# Real-Time Traffic Prediction Using ADAptive GRAdient Descent

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***Abstract*—Urban traffic congestion remains an ongoing issue that requires advanced traffic management solutions. Accurate traffic forecasting plays a crucial role in Intelligent Transportation Systems, helping to mitigate congestion and improve mobility. Traditional machine learning approaches have been widely used for prediction tasks, often relying on large volumes of historical data for training. However, real-time adaptability is essential for dynamic traffic conditions. In this study, we leverage real-time traffic data and employ ADAptive GRAdient Descent, an online learning method that adaptively adjusts learning rates, allowing efficient updates as new data become available. To evaluate its performance, we implemented our approach on traffic data from a network of streets in Muscat, Oman, demonstrating its ability to provide accurate and timely congestion forecasts.**

***Index Terms*—Online Learning Methods, Real-Time Data, Traffic Congestion Prediction, ADAptive GRAdient Descent.**

## I. Introduction

Traffic congestion is considered one of the major ongoing issues in the modern world. It has been increasing in both developed and developing countries, representing an undeniable threat to the quality of life. Traffic congestion occurs as a result of a demand-supply imbalance in the transportation networks. When the number of vehicles on the road increases or the capacity of roadways diminishes for a variety of reasons, traffic flows slow down. It causes plenty of issues, including longer travel times for drivers, higher fuel consumption, greenhouse gas emissions, and greater vehicular crash rates.

That is why traffic congestion remains a critical and ongoing research topic in Intelligent Transportation Systems (ITSs). The most effective way to manage this issue is through prevention, which requires accurately predicting traffic congestion and anticipating it before it occurs.

Numerous machine learning approaches have been used to predict traffic. However, a significant limitation of these methods is that they rely on historical datasets to train the model and adjust their parameters based on the entire dataset at once. In contrast, online learning techniques offer a dynamic alternative by continuously updating their parameters as new data becomes available. This sequential adaptation enables real-time updates and rapid predictions, making online learning particularly well-suited for real-time applications. These methods have been widely applied in various fields, including virtual energy storage management, medical data analysis, and flight control.

In this study, we focus on the use of online learning techniques for traffic congestion prediction. Specifically, ADAptive GRAdient Descent (ADAGRAD), which effectively adapts learning rates based on past gradients, making it particularly advantageous for handling real-time traffic data. We use Google Maps API to collect real-time data. Our model's prediction results are afterward compared with actual traffic conditions, demonstrating precise and reliable prediction results.

The paper is organized as follows: Section 2 presents a literature review of the existing methods including machine learning methods and online learning methods. Section 3 describes our decentralized model developed to manage traffic congestion, the principle of features generation and prediction horizons calculation, and the use of ADAGRAD in traffic prediction. Section 4 presents the case study of Muscat, describing the studied road network. In section 5, we show the results generated by our model. Finally, Section 6 presents the conclusions and some perspectives.

## II. State of the art

The study of traffic prediction has been extensively explored in the literature. Within this context, models addressing traffic congestion can be categorized into three main classes:

- Traditional Models: This category includes statistical models such as Autoregressive Moving Average (ARMA) [Mai et al., 2014], [Shuona and Zeng, 2014], Autoregressive Integrated Moving Average (ARIMA) [Jian et al.,

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2020], [Irhami and Farizal, 2021], Seasonal ARIMA (SARIMA) [Sadeghi Gargari et al., 2022], [You et al., 2022], and the Kalman Filter (KF) [Momin et al., 2023], [Emami et al., 2020], among others.

- Machine Learning Models: This category encompasses Linear Regression models [Hongyu et al., 2002], [Hongyu et al., 2003], Support Vector Machines (SVM) [Toan and Truong, 2021], [Guancen et al., 2022], Decision Trees (DTs) [Crosby et al., 2016], [Alajali et al., 2018], and their ensemble variants, such as Random Forests (RFs) [Yifan et al., 2022], [Shaofu and Hengyu, 2020] and Gradient Boosting Machines (GBMs) [Lartey et al., 2021], [Menguc et al., 2023]. It also includes k-Nearest Neighbors (k-NN) [Zhuang and Cao, 2023], [Mladenović et al., 2022] and Support Vector Regression (SVR) [Guancen et al., 2022], etc.
- Deep Learning Models: As a subfield of machine learning, deep learning models include Feedforward Neural Networks, Recurrent Neural Networks (RNNs) [Park and Rilett, 1999], [Wisitpongphan et al., 2012], specifically Long Short-Term Memory (LSTM) [Anwar et al., 2023], [Naheliya et al., 2024] and Gated Recurrent Units (GRU) networks [Saini and Sharma, 2022], [Jeong et al., 2021]. This category also features Graph Neural Networks (GNNs), such as Graph Convolutional Networks (GCNs) [Rongzhou et al., 2020], [Dai et al., 2020] and Graph Attention Networks (GATs) [Huang et al., 2021], [Chu et al., 2023].

All the presented models successfully identify complex patterns and relationships within traffic data, demonstrating their effectiveness for traffic congestion prediction. However, their heavy dependence on large datasets for training has led to a predominant reliance on historical data. A major challenge with these models is their difficulty in adapting to the highly dynamic nature of traffic when dealing with real-time data. Incorporating real-time data significantly increases complexity, requiring careful consideration of rapid road condition fluctuations. To address this, we investigate the use of online learning methods, which are particularly well-suited for real-time applications due to their ability to update models continuously as new data becomes available. Online learning allows adaptive and rapid predictions, making it highly relevant for traffic congestion forecasting. Various approaches exist within this paradigm, including Stochastic Gradient Descent (SGD), Adaptive Gradient Descent (ADAGRAD), Online Passive-Aggressive (PA), Root Mean Square Propagation (RMSprop), and AdaDelta. These techniques have been applied across different domains. For instance, Khan et al. [Khan et al., 2022] developed a machine learning-based stochastic gradient descent approach to optimize medical record management and daily transactions in e-Healthcare applications. Similarly, Vijayalakshmi et al. [Vijayalakshmi et al., 2022] tackled the integration of renewable energy sources (RES) in smart grids, employing Artificial Neural Networks (ANN) and SGD to predict air conditioner energy capacity, thereby facilitating Virtual Energy Storage System (VESS) implementation. Additionally, Muhammad and Anjani [Muhammad and Anjani, 2023] leveraged both SGD and Adam optimization for stock price prediction, successfully forecasting next-day stock values. Nabipour et al. [Nabipour et al., 2020] explored stock market prediction, using ADAGRAD. Their research focused on the prediction of stock market values in different sectors, including petroleum and non-metallic minerals.

Given the success of online learning in real-time adaptation across various fields, we apply these methods to traffic congestion prediction. Specifically, we used ADAptive GRAdient Descent to predict traffic congestion in Muscat, Oman. The flexibility of ADAGRAD aligns well with the real-time nature of traffic patterns, enabling continuous updates and improving system responsiveness to sudden fluctuations. In the next section, we present our approach in details.

## III. Traffic congestion management

We developed an infrastructure-based approach designed to address the challenge of real-time traffic data. This approach accounts for various prediction horizons and dynamically adapts predictions based on the real-time traffic conditions within the studied area. For this purpose, we used intelligent Variable Message Signs (VMSs), which, unlike traditional Variable Message Signs, possess the capability to collect data from multiple sources, conduct traffic analysis, estimate current traffic conditions, and predict future traffic values. Each VMS is strategically placed at a specific road segment within the network. These VMSs collaborate by exchanging information throughout the network to estimate and predict traffic conditions effectively.

### *A. Traffic estimation*

Each VMS collects real-time data from Google Maps API, in order to calculate traffic features. These features help to estimate the real status of traffic in the studied road and are used later for the prediction of the future traffic values.

- Real-time data from Google Maps API
  To acquire real-time traffic data, we used Google Maps API, specifically the Directions API and the Distance Matrix API[1]. These APIs provide essential metrics, including Travel Distance (TD) and Travel Time (TT), for a set of origin-destination pairs. By leveraging this data, we extracted detailed traffic information for the selected road segments between predefined start and end points. This data is then used for traffic estimation on the road network and serves as the basis for feature calculations, which we elaborate on in the following section.
- Features calculation
  Google Maps API provides two types of travel time estimates between two points: the estimated travel time, representing typical duration under free-flow conditions,

[1]https://developers.google.com/maps

and the actual travel time, reflecting real-time duration based on current traffic conditions.
Knowing the actual real Travel Time value, we can calculate the average speed and compare it with the maximum allowed speed in the same road. This is how our features are generated.
Equation 1 illustrates the calculation of our features.

$$F_{i,j} = \left[ \left( \frac{TD_{i,j}}{TT_{i,j}} \right) \frac{1}{V_{\max_{i,j}}} \right] \times 100 \quad (1)$$

Where:
$F_{i,j}$ is the feature from point i to point j.
$TD_{i,j}$ is the Travel Distance between the two points i and j.
$TT_{i,j}$ is the actual real Travel Time from point i to point j.
$V_{\max_{i,j}}$ is the maximum permissible speed in the road from point i to point j.

Following the classification proposed by [He et al., 2016], the feature value ranges from 0 to 100. Values below 25 indicate heavy congestion, those between 25 and 50 suggest mild congestion, and values above 50 correspond to smooth or very smooth traffic conditions.

All the VMSs of our network work simultaneously. Each road sign generates three distinct features taken at different timestamps. Based on the time windows between these times, we determine our prediction horizons. We describe this principle in details in the next section.

### *B. Traffic congestion prediction*

In our study, predictions are made after the generation of three features across time, collected from all the working VMSs in our studied network. In the following, we define the principle of prediction horizons and describe its calculation process.

- Prediction Horizons calculation
  let $F_i$ represent the feature generated at time $t_i$, where $i$ varies from 1 to $n$, and $n$ is the number of features. The time window for generating the next feature $F_{i+1}$ is determined by the value of $F_i$:

$$t_{i+1} = t_i + \begin{cases} 1 \text{ minute} & \text{if } 0 \leq F_i < 25, \\ 5 \text{ minutes} & \text{if } 25 \leq F_i < 50, \\ 10 \text{ minutes} & \text{if } F_i \geq 50. \end{cases} \quad (2)$$

  This process of features' generation continues, giving subsequent features based on the previous ones. Predictions are made after every set of three features for a single VMS. The prediction horizon for each set, $HZ_k$, is calculated by summing the time windows of the three features:

$$HZ_k = \sum_{i=1}^{3} \Delta t_{k,i} \quad (3)$$

  Where, $k$ represents the index of the feature set, and $\Delta t_{k,i}$ is determined by the value of the feature at time $t_i$ according to the specified traffic conditions.

- Real-time traffic prediction using ADAGRAD
  We start by importing the essential libraries: torch, torch.nn.functional, torch geometric.data, pandas, numpy, and xlsxwriter. We define the number of features per VMS and the number of output predictions. We use three features per VMS and one output prediction. The process iterates over time to generate all required predictions for the selected time period. The subsequent step is the generation of features for each VMS, which are then converted into PyTorch tensors. These tensors are compiled into a data instance object that includes all the data from the active VMS within the network. For the ADAGRAD implementation, we define the OnlineADAGRAD class, which contains the fit and predict methods for the training and prediction processes. The system's effectiveness depends on the chosen learning rate, the number of epochs, and the adaptive nature of the ADAGRAD optimizer. After experimenting with different settings, we determined that a learning rate of 0.01 and 2000 epochs provided optimal results. The ADAGRAD optimizer adapts the learning rate for each parameter individually, allowing the model to manage varying feature scales effectively. During the prediction phase, the trained model applies the learned weights to forecast traffic congestion values, which are then scaled and outputted.

**Data:** Real-Time Data from External Source
**Result:** Traffic Prediction Values
Initialization;
Define the number of features (`num_features`);
Define the number of output predictions (`num_Predictions`);
Generate features for each VMS:
$X \leftarrow$ `generate_features()`;
Create a `Data` instance object from features:
$data \leftarrow \texttt{Data}(x = X, y = Y)$;
Initialize the Online ADAGRAD model:
$model \leftarrow \texttt{OnlineADAGRAD}(\text{learning\_rate} = 0.01, \text{num\_epochs} = 2000)$;
Train the model:
$model.\texttt{fit}(data.x, data.y)$;
Test the model:
$predictions \leftarrow model.\texttt{predict}(data.x)$;
**for** $i$ *in range(len(predictions))* **do**
    Print prediction:
    $\texttt{print}(predictions[i] \times 100)$;
**end**

**Algorithm 1:** Online ADAGRAD for Traffic Congestion Prediction

## IV. Case study: Muscat, Oman

We studied traffic in the roads presented in Figure 1, mainly Al Khoudh Street, Al Mazoon Street, and al Shabab Street. These streets are major arterial roads in Muscat, Oman, connecting local roads with highways. They serve both residential and commercial areas and experience heavy traffic during peak hours. Al Khoudh Street connects key zones like schools, universities, and shopping centers, contributing to high traffic volumes. Al Mazoon Street primarily serves residential areas with fluctuating congestion, while Al Shabab Street provides access to commercial zones and faces substantial traffic.
We studied specific sections of these roads, as shown in Figure 1, considering seven roundabouts. VMSs were deployed between them, with red arrows indicating traffic flow.

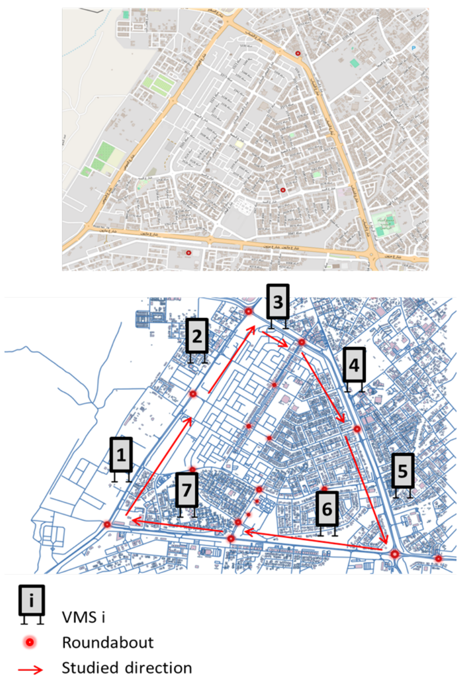


Fig. 1. Studied network in Muscat, Oman

Table I provides the coordinates of the origin and destination.

TABLE I
Coordinates of Variable Message Signs

| VMS | Origin Coordinates | Destination Coordinates |
|---|---|---|
| VMS 1 | 23.618543, 58.180507 | 23.632900, 58.190293 |
| VMS 2 | 23.632900, 58.190293 | 23.642356, 58.196889 |
| VMS 3 | 23.642356, 58.196889 | 23.639201, 58.202899 |
| VMS 4 | 23.639201, 58.202899 | 23.629523, 58.209609 |
| VMS 5 | 23.629523, 58.209609 | 23.615853, 58.214165 |
| VMS 6 | 23.615853, 58.214165 | 23.616766, 58.195247 |
| VMS 7 | 23.616766, 58.195247 | 23.618543, 58.180507 |

The study focuses on the peak hours from 09:00 to 11:00 AM on 08/11/2023. Real-time data recorded during this period serves as input, while the system outputs traffic predictions for the seven VMSs.

## V. Results and discussion

This section presents the results of our model. Figures 2 to 8 illustrate the traffic prediction values produced by the seven road signs deployed within our network. The blue curves represent the prediction values generated by our model, while the red curves represent the actual traffic conditions on the roads.

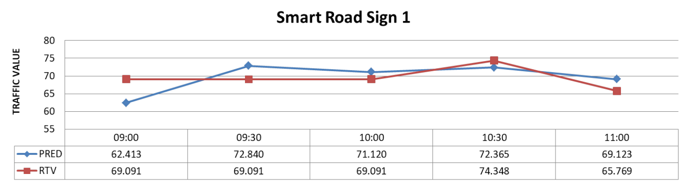


Fig. 2. Traffic prediction values and real traffic values of Variable Message Sign 1.

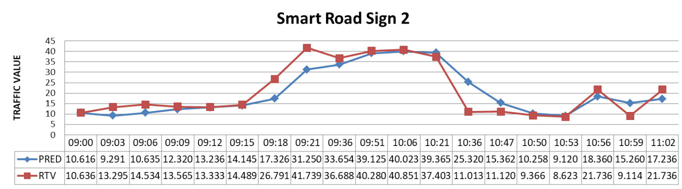


Fig. 3. Traffic prediction values and real traffic values of Variable Message Sign 2.

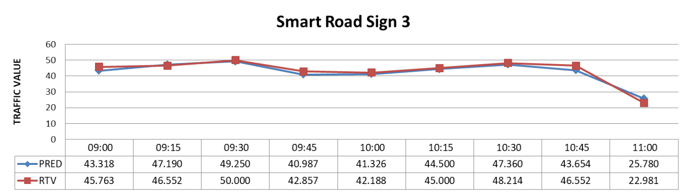


Fig. 4. Traffic prediction values and real traffic values of Variable Message Sign 3.

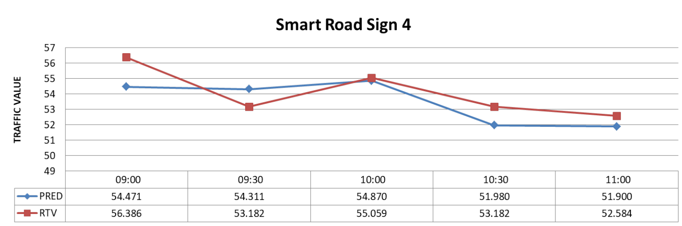


Fig. 5. Traffic prediction values and real traffic values of Variable Message Sign 4.

If we take a look at the predicted traffic values of VMS 1 (Figure 2) at different times, we can see that the prediction at 09:00 shows a small gap from the actual value, when

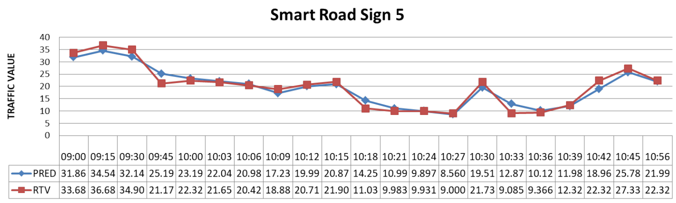


Fig. 6. Traffic prediction values and real traffic values of Variable Message Sign 5.

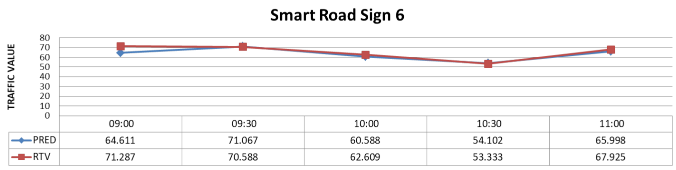


Fig. 7. Traffic prediction values and real traffic values of Variable Message Sign 6.

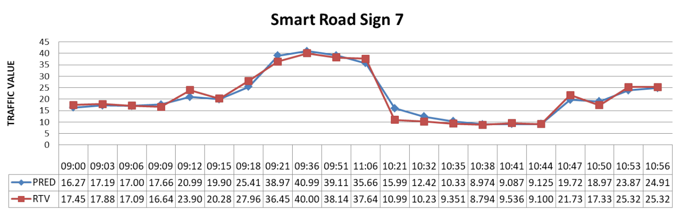


Fig. 8. Traffic prediction values and real traffic values of Variable Message Sign 7.

compared to the other points in the graph. Subsequent predictions get closer to reality by the time. Notably, the 10:00 and 10:30 predictions are very accurate, aligning closely with the real traffic.

Examining Figure 3, a noteworthy observation is the significant difference in the number of predictions between VMS 1 and other VMSs, like VMS 4 and VMS 6. The Variable Message Sign 2 generates 19 prediction values in a two-hour period. The short prediction horizons for this VMS indicate severe congestion on the studied road. Initial traffic values range from 10.636 to 14.489, escalating to 41.739, which is considered as a mild congestion, before returning to lower traffic values.
The curves in Figure 3 illustrate how the predictions mirror the traffic fluctuations. However, some notable deviations occur: the first one at 9:21, where our model predicts a value of 31.25, while the actual traffic value is 41.739, and the second one at 10:36 where the predicted value is 25.32 while the real traffic value is 11.013.
This is explained by the sudden traffic change from within a short time. However, immediately after these deviations, the system was able to correct itself and generate results very close to the real traffic values.

Figure 4, 6, 7 and 8 illustrate the outcomes associated with VMS 3, 5, 6, and 7, respectively. The prediction and real traffic value curves almost overlap in these three figures, indicating good model performance for these VMSs.

Figure 5 shows the predicted and real traffic values for VMS 4, with the closest match occurring at 10:00. Slight underestimations are observed at 09:00 and 10:30, while the prediction at 11:00 slightly overestimates the real value. The model performed well for this message sign but could be improved to reduce deviations at certain timestamps.

Overall, our model reached accurate results in traffic prediction, with the predicted values closely aligning with real traffic patterns. However, challenges arise when traffic behaves unpredictably, showing sudden spikes or drops. In such cases, the model does not always capture these abrupt changes. However, we observe that after these sudden variations, the system adapts, corrects itself, and produces accurate predictions for subsequent time steps.

## VI. Conclusion

In this paper, we explored the application of online learning techniques for traffic congestion prediction, employing ADAPtive GRAdient Descent. We used intelligent Variable Message Signs that collaboratively monitored traffic conditions across a roads network in Muscat, Oman. Real-time data, sourced from the Google Maps API, were processed to extract relevant features for prediction.
By leveraging real-time data, our model provides timely insights, enabling dynamic route adjustments and facilitating data-driven decision-making. The system was evaluated using seven Variable Message Signs, each generating predictions across different prediction horizons. The results, compared with actual traffic data, demonstrated the model's effectiveness in accurately predicting traffic congestion. Furthermore, the model exhibited strong adaptability to continuously evolving traffic patterns.
As a future direction, we aim to enhance the system's performance by integrating additional data sources, such as weather conditions or incident reports. Additionally, combining ADAGRAD with other methods may be a promising approach to improving the model's ability to detect and adapt to sudden variations.

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