for Transport 2020). To carry out a feasibility study, the M8 motorway was selected as the traffic analysis zone. The M8 is very well-known as one of the heavily congested motorways in the U.K. The total length of the motorway is 61 miles (98 kilometers), connecting two of the largest cities in Scotland, Glasgow, and Edinburgh (Mashall 2020). To employ quality data on aspects of accuracy, consistency, and amounts, a total of 13,152 data points were collected from the M8 motorway in and around two major cities and three towns, including Glasgow, Edinburgh, Baillieston, Chapelhall, and Livingston (Department for Transport 2020). Figure 1 illustrates two-way directions of the M8 motorway between Glasgow and Edinburgh, where the traffic data were collected. Figure 2(a) summarizes the collected AADF values.

In general, each different city and town may have its own unique traffic patterns based on external conditions, such as population, weather, and other unobserved characteristics (Geedipally, Shirazi, and Lord 2017; Bae and Choi 2021; Bae, Choi, and Oh 2017). Hence, the variation of external conditions can affect the modeling process to calibrate existing AADF against highway roadworks. To improve the accuracy and reliability of the proposed model at the macro level, three different external calibration indicator datasets were collected, as depicted in Figure 2(b–d), respectively: (1) demographic records; (2) rainfall; and (3) snowfall. Demographic records (i.e. population per year) during the study period were extracted from the National Records of Scotland (Scottish Government 2020). Precipitation datasets including rainfall and snowfall were collected from Weather Online U.K. (WeatherOnline 2020).

In line with the datasets delineated above, highway roadworks carried out during the study period were collected from the Office of Scottish Road Works Commissioner that is an independent public official to improve roadwork plans and operations in Scotland (Office of the Scottish Road Works Commissioner 2020). To classify roadworks, Transport Scotland (2020) defines a number of different types of roadworks, as shown in Table 1.

Based on the defined roadwork types, the collected datasets were classified mainly into seven different groups: major works; minor works (with and without excavation, mobile,

![Figure 1. Traffic analysis zones: M8 motorway between Glasgow and Edinburgh. (a) Annual Average Daily Flow (AADF). (b) Population size. (c) Rainfall (mm). (d) Snowfall (mm).]
and short duration); urgent works; emergency works (including remedial dangerous); standard works; substantial works and road restrictions.

Figure 3 illustrates the proportion of highway roadworks collected during the study period. In detail, the majority of roadworks consists of minor (46%), standard (22.8%), and major works (18.9%). As stated previously, given the proportion of collected roadwork data, the proposed calibration models were focused on these three types of roadworks.

Table 1. Description of Roadwork Types in Scotland, U.K. (Transport Scotland 2020).

<table>
<thead>
<tr>
<th>Roadwork type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Major works</td>
<td>Roadworks that are likely to significantly affect traffic flows and the structure of the road</td>
</tr>
<tr>
<td>Minor works (with excavation)</td>
<td>Roadworks not exceeding a three-day planned duration and 30 meters of works or 20 square meters of reinstatement</td>
</tr>
<tr>
<td>Minor works (without excavation)</td>
<td>Roadworks that are not sensitive to traffic flows (e.g. manholes, chambers, operating valves, poles, lamps, signs, etc.)</td>
</tr>
<tr>
<td>Minor works (mobile and short duration)</td>
<td>Roadworks without excavation, which allows continuous traffic operations with periodic stops</td>
</tr>
<tr>
<td>Urgent works</td>
<td>Unplanned roadworks that are immediately necessary to prevent further deterioration of roadways</td>
</tr>
<tr>
<td>Emergency works</td>
<td>Unplanned roadworks that are highly likely to cause danger to properties or people</td>
</tr>
<tr>
<td>Standard works</td>
<td>Roadworks that are not major, minor, urgent or emergency works</td>
</tr>
<tr>
<td>Substantial works</td>
<td>Reconstruction, widening, resurfacing</td>
</tr>
<tr>
<td>Road restrictions</td>
<td>Full-lane closure</td>
</tr>
</tbody>
</table>

Figure 2. Traffic data and calibration indicators collected from the traffic analysis zones.
roadworks. A set of collected roadwork types, AADF, and calibration indicators were then mapped with each other on a weekly basis (i.e. weekdays, weekends, holidays) to effectively train the dataset in supervised learning. Table 2 summarizes the variables used in this study.

A two-stage approach to modeling the schematic calibration framework

The proposed modeling framework was developed through a two-stage approach: (1) developing a supervised learning model to predict AADF affected by roadworks under different demographic and weather conditions and (2) creating practical equation models that calibrate AADF data against roadwork types in conjunction with the identified calibration indicators (i.e. population, rainfall, snowfall).

Stage I aims to develop a supervised machine learning model, using feedforward neural networks (FNN). FNN is flexible to be applied in any system and effective in modeling highly nonlinear systems (Bae, Choi, and Oh 2017). Given different types and units of variables used, FNN was adopted in this study. As one of the widely used FNN techniques, the Multi-Layer Perception (MLP) neural network was employed. The MLP network is defined as an ANN having at least three layers of neurons that are interconnected: (1) an input layer; (2) one or more hidden layer(s); and (3) an output layer (Kumar 2016). During the supervised learning process, all inputs are mapped on the corresponding outputs. The difference between the predicted outputs and target values is minimized.
serves as a baseline to adjust the weights of neurons iteratively, thereby minimizing the total error over all input-output pairs (Abdi and Moshiri 2015). Although the MLP network has a more complex structure requiring iterative training, which might be slow for a large number of hidden nodes and datasets, many previous studies underlined that MLP networks are compact and yield better learning outcomes, compared to other types of networks (Yu et al. 2011; Santos et al. 2013; Ilonen, Kamarainen, and Lampinen 2003; Bissacot et al. 2016).

Stage II employs the predicted outputs achieved from Stage I, specifically aiming at creating practical equation models using a curve-fitting technique. Stage II is intended to overcome the ‘black-box’ nature of ANN. Concurrently, it aims to provide decision makers with easy-to-use models and advanced knowledge of AADF affected by highway roadworks under different demographic and weather conditions.

Stage 1: developing a supervised learning model

Determining the network architecture

The proposed learning model consists of a total of 14 inputs and 1 output, which is designed with three layers of neurons: (1) an input layer; (2) one hidden layer; and (3) an output layer. The collected 13,152 data points were then divided randomly into three different sets: (1) a training set (60% of the original dataset); (2) a cross-validation set (20%); and (3) a test set (20%). The training set is aimed at identifying the optimal weight that can minimize network errors in the learning model; the cross-validation set is used to seek the optimal number of hidden nodes by monitoring errors; and the test set is used to find an appropriate stopping point of training during the learning cycles (Bae, Choi, and Oh 2017).

At the beginning of the modeling process, as one of the widely-used advanced back propagation (BP) algorithms, the use of the Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton algorithm was confirmed because BFGS often converges faster than other BP algorithms (Bissacot et al. 2016; Mohammadi and Zangeneh 2016; Lahmiri 2011; Dao and Vemuri 2002). The BP algorithm is a traditionally well-known method for training MLP FNN, which is formed in a supervised learning context (Mohammadi and Zangeneh 2016; Lahmiri 2011; Lau, Sun, and Yang 2019). The BP algorithm produces a response based on random weights. Through an iterative process by changing weights, the error rate between the network output and actual (target) values decreases. This computational procedure starts from the output neuron and continues backwards (Vijayalakshmi and Sugumar 2016; Mohammadi and Zangeneh 2016). To search for the most effective network model efficiently, the automated ANN search module provided by Statistica proprietary software was used.

Developing the most feasible learning model

The procedure of the network search started with establishing the total number of networks to train. A total of 500 different network datasets were considered, as alternatives to the network architecture. The learning structure was determined based on the minimum error among the shortlisted networks, each having a different number of
hidden nodes and combination of activation functions. The maximum number of hidden nodes in the hidden layer was set as 100. In other words, a trial-and-error method for determining the number of hidden nodes was applied with the increment of hidden nodes from 1 to 100 in the hidden layer of 500 different network alternatives having 16 different combinations of activation functions. In detail, the most widely-used activation functions were used as alternatives of hidden and output activations that included: (1) the identity function \( f(x) = x \); (2) the logistic function \( f(x) = \frac{1 + \exp(-x)}{1 + \exp(-x)} \); (3) the hyperbolic tangent function \( f(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)} \); and (4) the exponential function \( f(x) = x, \text{ if } x \geq 0; f(x) = \alpha(\exp(x) - 1), \text{ if } x < 0 \).

Among these alternatives, five shortlisted networks were retained. Table 3 shows the learning performance of the shortlisted network models retained from the 500 different networks trained by setting the maximum number of training cycles (i.e. epochs) at 1500; this allowed for determination of the appropriate training stopping point for each network model. An epoch represented a single completion of the training of all the given data (NeuroDimension Inc 2016). The name BFGS 70 indicates the BFGS algorithm followed by 70 epochs, which meant that this network model was found at the 70th training cycle.

Each network has its name depending on the complete multilayer network architecture, including the number of inputs, hidden nodes, and output. For example, the network named by MLP 14-48-1 stands for an MLP feedforward network with 14 inputs, 48 hidden nodes, and 1 output. The learning performance was significantly underpinned by connection weights and activation functions. As unknown parameters, the connection weights were estimated by the selection activation functions. As stated previously, the cross-validation set was used to determine the optimal number of hidden nodes, while the test set aimed to assess the generalization ability based on the selected activation functions.

The final model selection was demonstrated by comparing the error values in the cross-validation set shown in Table 3. As the final network architecture, the network named by MLP 14-16-1 with the logistic function for the hidden activation and the hyperbolic tangent function for the output activation was selected by comparing with the others. Accordingly, Figure 4 illustrates the final supervised learning model structure and convergence of data between training and test sets.

The learning performance of the developed learning model was measured by correlation coefficients between predicted outputs and target values of AADF, associated with the training, cross-validation, and test datasets. The correlation coefficient \( r \) quantifies the strength of association (i.e. the goodness of fit) between actual and prediction values.

Table 3. Shortlisted learning models.

<table>
<thead>
<tr>
<th>Network Architecture</th>
<th>Errors</th>
<th>Activation Function</th>
<th>Training Algorithm and Epoch</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train Set</td>
<td>Test Set</td>
<td>Cross-Validation Set</td>
</tr>
<tr>
<td>MLP 14-9-1</td>
<td>11,479,102.307</td>
<td>12,741,781.949</td>
<td>10,256,267.758</td>
</tr>
<tr>
<td>MLP 14-48-1</td>
<td>11,725,757.474</td>
<td>12,670,233.539</td>
<td>10,590,823.212</td>
</tr>
<tr>
<td>MLP 14-48-1</td>
<td>11,638,082.398</td>
<td>12,633,665.182</td>
<td>10,470,900.403</td>
</tr>
<tr>
<td>MLP 14-64-1</td>
<td>11,571,817.930</td>
<td>12,539,013.136</td>
<td>10,527,868.152</td>
</tr>
<tr>
<td>MLP 14-16-1*</td>
<td>11,278,588.859</td>
<td>12,796,593.786</td>
<td>10,122,517.107</td>
</tr>
</tbody>
</table>

Note: *Final learning model.
values, ranging from −1 to 1. Table 4 shows the results of the correlation coefficients ranging from 0.9096640 to 0.9239340, confirming that there exists significant learning performance of the selected final learning model.

### Stage 2: creating practical calibration models

Stage II aims to develop practical calibration equation models using a curve-fitting modeling technique. The proposed equation models provide a new focus on generalizing AADF against roadwork types associated with the identified calibration indicators. By comparing the results obtained from various fitting forms – such as linear, polynomial, splines – the second-order polynomial (i.e. quadratic) fitting form was selected to unveil the ‘black-box’ of the developed learning model. As shown in Table 5, AADF values were calibrated based on three different calibration indicators under each different roadwork type (i.e. major, minor, standard works).

#### Practical applicability: illustrative examples of major roadworks

A scenario-based illustrative example is provided to demonstrate how the proposed equation models can calibrate existing AADT values. To this end, the following conditions were applied:

- Existing AADF: 45,000
- Population size: 60,000
- Rainfall: 5 mm
- Snowfall: It is assumed that there is no snowfall because of the rainfall (i.e. snowfall = 0 mm)

### Table 4. Learning performance of the developed model.

<table>
<thead>
<tr>
<th>Predicted Value</th>
<th>Correlation Coefficient (r)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Training Set</td>
</tr>
<tr>
<td>AADF_Roadworks</td>
<td>0.9186643</td>
</tr>
</tbody>
</table>

Figure 4. Final supervised learning model: MLP 14-16-1 (BFGS 81). (a) Existing AADF versus Population size. (b) Existing AADF versus Rainfall. (c) Existing AADF versus Snowfall.
Table 5. A summary of AADF calibration models: impact of demographic and weather conditions on highway roadworks.

<table>
<thead>
<tr>
<th>Work Type</th>
<th>Calibration Indicator</th>
<th>Calibration Equations: $AADF_{\text{Roadworks}} = (X, Y, Z)$</th>
<th>Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Major Works</td>
<td>$x$</td>
<td>$X = 20357.3 + 0.0674 \cdot A - 0.0771 \cdot x - 3.1742 \cdot 10^{-6} \cdot A^2 + 3.4394 \cdot 10^{-7} \cdot A \cdot x + 1.493 \cdot 10^{-7} \cdot x^2$</td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>$y$</td>
<td>$Y = -21754.997 + 2.7404 \cdot A + 173.2677 \cdot y - 3.1978 \cdot 10^{-5} \cdot A^2 - 0.0079 \cdot A \cdot y + 2.7111 \cdot y^2$</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>$z$</td>
<td>$Z = -20421.512 + 2.6611 \cdot A + 1581.6817 \cdot z - 3.1051 \cdot 10^{-5} \cdot A^2 - 0.0281 \cdot A \cdot z - 25.0265 \cdot z^2$</td>
<td>(3)</td>
</tr>
<tr>
<td>Minor Works</td>
<td>$x$</td>
<td>$X = -4911.794 + 2.0995 \cdot A - 0.1018 \cdot x - 3.8954 \cdot 10^{-5} \cdot A^2 + 2.174 \cdot 10^{-6} \cdot A \cdot x + 1.0446 \cdot 10^{-7} \cdot x^2$</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>$y$</td>
<td>$Y = -24995.429 + 2.8556 \cdot A + 107.3601 \cdot y - 2.8798 \cdot 10^{-5} \cdot A^2 - 0.0019 \cdot A \cdot y - 0.0333 \cdot y^2$</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td>$z$</td>
<td>$Z = -24436.827 + 2.8359 \cdot A + 2402.2737 \cdot z - 2.863 \cdot 10^{-5} \cdot A^2 - 0.0201 \cdot A \cdot z - 162.3092 \cdot z^2$</td>
<td>(6)</td>
</tr>
<tr>
<td>Standard Works</td>
<td>$x$</td>
<td>$X = -4447.470 + 1.8188 \cdot A - 0.1372 \cdot x - 2.0962 \cdot 10^{-5} \cdot A^2 - 1.1237 \cdot 10^{-8} \cdot A \cdot x + 2.5495 \cdot 10^{-7} \cdot x^2$</td>
<td>(7)</td>
</tr>
<tr>
<td></td>
<td>$y$</td>
<td>$Y = -38128.533 + 3.5987 \cdot A + 314.8501 \cdot y - 3.8901 \cdot 10^{-5} \cdot A^2 - 0.0057 \cdot A \cdot y + 0.1512 \cdot y^2$</td>
<td>(8)</td>
</tr>
<tr>
<td></td>
<td>$z$</td>
<td>$Z = -37095.670 + 3.57 \cdot A - 4386.3242 \cdot z - 3.868 \cdot 10^{-5} \cdot A^2 + 0.0902 \cdot A \cdot z + 15.2807 \cdot z^2$</td>
<td>(9)</td>
</tr>
</tbody>
</table>

$x$: Population size  
$y$: Rainfall  
$z$: Snowfall  
$A$: AADF (before calibration).
As depicted in Figure 5, the existing AADF is compared with the corresponding indicators of population, rainfall, and snowfall. Accordingly, Table 6 shows a summary of the calibration results. By applying Equations (1), (2), and (3), the population size of 60,000 caused traffic congestion, by reducing existing AADF from 45,000 to 33,737 during major roadworks. Meanwhile, rainfall affected the level of mobility disruption, by reducing existing AADF to 35,964. It is noteworthy that major roadworks reduced AADF despite no snowfall.

Based on the results above, the range of calibrated AADF was achieved as shown in Equation (10). More specifically, Equation (11) reveals that major roadworks caused 19% to 25% more traffic congestion, compared to existing AADF of 45,000.

\[
33,737 \leq \text{AADF}_{\text{Major Roadworks}} \leq 36,450 \tag{10}
\]

\[
19\% \text{ decrease} \leq \left[1 - \frac{\text{AADF}_{\text{Major Roadworks}}}{\text{AADF}_{\text{Before Calibration}}} \right] \times 100(\%) \leq 25\% \text{ decrease} \tag{11}
\]
Similarly, other weather conditions were applied by holding the population size constant, in addition to the aforementioned baseline scenario. Table 7 shows the results of different weather scenarios of calibrated AADF under major roadworks (i.e. AADF = 45,000 and population size = 60,000). The main findings of this study reveal that existing AADF values as a single figure could be calibrated to take into consideration the impact of highway roadworks under different demographic and weather conditions.

Model validation

Measurement of bias

In addition to the correlation coefficient results of the developed model, the Kruskal-Wallis test approach to ANOVA was conducted. As a nonparametric statistical test, the Kruskal–Wallis test assesses statistically significant differences on a continuous dependent variable by two or more groups, replacing raw data with ranked data as a distribution-free test (Ott and Longnecker 2015). In this study, the Kruskal–Wallis test was employed to test the null hypothesis of no difference between the seven dataset groups (i.e. roadwork types), against the alternative hypothesis that there is a significant difference between the groups. The Kruskal–Wallis test result demonstrates that there is no significant difference among the training, cross-validation, and test sets ($H$-statistic: 354.0327, $p$-value < 0.0001), showing that the cross-validation and test sets to validate the developed training model are unbiased.

Measurement of forecast accuracy

To validate the forecast accuracy of the developed model, two different relative error measurement methods were employed: (1) mean relative squared error (MRSE) and (2) mean relative absolute error (MRAE). Both methods are well-known as indicators that measure the lack-of-fit, where the error is closer to zero, forecast accuracy is

### Table 6. AADF calibration: baseline scenario results.

<table>
<thead>
<tr>
<th>Calibration Indicator</th>
<th>AADF&lt;sub&gt;before calibration&lt;/sub&gt;</th>
<th>Calibrated AADF&lt;sub&gt;Major Roadworks&lt;/sub&gt;</th>
<th>Applied Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size ( = 60,000)</td>
<td>45,000</td>
<td>33,737</td>
<td>(1)</td>
</tr>
<tr>
<td>Rainfall ( = 5 mm)</td>
<td>35,964</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Snowfall ( = 0 mm)</td>
<td>36,450</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 7. Summary of scenario results: congestion ranges affected by major roadworks.

<table>
<thead>
<tr>
<th>Case</th>
<th>Calibration Indicator</th>
<th>Calibrated AADF&lt;sub&gt;Major Roadworks&lt;/sub&gt;</th>
<th>Congestion Range (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No rainfall and snowfall</td>
<td>Population (=60,000)</td>
<td>33,737</td>
<td>18% ≤ Congestion ≤ 25%</td>
</tr>
<tr>
<td></td>
<td>Rainfall ( = 0 mm)</td>
<td>36,808</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Snowfall ( = 0 mm)</td>
<td>36,450</td>
<td></td>
</tr>
<tr>
<td>Snowfall only</td>
<td>Population (=60,000)</td>
<td>33,737</td>
<td>18% ≤ Congestion ≤ 27%</td>
</tr>
<tr>
<td></td>
<td>Rainfall ( = 0 mm)</td>
<td>36,808</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Snowfall ( = 20 mm)</td>
<td>32,783</td>
<td></td>
</tr>
<tr>
<td>Rainfall only</td>
<td>Population (=60,000)</td>
<td>33,737</td>
<td>19% ≤ Congestion ≤ 24%</td>
</tr>
<tr>
<td></td>
<td>Rainfall ( = 20 mm)</td>
<td>34,247</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Snowfall ( = 0 mm)</td>
<td>36,450</td>
<td></td>
</tr>
</tbody>
</table>
higher (Michalski, Strak, and Piasecka 2017; Halid, Anneka, and Ismail 2014). The results of MRSE and MRAE shown in Table 8 confirm that the proposed model is accurate to calibrate and generalize existing AADF data against highway roadworks in junction with the calibration indicators.

Conclusions

Annual average daily flow (AADF) (i.e. annual average daily traffic (AADT)) is an essential parameter for highly congested large urban corridors because highway infrastructure projects adjacent to major cities often cause severe traffic congestion. However, existing methods focus on estimating AADF values themselves. Hence, they are incapable of projecting the impact of highway roadworks. In addition, although some previous studies have used ANN, existing methods fail to overcome its ‘black-box’ nature.

To fill these knowledge gaps, this study has proposed a new schematic calibration methodology that can extract the impact of highway roadworks under different demographic and weather conditions from existing AADF measurements at the macro level. More specifically, this study developed a supervised learning model to predict AADF affected by highway roadworks and created practical equation models that calibrate AADF data against roadwork types in junction with the identified calibration indicators (i.e. population, rainfall, snowfall).

To carry out a feasibility study, a total of 13,152 data points were collected from the M8 motorway in and around two major cities and three towns in Scotland, U.K. To improve the accuracy and reliability of the proposed model, three different calibration indicator datasets were collected, in addition to historical AADF: (1) demographic records; (2) rainfall; and (3) snowfall. Then, AADF data was mapped with the calibration indicators under the identified highway roadwork types on a weekly basis. Then, a supervised machine learning model using MLP networks was developed to predict potential AADF values affected by calibration indicators under seven different highway roadwork groups. Based on these predicted values, practical calibration equation models were created using a quadratic curve-fitting technique to overcome the drawback of ANN.

A what-if scenario-based illustrative example was then provided to demonstrate how the proposed equation models can calibrate existing AADF values to predict the impact of highway roadworks under different demographic and weather conditions. For the validation of the model, key assumptions on the random selection of training, cross-validation, and test data were demonstrated by conducting the Kruskal–Wallis test. Then, the robustness of the developed model was validated by measuring forecast accuracy with MRSE and MRAE.

The main findings of the study reveal that existing AADF values as a single figure could be calibrated to take into consideration the impact of highway roadworks under different demographic and weather conditions. This study is the first of its kind in dealing with the AADF calibration methodology to predict the impact of highway

Table 8. Forecast accuracy results: MRSE and MRAE.

<table>
<thead>
<tr>
<th>Mean Relative Squared Error (MRSE)</th>
<th>Mean Relative Absolute Error (MRAE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.014534</td>
<td>0.085989</td>
</tr>
</tbody>
</table>

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roadworks against existing AADF values, through a machine learning technique. In addition, for the first time, this study proposed practical equation models that could be used in transportation management scenario planning practices. Use of these practical models can benefit governmental transportation agencies and decision makers to estimate the impact of highway roadworks that is hidden in a single figure of AADF, under different demographic and weather conditions. The outcomes of this study could also help them better evaluate schematically existing AADF, considering highway roadworks in the future.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References


