Adaptive Dimming of Highway Lights Using Recurrent Neural Networks

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Abstract. Highway operators are in a constant search of techniques and methodologies that can reduce their energy footprint. In this respect, the installation of dimmable light-emitting diode lights on the open road section of highways appears to be a promising solution, due to the reduced energy consumption (compared to high pressure sodium lamps) and the ability to adjust their brightness at various levels, based on the road's traffic load. However, setting the desired level of light intensity cannot be performed instantly, due to safety and contractual reasons that a highway operator must follow. For this reason, an adaptive and intelligent system is proposed in this work, that models traffic load and is able to predict its future trend, based on current load and light intensity measurements. In this way, the unnecessary use of the lighting equipment is avoided, as brightness is dropped to a minimum level when traffic load is predicted to be low. The proposed model is based on recurrent neural networks and more specifically on long short-term memory cells that are able to model complex dependencies in data with temporal correlations, like traffic load measurements. The overall approach is evaluated on relevant data provided by Olympia Odos S.A. that operates the Elefsina-Korinthos-Patra highway in Greece, with promising results.

Keywords: Traffic load prediction · Highway Lighting · LED Lighting · Intelligent Traffic Control Systems · Recurrent Neural Networks · Long Short-Term Memory

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1 Introduction

The transportation sector, along with the organization and operation of road networks and traffic management, is of pivotal importance for the economic development of countries and the improvement of the quality of life of their citizens. Nowadays, in a period of rapid development and application of innovative solutions in transportation technologies, the ability to integrate smart systems that can tackle complex problems and enhance the level of the provided services is challenging.

Especially in the area of highway lighting, new possibilities emerge, as light-emitting diode (LED) lights allow the adjustment of their brightness, a process also known as dimming [6]. In contrast, traditional lighting methods, such as high pressure sodium (HPS) lamps incur high operating costs, due to their increased energy consumption and corresponding equipment maintenance and replacement needs [5]. Additionally, their environmental footprint must be also taken into account, since the inability to adjust their brightness results in light pollution that affects negatively both the residents of the neighboring areas adjacent to highways, as well as the local flora and fauna.

Even though LED lights can be dimmed, this process cannot be performed instantly, based on the current traffic load, as it requires a certain amount of time during which the traffic load and consequently the light intensity requirements may change. For this reason, the development of a machine learning (ML) algorithm that will be able to model and predict the traffic load for near-future time windows (e.g. within the next hour), based on current traffic data and lighting conditions, is necessary. In this manner, the available equipment is used in an energy efficient way, as brightness is limited to a minimum level when the road traffic is predicted to be low.

This work predominately focuses on the development of an ML algorithm that predicts future traffic load. The said algorithm is going to be part of a broader intelligent architecture that ingests predictions along with weather data and road incidents and selects the desired dimming level, based on a decision making process and a rule set defined by the concessionaire of the highway (Fig. 1). The developed system has been tested on data from the Elefsina-Korinthos-Patra highway in Greece, which are provided by the concessionaire, Olympia Odos S.A. The expected benefits of the overall intelligent lighting system, apart from being an end-to-end solution for brightness management in open highways, are energy savings, reduction of the CO_2 footprint as well as light pollution, while at the same time assessing the desired levels of safety and traffic quality, especially during low visibility time periods (night, cloudy weather, etc).

The rest of the paper is organized as follows; Sect. 2 overviews related work, Sect. 3 outlines the benefits of LEDs over other legacy technologies and Sect. 4 presents Intelligent Traffic Control Systems. Section 5 discusses the traffic load prediction module, starting from the data acquisition process (Sect. 5.1), continuing with the machine learning algorithm (Sect. 5.2), the description of the optimal model (Sect. 5.3) and the evaluation the obtained results (Sect. 5.4). Finally the paper concludes in Sect. 6.

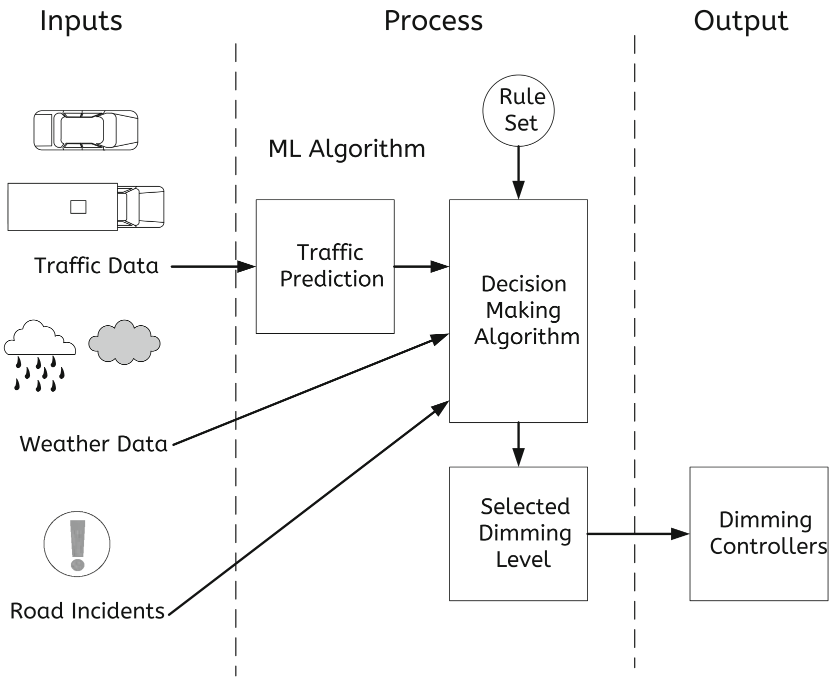

Fig. 1. The overall intelligent lighting system architecture

2 Related Work

Traffic prediction has been extensively studied, especially in the framework of smart cities [18]. The main objective in this case is to employ machine learning methodologies in order to predict traffic jams and other road incidents that might hinder the flow of traffic. This type of information is particularly useful to urban planners, transportation authorities and to individuals and parties involved in the planning and development of the transportation infrastructure and services within cities.

Recently, highway traffic prediction has also emerged as an active research field, especially with the availability of both private and public relevant datasets. For example, private data provided by South Korean highways have been used in [31], where the authors employed long short-term memory cells for highway vehicle speed prediction, along with bayesian optimization and meta-learning for hyper-parameter tuning. Or in [2], where real-time traffic flow is modelled by a Bayesian classifier and support vector regression. In [16], structural state space models are utilized for short-term highway traffic state prediction and are evaluated on data from the northern Taiwan highway network.

Many works are based on public data provided by the California Department of Transportation Caltrans Performance Measurement System (PeMS)[1]. In [30], the authors propose an intelligent system based on empirical mode decomposition and least-squares support vector machines. The spatial and temporal correlations existent in PeMS traffic data are also examined in the context of diffusion convolutional recurrent neural networks [15], graph convolutional networks [27] or attention-based periodic-temporal neural networks [25].

Finally, in [17], the authors have a similar objective to our own; they propose a smart highway lighting system based on road occupancy. Nevertheless, their actual approach is rather simplistic as they develop a probabilistic model which is evaluated on simulated data. To the best of our knowledge, our proposed methodology is among the first to study the problem of highway traffic prediction using machine learning techniques and for the purpose of adjusting the intensity of the lighting systems.

3 Light Emitting Diodes

Reducing the operating costs of highways while at the same time complying with safety levels defined by national and international regulations, is one of the biggest challenges faced by all parties involved in the infrastructure of transportation networks (states, construction companies, operating and management companies). In particular, highway management companies put a constant effort in modernizing their equipment by adopting smart methods to reduce their energy footprint, such as replacing traditional lighting devices with dimmable LEDs.

Even though initially LEDs exhibited greater life cycle costs compared to HPS luminaire [29], recent developments, such as the price drop of LED lamps thanks to higher production and more players in the market (particularly from China), as well as their better efficacy, compared to other technologies, have resulted in an increased market penetration [8]. In particular, from 120 $\frac{\mathrm{lm}}{\mathrm{W}}$, which was comparable to the 90–100 $\frac{\mathrm{lm}}{\mathrm{W}}$ of the legacy technologies, LEDs achieve efficacies of more than 160 $\frac{\mathrm{lm}}{\mathrm{W}}$ on professional lighting applications like in highways, parking lots, etc [5].

The use of dimmable LED lighting on highways ensures a significant reduction in energy consumption - and hence operating costs - without reducing the light quality or affecting road safety [13]. A reduction in energy consumption is still possible even when no new lighting studies have been performed and the old equipment is just replaced with the new one [33]. This is attributed to two factors; (i) the better efficacy of the LED lamps and therefore the need to use considerably smaller installed power, compared to other lamp types (e.g. HPS), in order to achieve the same light coverage, (ii) their ability to be used in a selective and controlled manner, according to the actual requirements of each occasion. Moreover, the correct use of the dimming feature can contribute to

[1] https://pems.dot.ca.gov/.

further increasing the efficiency of LED lights, while this ability can also contribute to the reduction of light pollution, which disturbs the ecological balance, as it has a great effect on the animal life and well-being [28].

4 Intelligent Traffic Management Systems

Intelligent traffic management systems (ITMS) are systems that monitor road networks and whose use can aid operators draw dynamic conclusions. ITMS collect data from a multitude of sources, such as cameras, sensors, mobile phones etc, that are subsequently processed in order to draw insight out of them. ITMS constitute an active, multidisciplinary research field, as they make use of technologies like big data analytics, machine learning, Internet of Things (IoT) and others. A number of studies in the relevant literature summarize useful conclusions from pilot applications of such systems [12,22].

The benefits of ITMS can be visible in various aspects, including the effective use of real-time data [11], the capability of managing big data loads from various sources [19,24], the automatic adaptation to traffic loads [7,14], the constant adaptation to changes in their environment and the possibility of preemptive predictions [21,26]. Their application in adjusting the brightness of the lights of the open road section of highways can be seen as achieving the optimum tradeoff between road safety and energy consumption [7,20]. On the one hand, the highway operators seek to reduce operational costs as much as possible. On the other hand, street lighting is necessary for the safety of the road users, while regulations mandate that it should be set above certain thresholds, depending on current traffic conditions. At the same time, dimming the LED lights can not be performed instantly, but requires a time frame of 10 minutes in order for the brightness to reach the desired level. Obviously, continuously alternating brightness levels is not productive at all.

In this respect, an intelligent and adaptive lighting system that reads current traffic conditions and predicts their trend for the near-future (e.g. the next couple of hours) can be very useful. Based on the said predictions, the operator can lower the brightness level when necessary, reducing operational costs and achieving energy savings, without affecting road safety. In the current work, the adaptive lighting system is studied with respect to the traffic prediction module. More specifically, ML algorithms are going to be implemented, based on recurrent neural networks with long-short term memory units. The respective models are going to be trained on traffic data from the Elefsina-Korinthos-Patra highway in Greece, provided by Olympia Odos S.A.

5 Traffic Load Prediction

This Section presents the key components of the traffic prediction module, that is an integral part of the overall intelligent lighting system architecture (Fig. 1). Initially, data acquisition is discussed (Sect. 5.1), proceeding with the description of the implemented ML algorithms (Sect. 5.2), following with the description

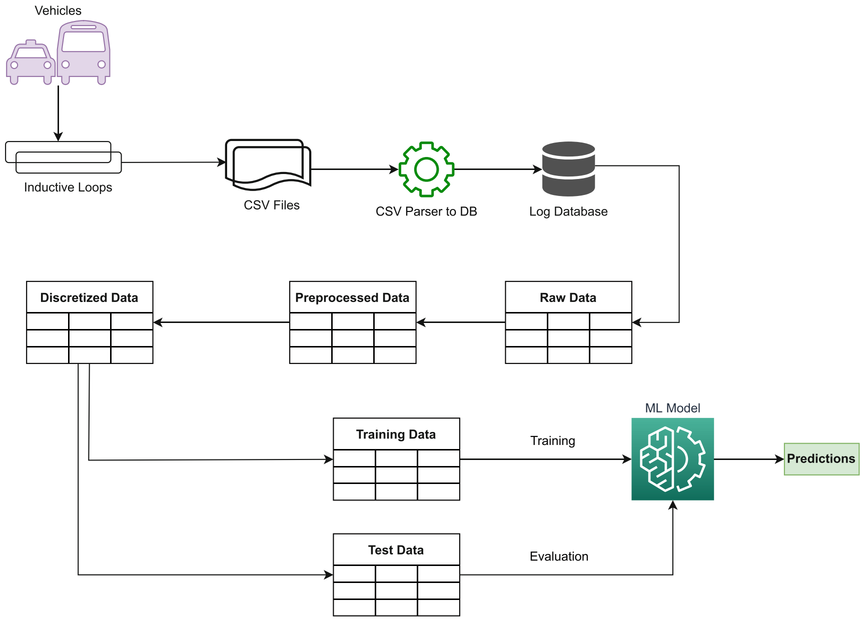

Fig. 2. The Traffic Load Prediction module

of the optimal model (Sect. 5.3) and finally ending with the evaluation of its performance (Sect. 5.4). The overall procedure is depicted on Fig. 2.

The traffic data for the consecutive analysis originate from the Elefsina-Korinthos-Patra (Olympia Odos) highway in Greece, have been collected in 2018 and are provided by Olympia Odos S.A. The full length of the highway is depicted in Fig. 3, along with the toll stations.

5.1 Data Acquisition

Traffic load data acquisition can be performed in a number of ways, either *intrusive* or *non-intrusive*, including magnetic field detectors (magnetometers), pressure detectors, cameras, microwave radars, bluetooth and GPS trackers. In the case of the Olympia Odos highway, the chosen solution are inductive loop detectors, placed on the road surface (Fig. 2, top left). Those devices are comprised of a coil, through which an electric current passes. The presence of metallic objects or other sources of electromagnetic interference around the coil alter its self-inductance and therefore permit it to function as a vehicle detector. An inductive loop detector is comprised of a controller, along with the accompanying cable which is mounted on the road surface (at the highway intersections in the examined case - Fig. 3).

The raw data from the controllers of the inductive loops are read in comma-separated value (CSV) format and are subsequently stored on a log database (Fig. 2, top row). Every entry in the database corresponds to one of the 40

Fig. 3. The full length of the Olympia Odos highway in Greece, along with the toll stations

measurement points in each direction of the highway. At each measurement point, sensors are placed on each lane and are equipped with a counter that stores the number of vehicles that pass over it. In the analysis that follows, we have selected only the main highway sensors, as their information is more relevant to those on the exit ramps, when predicting the traffic load of the highway. The selected group of sensors can detect the vehicle type (e.g. motorbike, car, lorry), their average speed and the occupancy degree (percentage) of the road. Every six minutes, each sensor stores the contents of its counter into the database (Table 1).

Table 1. Sensor data stored in the database (every 6 min)

Feature	Example
Timestamp	2018-01-04 10:12:00
Sensor location	VDS ZEV M T96,6
Highway direction	EPT-T
Highway lane	1
Lane occupancy (%)	1.3%
Average speed of vehicles	126 $\frac{km}{h}$
Total number of vehicles	24

Prior to providing the data as input to the machine learning algorithms, a number of preprocessing steps are necessary (Fig. 2, second row). Initially, the data are inspected for missing or corrupted values, which are subsequently removed from the dataset. Then, the measurements for each lane are aggregated per sensor location and direction, in order to obtain the total traffic load. Figure 4 displays the average daily traffic load at the EPI-E location (Epidavros, direction to Elefsina) for the examined time period (February 2018 to November 2018), after it has been preprocessed.

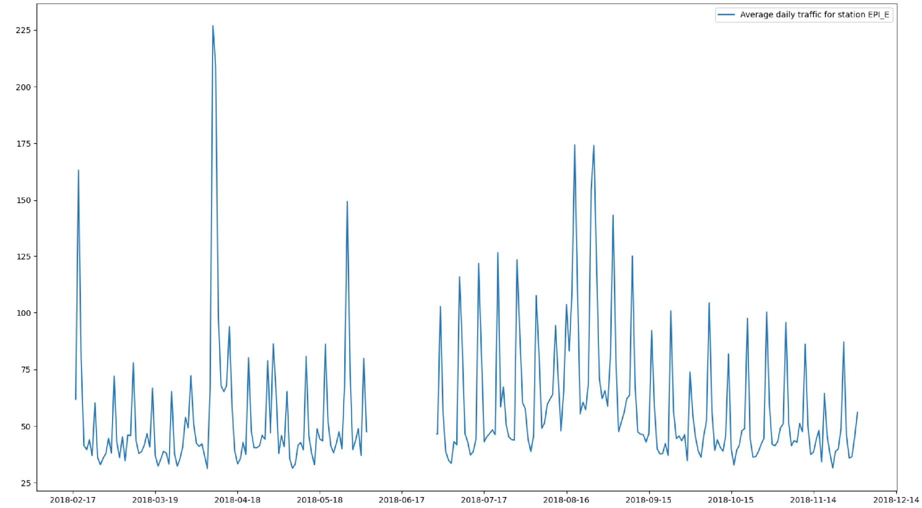

Fig. 4. Average daily traffic for the examined time period (February 2018 to November 2018) at the EPI-E location (Epidavros, direction to Elefsina)

A closer inspection of the displayed data reveals the expected temporal correlations in traffic load. For example, there are evident two main seasonalities in the data; namely, weekdays and weekends. Weekends exhibit larger traffic volumes and this is especially characteristic of Sundays, when many travelers return to Athens via Elefsina. Other sources of seasonal data (increased traffic loads) are holiday seasons (Easter, summer), public and national holidays, as well as random events (e.g. accidents) that may occur on the highway. It is also worth mentioning that the "gap" appearing around June 2018 is due to a malfunctioning of the given induction loop for the said period, which has been detected (and the corresponding values removed) during the preprocessing phase.

5.2 Machine Learning Algorithms

As it is evident both from the analysis in Sect. 5.1 and Fig. 4, the nature of the examined problem is that of *time series forecasting* [3]. In simpler words, the objective is to predict the evolution of the time series (here, the traffic load) over time, implying that, as there is a temporal correlation between the current traffic load and its past values, there should also be a correlation between present values and future ones. If we are able to predict future traffic loads with a certain confidence for the next hour, then we are able to proactively increase the brightness levels and reactively decrease them, based on those predictions.

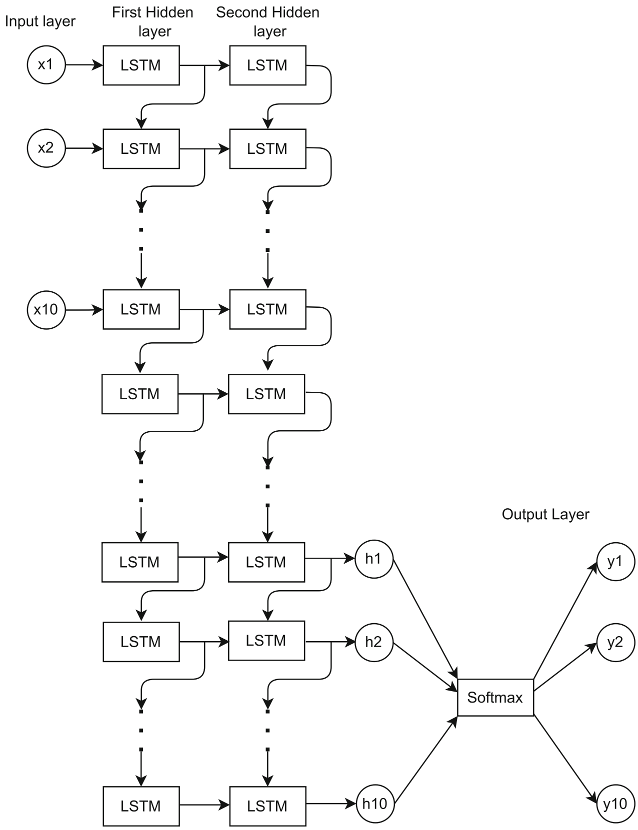

Fig. 5. The implemented machine learning model (recurrent neural network with LSTM cells)

Time series forecasting has been extensively studied in the framework of machine learning algorithms, employing a variety of techniques, including regression, neural networks, support vector machines and random forests [1]. Among the most prominent methodologies are recurrent neural networks (RNNs) [9], which are an extension to feed-forward, artificial neural networks (ANNs), where a feedback loop has been added between the output of each neuron and its input. The presence of the said feedback loop is considered to address the temporal dependencies in sequences of data [23].

The building blocks of RNNs are the recurrent neurons, which are also called units and are stacked in layers from the network input to output (Fig. 5), in a similar fashion to the ordinary neurons of ANNs. The most popular RNN units are the long short-term memory (LSTM) cells [10] and the gated recurrent units (GRUs) [4]. In this work, we have experimented with networks featuring both types of recurrent neurons.

The input to the RNN network is the past traffic load data, in temporal order and its output are the predicted traffic load values, again in temporal order. According to the analysis of Sect. 5.1, the measurement period is 6 min, therefore, if the objective is to predict traffic for the following hour, then the subsequent 10 values need to be predicted. Consequently, the network output is of size 10. The network input size is related to how far it is necessary to “look back” in time in order to be able to produce accurate predictions for the future. If the time window (in the past) is very short, we might miss useful correlations for our analysis; on the other hand if it is too long, we might introduce noise into the model, in the form of unnecessary information. After an initial experimentation, it has been found out that the optimal time window in the past is also one hour; that is, the model reads the past hour’s measurements (10 values) in order ot predict the following hour’s load (10 predictions). In essence, the overall RNN architecture falls in the category of a *many-to-many* prediction, where the input size is equal to the output size (Fig. 5).

Finally, the type of the predicted values need to be determined. An obvious choice would be to treat the problem of traffic prediction in the form of regression; that is to output the exact value of the future traffic load. However, such a modelling is not fit for the case we are examining, as we are interested in determining the traffic level (and subsequently, adjust the brightness of the LED lights) rather than a precise value. For this reason, apart from studying it in the context of regression, we have also decided to discretize the output to categories of N cars; that is, to treat it in the form of multiclass classification (i.e. in the first category fall predictions of up to N cars, in the second between N and $2N$ and so forth - Fig. 2 second row, left).

5.3 Optimal Model

Having determined the main aspects of the proposed architecture in Sect. 5.2, we proceed with tuning its parameters and hyper-parameters in order to obtain as accurate predictions as possible. These include the activation functions used in the recurrent (hidden) layers and in the output layer. In the former case, the hyperbolic tangent has been chosen, as its smoothness has been found to be helpful during network training. In the latter case, the softmax function has been chosen, as the problem is multiclass and because it can convert the output of the neurons into probabilities (that sum up to 1). Finally, categorical cross-entropy has been used as the loss function, as it is common for classification problems.

Other hyper-parameters include the number of hidden layers, the number of neurons per hidden layer, the type of the recurrent units in the hidden layers, the Dropout rate and the number of training epochs. Their optimal values have been determined from an initial search space through exhaustive grid search and cross-validation. Table 2 summarizes both the search space for the said hyper-parameters, along with their optimal values.

Figure 5 displays the architecture of the optimal model. It is comprised of two hidden layers of 70 LSTM neurons each (2^{nd} and 3^{rd} columns). The outputs

Table 2. Hyper-parameter search space and optimal values

Hyper-parameter	Search space	Optimal value
Number of hidden layers	$[1, 2, 3]$	2
Number of neurons per hidden layer	$[30, 40, 50, 60, 70]$	70
Recurrent unit types	[LSTM, GRU]	LSTM
Dropout rate	$[0, 0.01, 0.1]$	0
Number of training epochs	$[10, 20, 30]$	30

of the 10 last LSTM cells of the second hidden layer are aggregated in the output layer (last column).

5.4 Evaluation

The optimal model of Sect. 5.3 has been trained on inductive loop data, according to the process described in Sect. 5.1. In order to avoid overfitting, the model has been trained on data from one location (KOR_E - Corinth, direction to Elefsina) and has been evaluated on two other locations, on both directions of the highway (AKO_E - Ancient Corinth, direction to Elefsina and AKO_T - Ancient Corinth, direction to Patras). Table 3 summarizes model performance on the training and the test data. The examined metrics are the *mean absolute error* (MAE), the *root mean square error* ((RMSE) and the *mean absolute precentage error* (MAPE) [32]. Those metrics are defined in Eqs. 1–3 below

$$MAE = \frac{1}{M}\sum_{i=1}^{M}|\hat{y}_i - y_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(\hat{y}_i - y_i)^2} \tag{2}$$

$$MAPE = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{\hat{y}_i - y_i}{y_i}\right|(\%) \tag{3}$$

where M are the total measurements in the training/test datasets, $\hat{y}_i$ is the prediction and y_i is the actual measurement. MAE and RMSE are regression metrics (by their definition correlated), quantifying the deviation between predicted and actual values (RMSE penalizes larger deviations more) and their optimal value is zero (therefore the smaller MAE and RMSE values, the better). MAPE, on the other hand, is the normalized version of MAE. Accuracy measures how many times $\hat{y}_i$ is equal to y_i in the training/test dataset and we also provide results for the discretized accuracy (multiclass classification problem described in Sect. 5.2); that is when we model system output in categories of N cars each.

A closer examination of the results presented on Table 3 validates the performance of the proposed approach. When traffic prediction is examined as a regression problem (first 4 result rows of Table 3), the optimal model of Sect. 5.3

Table 3. Model evaluation on the training (2nd column) and test data (3rd-4th columns)

Metric	Performance		
	KOR_E	AKO_E	AKO_T
MAE	10.15	8.68	9.30
RMSE	17.05	14.94	15.98
MAPE	20.33%	28.21%	28.40%
Accuracy	57.96%	61.82%	59.85%
Accuracy ($N = 20$)	93.01%	95.50%	94.99%
Accuracy ($N = 40$)	98.70%	99.50%	99.19%
Accuracy ($N = 60$)	99.69%	99.87%	99.72%

is able to make predictions that are only a few vehicles apart from the actual load. On the other hand, when the same problem is treated as (multiclass) classification (last 3 result rows of Table 3), the performance, in terms of the accuracy metric, is excellent, exceeding 99% in both the training and the test data. As discussed earlier (Sect. 5.2), the discretization of the network output into categories (classification problem) facilitates its integration into the overall intelligent lighting system (Fig. 1), without sacrificing the quality of the obtained predictions.

6 Conclusions

In this work, a machine learning model for traffic prediction, based on recurrent neural networks, has been presented. The said model is a component of a greater architecture, an intelligent lighting system, that adjusts the brightness of dimmable LED lights on the open road section of highways, reducing energy costs, as well as the overall environmental footprint of the road operators. The obtained results, both qualitative and quantitative, are very encouraging and the overall architecture is currently implemented on a larger scale, on the Elefsina-Korinthos-Patra highway in Greece.

Naturally, the current implementation can be further extended. For example, more data may be integrated into the model, in the form of domain knowledge (e.g. certain days that are expected to witness high traffic loads, like public holidays). Additionally, outlier detection can be useful as a further preprocessing step, as it has been observed that certain values recorded by the inductive loops are out of the ordinary and may be attributed to errors/interference during data acquisition. Finally, it is worth building more complex models, that consider data input from more than one locations.

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