Intelligent Traffic Light Control

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Abstract

Among the global problems emanating from vehicular traffic across various cities, which include but not limited to, security, parking, pollution and congestion and with the fact of the impracticality of changing the infrastructure of urban area, researchers in most cases consent that such problems may be alleviated by correctly staging the traffic lights which helps in improving the flow of vehicles across cities. In order to efficiently solve this congestion issue, reduce the total journey duration experienced by each vehicle, increase the total number of vehicles reaching their destination per unit of time and to decrease the amount of pollution emitted by the moving vehicles, this problem is addressed. Two different approaches are proposed, the first approach is a proactive approach based on Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) to predict the traffic congestion in advance by training the machine learning models with the collected historical data. The second proposed approach is a real time reactive approach which is using different meta-heuristics and compare them together to find the near optimal solution for traffic light cycle time.

Keywords: Information and Communication Technology, Internet of Things, Neural Network, Fuzzy Logic System, Artificial Intelligence.

1.Introduction

Nowadays, traffic congestion is considered one of the hottest research topics around the world for both individuals and stakeholders. Problems such as high delays, CO and CO2 emissions and car accidents caused by traffic congestion should be mitigated. One of the intuitive solutions is to expand the infrastructure to accommodate the significantly increasing number of road users, but this solution is not economically effective McCrea et al. (2010)-J. C. Spall and D. C. Chin (1997). So, most research directions are heading towards the Intelligent Transport System (ITS) to handle this growing issue which are affecting many sectors.

Smart traffic light is deemed to be one of the applications of ITS. Traffic lights were firstly used in Westminster, London in 1868 and the first usage of the current traffic light with the three colors (red, yellow and green) was in 1918 in New York, where it is manually controlled by a human Hewage et al. (2004).

Two other traffic lights appeared lately, which is the pre-timed traffic lights which is preprogrammed to work according to a predefined fixed time. The other type is called traffic actuated lights, where the traffic light cycle time is dynamically determined based on the collected information by cameras and sensors, to identify the traffic density Prabuchandran et al. (2014). Many technologies are playing a vital role in designing a smart traffic light, such as the Information Communication Technology (ICT), Internet of Things (IoT) and machine learning. A lot of advantages brought by the advent of the ICT concept, which can be simply summarized by the performance improvement it brings to the city operations in general and traffic flow in specific. These advantages are caused by the embedded communications involved between different physical devices (sensors, vehicles, digital technologies, etc.) which helps in collecting information needed to make a better decision about the traffic light cycle time M K et al. (2018).

Whereas, machine learning models are widely used in different applications, including the smart traffic light. Theses machine learning models are used to make predictions for a better decision-making process to solve any issue in a proactive manner. To train these machine learning models a monitoring system should be deployed to gather as much information as possible for better prediction accuracy, which could be accomplished by the help of sensors and the Internet of Things (IoT) network. However, despite the existence of machine learning models in the literature which predicts the future traffic congestion but there is always a room for improvement to design a machine learning model with higher prediction accuracy and also to explore and design more models and compare them with the existing ones Rahmat et al. (2020). On the other side, a reactive approach should also be investigated. Where the actions conducted by the smart traffic light are taken based on the current state of the network. This problem has been identified to be NP complete problem Mohebifard et al. (2019). Thus, it is impossible to find the optimal solution in a polynomial time, so we propose meta-heuristics algorithms to find near optimal cycle time for traffic lights and the best phase sequence of traffic lights. and compare our solutions with traditional solutions and other meta-heuristic algorithms J. Sanchez et al. (2008).

The rest of the paper is organized as follows. Section 2 discusses related work in more details. In section 3, our proposed methodology is introduced. The obtained results analysis is explained in section 4. Finally, conclusions and future works are drawn in the last section.

2.State-of-the-Art

In this section, different approaches proposed in the literature can be classified in many ways. The first classifications more concerned about the way the problem is solved, some researchers are solving the problem by only collecting the local information of each traffic light and make decisions based only on this local information, which is called the dynamic approach. On the other hand, others were pointing out that both local information and other information collected by the neighbors are important to have a better decision and to reach a near global optimal solution, this way of solving the problem by collecting both local and neighbors information is called the adaptive approach. However, either the proposed approach in the literature is classified as an adaptive or dynamic approach, it can also be sub-classified as a reactive or proactive approach. Where in the reactive approach, the data are collected in real time and based on the congestion status in the road network at that moment, the algorithm decides the suitable green cycle time. While in the proactive approach, the decision is made in advance by either using historical data to train the machine learning models to predict the road network congestion status and depending on this prediction the suitable green cycle time is identified or by repetitively learning from experience by doing a set of actions as performed in Q-learning method.
As stated earlier, one of the simplest solutions to handle the traffic congestion is the traffic light. However, each traffic light should have a control module to switch between red, yellow and green lights whenever is needed. The control approaches exist in the literature can be categorized into either fixed time, dynamic or adaptive control approach as depicted in Figure 1 below, where the adaptive control approach can be furtherly categorized into either a distributed or centralized approach. Where the management and decision-making process are accomplished in a centralized node or distributed nodes.

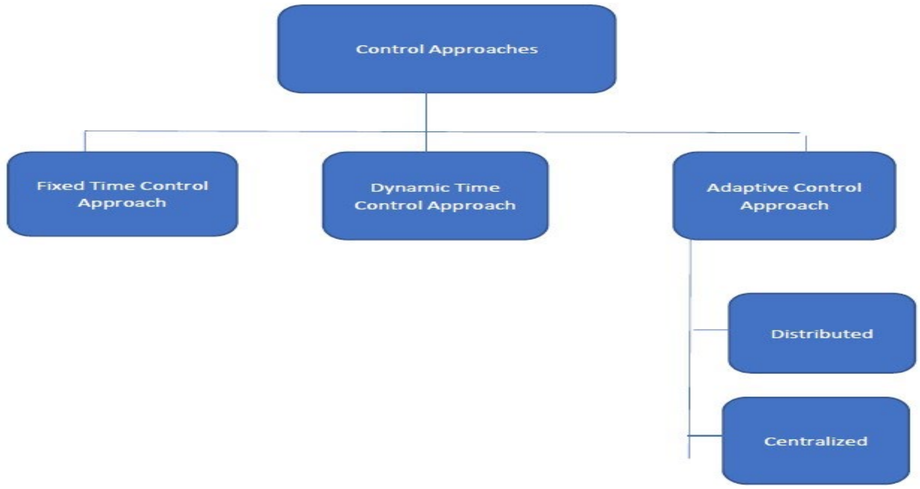

Figure 1. Classification of Traffic Light Control Approaches

In the near past, traffic congestion was not a big issue that needs to be addressed by researchers, so all traffic lights were controlled by a fixed time control approach where the switching between red, yellow and green lights is performed after a fixed period of time regardless of the traffic congestion status. In this approach, there is no intelligence at all, and the overall system is not able to react to traffic congestion changes whether it is sharp changes or not. Nowadays, this approach should be obsolete and no longer be used in order to mitigate the traffic congestion which is exponentially increasing day after day.

2.1. Classification of Traffic Light Approaches:

In this section, an overview of different approaches introduced in the literature are explained and each one of them is classified in their respective type of approach.

2.1.1. Dynamic Approaches:

Other followed approach proposed by researchers is the dynamic approach where the decision-making control is performed based on the local congestion status on each traffic light while overlooking the congestion status at neighboring intersections. As an example, for this approach in the literature, authors in Prabuchandran et al. (2014) and Y. Feng et al. (2015) are both using local congestion information at each intersection to make their decision for switching between red and green. However, work in Prabuchandran et al. (2014) is a multi-agent system which means information are exchanged between neighboring intersection without taking the advantage of having that information and exploiting it in the decision-making process.

2.1.2. Adaptive Approaches:

The last approach is called adaptive control approach. In this approach, information is exchanged between neighboring intersections for a better decision making and to reach near optimal global solution. Adaptive control approach can be furtherly categorized into distributed or centralized.
Some of the well-known centralized adaptive control systems are Sydney Coordinated Adaptive Traffic System (SCATS) And Split Cycle Offset Optimization Technique (SCOOT)R. Bretherton et al. (1996),SCOOT is an adaptive technique considered in the management and control of traffic signals in urban regions to automatically deal with the traffic flow fluctuations via the application of on-street detectors integrated on roads. The significance of this tool is evident in situations where traffic patterns seem unpredictable, another well-known adaptive control system which is categorized as a distributed approach is Real time Hierarchical Optimized Distributed Effective System (RHODES).

Another distributed adaptive control approach is the Urban Traffic Optimization by Integrated Automation (UTOPIA)/System for Priority and Optimization of Traffic (SPOT), this approach is considering both public and private vehicles K. Wood (1993). Two broad solution approaches are followed by the researchers to tackle the issue of designing the adaptive/dynamic smart traffic lights. The first solution approach is the reactive approach, where the control module inside each traffic light taking its decision based on the current status of the road network which can be easily detected by different devices (sensors, cameras, etc.). Another solution approach is called the proactive approach, where the congestion is predicted using different machine learning models.

2.1.3. Proactive Approaches:

Machine learning techniques can be used to handle the issue of sharp changes in traffic patterns by designing a mathematical prediction model to predict the potential changes/congestions that could happen in the road network. Different learning techniques fall under the umbrella of machine learning, such as the reinforcement, supervised and unsupervised learning techniques.
In Wiering and Marco (2000) Wiering et al. (2004), a transition model is proposed which has calculated waiting time for both green and red lights at each intersection. In this work, a multi-agent reinforcement learning is proposed to control traffic lights. The study focused on cars, where each car estimates its own waiting time and communicates it with the nearest traffic light. Position and orientation of vehicles in the queue, and their destination address was defined as states. Whereas, the movement between red and green phase was defined as action, and for the reward function, if a car remained at the same place then r= 1 otherwise r =0.
In Liu et al. (2017), the proposed system design is based on the usage of Q-learning which falls under the reinforcement learning techniques. This approach considered both vehicles and pedestrians. Q-learning technique is composed of two main phases which are exploration and exploitation phases. In exploration phase, the Q-learning agent is randomly exploring the environment around, after the environment is learned an exploitation phase is starting with an objective to maximize the rewards in the whole system. As described in D. Srinivasan et al. (2006), each Q-learning agent has its own local database, which is fed by data coming from sensors, local cameras and information coming from neighboring intersections. Those information act as an input to the Q-learning computation module. Finally, the decision made by the computation module is passed to control module to switch between red and green light at the near optimal computed time.

2.1.4. Reactive Approaches:

There are a lot of researchers which have manipulated traffic light staging problem. These studies we can classify into three resolution techniques: 1) mathematical models; 2) fuzzy logic approaches; and3) biologically inspired optimizers. Fuzzy Logic Set (FLS) is appropriate method when there is uncertainty or incomplete information about the environment which we are trying to improve. The features of FLS are its ability to add expert knowledge in their design and also easier to understand by operator compared to Neural Network (NN) models.

Various research studies utilize a fuzzy part within the intersection system control, normally merged with various computational intelligence method or heuristic D. Srinivasan et al. (2006). Some researchers B. P. Gokulan and D. Srinivasan (2010) employed a type-2 fuzzy set in developing a distributed signal control system that is multi-agent traffic-responsive. After testing on virtual road networks, the system results indicated superior technique performance in dealing with planned and unintended incidents and obstructions. Lim et al. GiYoung Lim et al (2001) derived a fuzzy logic controller during a single intersection’s real-time local optimization. Years later, other experts Karakuzu et al. (2010) developed a traffic simulator utilizing fuzzy logic agents for traffic lights at isolated intersections. The findings indicated a reduction of the vehicles’ queue on the highways, nonetheless, their applications remain highly compromised when perceived economically, while deploying the system necessitated a huge inversion.
Also, Mehan and Sharma Mehan et al. (2011) developed fuzzy logic controller for 4-way intersections appropriate for mixed traffic.

Nair and Cai (2007) M. Nair and J. Cai (2007) used Fuzzy Logic Controller (FLC) for an isolated signalized intersection to make the traffic flow smoothly and reducing the delay time and dealing with traffic flow under both normal and abnormal traffic conditions. Whereas, Mojtaba, Iman, and Mohammad, 2014 Salehi et al. (2014) applied fuzzy logic for multi-agent-based traffic light control system by exploiting wireless sensors to manipulate problems such as congestion, speed, and traffic irregularity. The parameters like traffic density and queue length are extracted by image processing techniques.

A study by McCrea and MoutariMcCrea et al. (2010) merged knowledge-founded and continuous calculus-founded models with the intent of defining the road networks' traffic flow. In another study, Tolba et al. Tolba et al. (2005) offered a Petri net-founded model to indicate traffic flow, from both macroscopic and microscopic perceptions, consideration of vehicles' individual trajectories and observation of global variables, respectively.

Schutter and Moor DeSchutter et al. (2000) built a model, where the queue lengths are considered as a function of the time. The purpose of their study is to find an optimal traffic light switching scheme allowing the red-yellow-green light cycle time to be variable from one cycle to another. BabichevaT. S. Babicheva (2015) proposed the queuing theory methods for traffic light timing optimization takinginto account the Poisson process for traffic flow in lanes. There are a lot of researchers used biologically inspired techniques for traffic lights control system. These techniques are derived from fields of biology for solving complex computational problems and the use of the natural world experiences to solve real world problems in general and traffic problems specifically. The main topics of biological inspired computing are such as (Artificial neural networks, Genetic algorithms, Particle swarm optimization, and Cellular Automata, …. etc) N. Henschke et al. (2015).

Brockfeld et al. Brockfeld et al. (2001) utilized a Cellular Automata (CA) model whereby the city network was investigated as a simple squared area having some normal streets and four junctions. Another study by Spall and Chin J. C. Spall and D. C. Chin (1997) illustrated a Neural Network (NN) considered in configuring traffic lights' control parameters. For this technique, the vehicles necessitated an extra model in data management. Rouphail et al. Teklu et al. (2007) made the very first attempt, by coupling a GA (Generic Algorithm) with CORSIM (CORridorSIMulation) J. Kennedy and R. C. Eberhart (2001), amicro-simulator in the optimization timing of Chicago city's 9 intersections. Based on the length of the queue, the results were limited as a result of the GA's convergence behavior.
Sanchez-Medina et al. J. J. Sanchez-Medina et al. (2010) applied GA for improving traffic flow system where cellular automata-based simulators used in this study to evaluate each solution.

In Gökçe et al. (2015), a macroscopic traffic simulation model called TRANSYT-7F (TRAffic Network StudY Tool, version 7F.) was used, where applied GA and a hill-climbing method are employed. TRANSYT-7F treated with a group of vehicles rather than individual vehicles separately. In the work of Teo et al. K. T. K. Teo et al. (2010), GAwas also used; in this study the input was the queue length and the output were optimized green time for an intersection. Because of slow of convergence behavior of the genetic algorithm the cost of simulation will be high for large network. Systems consist typically of a population of agents interacting locally with one another and with their environment. The inspiration often comes from nature, especially biological systems. The agents follow very simple rules, and although there is no centralized control structure dictating how individual agents should behave, local, and to a certain degree random Swarm Intelligence (SI) systems contain usually population of agents which are communicating with one another and with their environment. Those systems derived from nature especially biological systems, example on those systems is Particle Swarm Optimization (PSO). PSO is a population-based meta-heuristic inspired from the birds' social behavior within a flock, whose initial purpose was to continually optimize problems Teklu et al. (2007) D. Van Vliet (1982).

In Chen and Xu Vilarinho et al. (2017), where the authors utilized PSO algorithm in having a fuzzy logic controller trained, situated at each junction by estimating the efficient time of green for each traffic light's phase. In Kachroudi and BhouriKachroudi et al. (2009) utilized a PSO's multi-objective version to optimize cycle programs by utilizing a predictive model control founded on a public transport progression system. In J. García-Nieto et al. (2013) the authors proposed an optimization technique where a PSO identifies successful traffic light cycle programs. Two large and heterogeneous metropolitan locations comprising of numerous traffic lights situated in two major cities have been tested in this study using this model. The present algorithm has been able to effectively obtain traffic light cycle programs for the two cities. The present PSO model has shown quantitative improvements based on the following objectives: a) the general journey duration and b) the total vehicles reaching their destination. Another study conducted in Hu W et al. (2016) proposes an Inner and Outer Cellular Automaton mechanism joint with Particle Swarm Optimization (IOCA-PSO) method to achieve its purpose which is to satisfy a dynamic and real-time optimization scheduling of traffic signals Mirjalili et al. (2017).

3.Proposed Research:

our proposed work is separated into two different phases as shown in the figure below. In the first phase, a proactive approach is introduced to predict the road congestion status which will help the control module inside each traffic light to take the right decision regarding the green time based on the predicted congestion status. This has been implemented and tested under two different scenarios as described below. Two types of deep learning algorithms have been used to perform the prediction task and their performance have been compared with other algorithms in the literature. One of the main challenges that we encountered during the implementation of the first phase is answering the research question of what are the best values that should be used for the different and many hyper-parameters used in our machine learning models to give use the minimum loss possible?

Phase 1: Road Congestion Prediction

The proposed proactive approach, which is called road congestion prediction phase is divided into four parts as follows:

- **Data Collection (Dataset generation):**

In data collection part we used OpenStreetMap (OSM) and Simulator of Urban Mobility (SUMO) software, to generate the selected map and run the traffic through this map, respectively. SUMO software is a tool used for simulation and analysis of road traffic systems, it can also be used for research purposes like traffic forecasting, evaluation of traffic lights, route selection or in the field of vehicular communication systems.

After downloading the map data from OSM, it automatically opens new window for SUMO software to define the simulation time and other parameters before running the defined scenario. SUMO then generates an CSV file, which will be used as historical data file in the prediction algorithms for the training purposes.
Our prediction algorithms are tested and evaluated using two different scenarios, namely, medium congestion scenario, and high congestion scenario for area cover Montreal City (Downtown) with the following parameters.

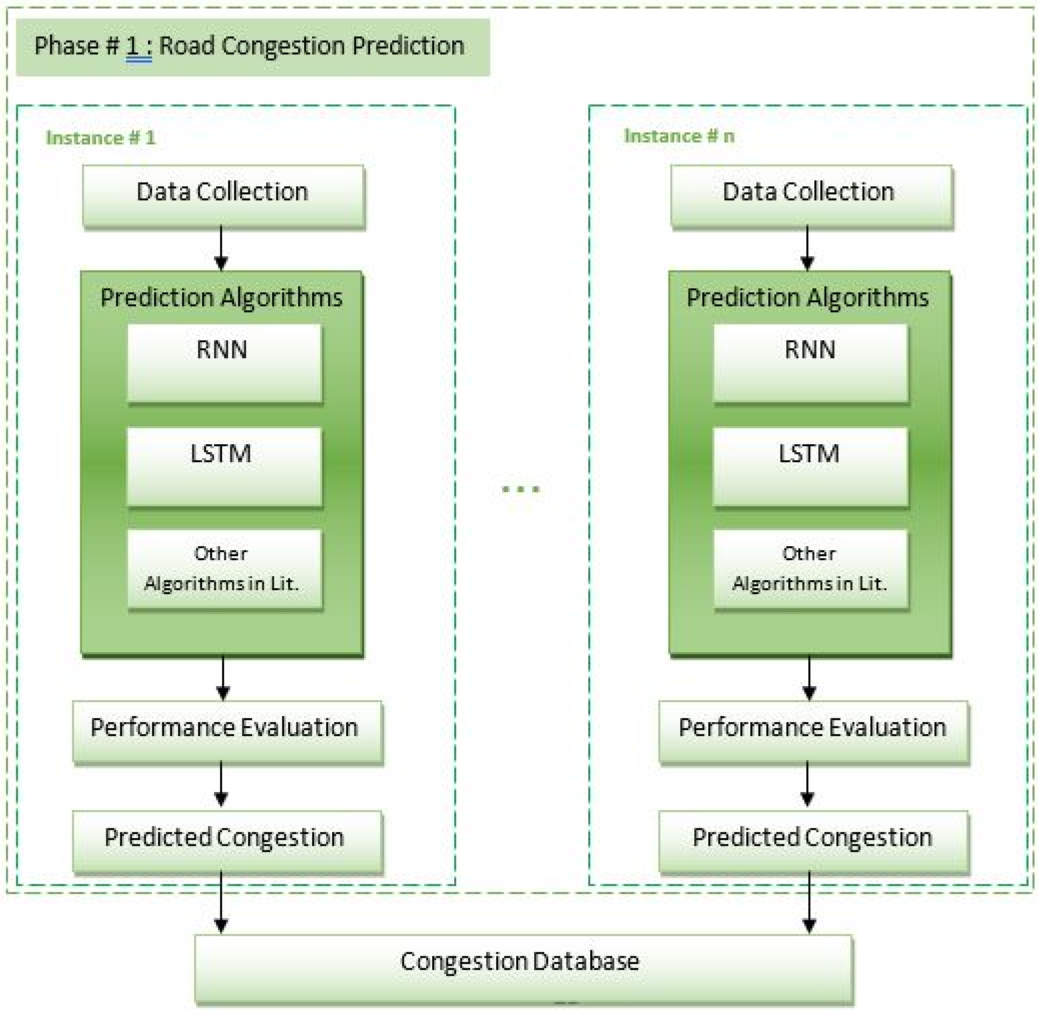

Figure 2: Proposed Architecture

Table 1: SUMO Simulation Parameters

	Medium Congestion Scenario	**High Congestion Scenario**
Area	Montreal (Downtown area)	Montreal (Downtown area)
Simulation Software	SUMO, OSM	SUMO, OSM
Simulation Time	60 minutes	60 minutes
Number of Vehicles	300buses, 900 cars, 20trucks	800 buses, 2200 cars, 100trucks
Delay	10 ms	10 ms
Through Traffic Factor	1	1
Data Collected	Waiting time, CO, CO2, # of Vehicles, etc.	Waiting time, CO, CO2, # of Vehicles, etc.

Through traffic is a factor that indicates how many times the edges at the simulation area boundaries are selected compared to the edges inside the simulation area, the lower this value the more the edges inside the simulation area are selected. In our scenarios, we chose this to be 1 to increase the level of congestion. The delay between any two consecutive records in the csv file is equal to 10 ms to know the changes in the congestion levels.

- **Prediction Algorithm:**

As previously explained in the background section, either in LSTM or RNN prediction algorithms, there will be a lot of hyper-parameters (Table 2) that need to be tuned to give us the best results. For example, each neural network composed of three different layers, which are the input layer, hidden layer and output layer. The number of hidden layers, hidden units in each layer and the activation functions should be chosen to give the best prediction results. It is known that the model complexity increases as the number of hidden layers and hidden units increases. However, model loss could be improved as a result of increasing the number of hidden layers/units. An optimal number of numbers of hidden layers/units should be selected in order to have an acceptable value of loss along with an acceptable amount of complexity. On the other hand, different activation function can be used for each neuron and each one of them provide different complexity and loss values.

Table 2: Hyper-parameters for RNN and LSTM

	RNN	**LSTM**
Number of Hidden Layers	1	1
Number of Hidden Units	10	10
Activation Function	Tanh	Tanh
Training Data Percentage	67%	67%
Test Data Percentage	33%	33%
Number of Iterations	1000	1000
Look Back	1	20

In our proposed prediction algorithm, the optimal number of hidden layers was one with 10 units per hidden layer and the tanh activation function has given us the best values for loss. Dataset was split into training (67%) and testing datasets (33%) to validate our model, with a number of iterations equal to 1000. The look back parameter is equal to 20 in LSTM and 1 in RNN, the look back parameter can be simply defined as the number of previous inputs the model is looking back to make its prediction.

- **Performance Evaluation:**

In order to evaluate the performance of our proposed algorithms, the following performance measures are calculated:

Mean Square Error (MSE):

$$\text{MSE}(\bar{X}) = \text{E}\left((\bar{X} - \mu)^2\right) = \left(\frac{\sigma}{\sqrt{n}}\right)^2 = \frac{\sigma^2}{n} \tag{1}$$

Where σ^2 is the population variance and n is a random sample of size from a population. MSE is a measure of the quality of the estimator which measure the average of the squares of the errors that represent the difference between the estimated values and the actual value.

Mean Absolute Error (MAE):

$$\text{MAE}(\bar{X}) = \text{E}\,|\bar{X} - \mu| = \left(\frac{\sigma}{\sqrt{n}}\right) \tag{2}$$

MAE is a measure of the quality of the estimator which measure the average of the absolute difference of the errors that represent the difference between the estimated values and the actual value.

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{SS_{regression}}{SS_{total}} \tag{3}$$

Where $SS_{regression}$ is the sum of squares due to regression and SS_{total} is the total sum of squares.

- **Predicted Congestion:**

As shown in the proposed architecture figure above, after the congestion is predicted at each traffic light, this is called a local congestion status. Therefore, to design a global based smart traffic light, an exchange of the congestion status at each traffic light should be performed. After this exchange, each traffic light will have a global awareness on the congestion status at its intersection and all neighboring intersections. Now the database is ready to be used in the second phase, which is explained below.

4.Results Analysis:

As noted previously, our proposed prediction algorithms are tested under two different scenarios, namely, medium congestion scenario and high congestion scenario:

Medium Congestion Scenario:

As it is shown in the figure 3(a) below, the mean absolute error in LSTM model, for both the training and test dataset are close to zero and the convergence rate is high (reached to the best solution after around 250 iterations) and there is no big difference between the testing and training MAE, which indicates that our model is working perfectly.

In figure 3(b), MSE is calculated for LSTM model. The same behavior is noticed for this kind of performance measure. LSTM model converges after around 225 iterations with a very low loss value. Compared to the above results obtained by LSTM, RNN model performs worse in terms of convergence rate (reached to the best solution after 400 iterations) as shown in figure 3(c), it also clear that there is some distortion in the RNN results which is not the case in LSTM model. When it comes to the calculation of MSE for the RNN model, the amount of distortion is slightly higher the one obtained in the LSTM model with more time to converge.

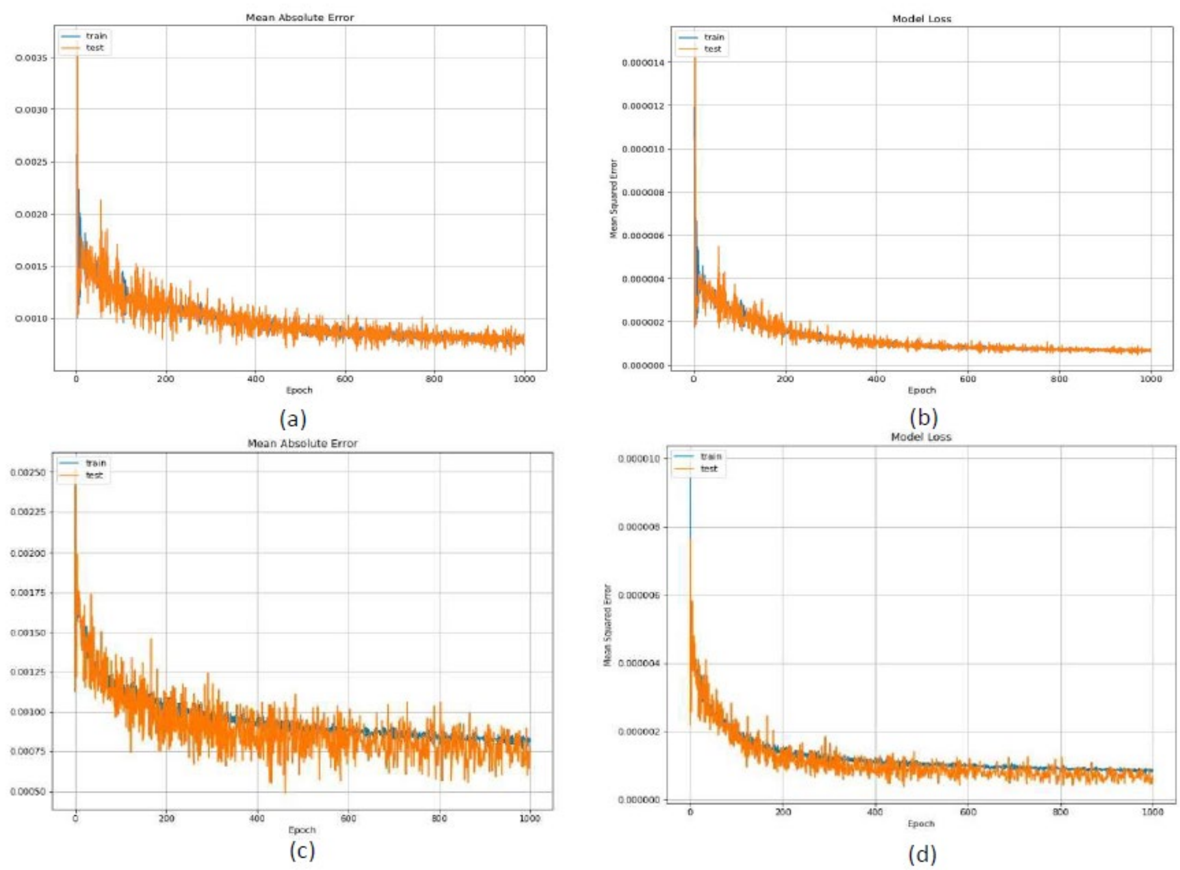

Figure 3. MAE and MSE for LSTM and RNN models in Medium Congestion Scenario. (a) MAE in LSTM model (b) MSE in LSTM model (c) MAE in RNN model (d) MSE in RNN model

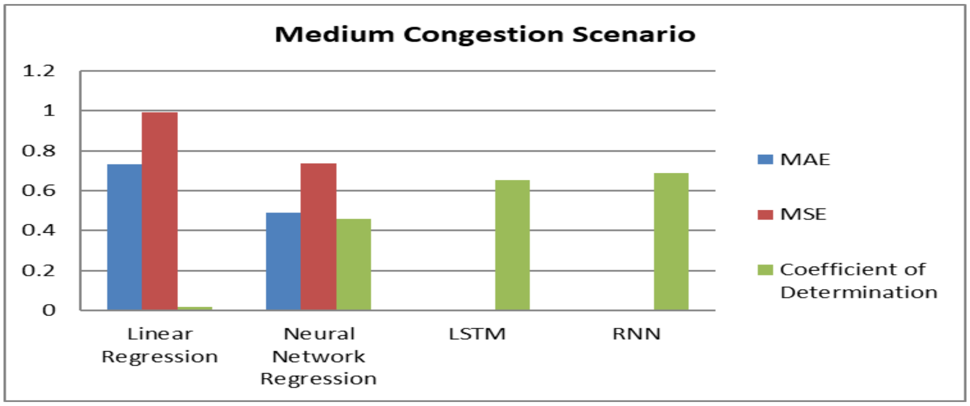

Figure 4. Comparison with other algorithms- Medium Congestion

In order to evaluate the performance of our algorithms, they have been compared with other known regression algorithms such as the linear regression and neural network regression. In the above figure, it is clearly shown that LSTM and RNN performs way better than the linear regression and Neural network regression in terms of MAE, MSE and Coefficient of determination.

High Congestion Scenario:

As defined in Table 1 above, another scenario with high congestion is defined and the results obtained for this scenario are explained below.

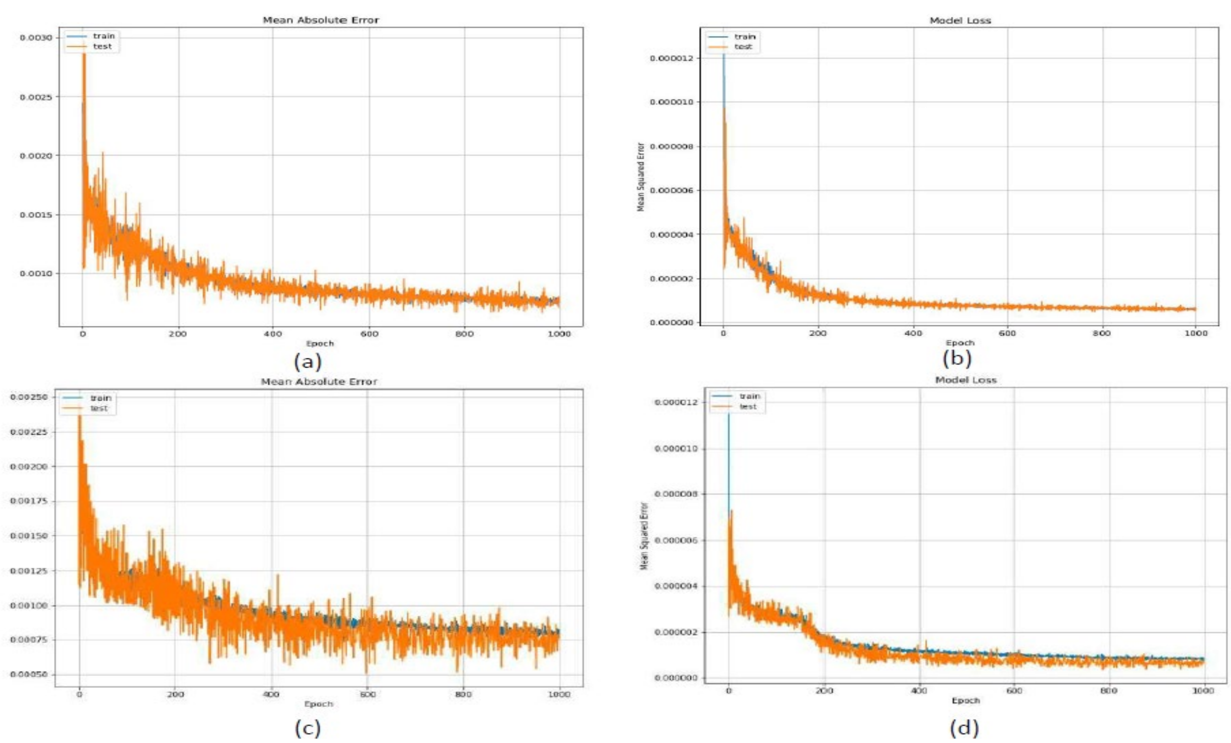

Figure 5. MAE and MSE for LSTM and RNN models in High Congestion Scenario. (a) MAE in LSTM model (b) MSE in LSTM model (c) MAE in RNN model (d) MSE in RNN model

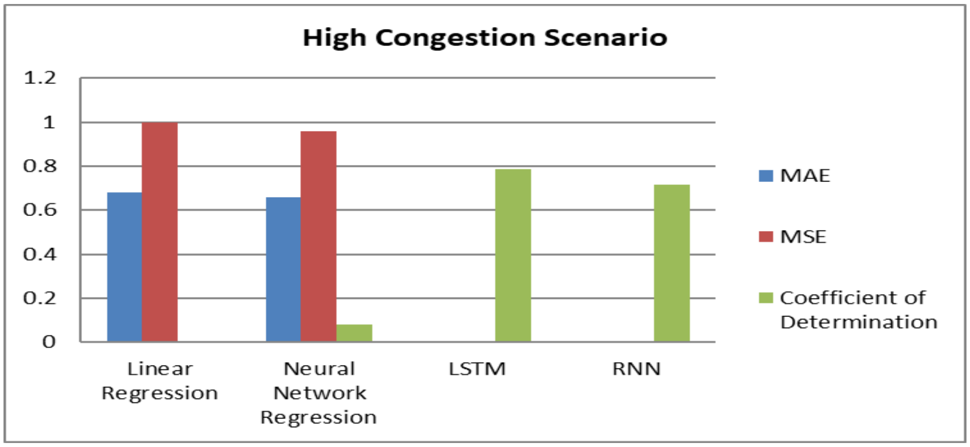

Figure 6. Comparison with other algorithms- High Congestion

Compared to the medium congestion scenario, the model takes more time to converge but also it has an excellent low error values with not a lot of distortion. As shown in figure 5(b), the mean square error is very low with almost no distortion between the training and test data. It takes almost 225 iterations to converge to the best solution. When RNN model is used instead of LSTM, distortion is clear in the figure 5(c) and 5(d) with more time to converge as well. When comparing our obtained results with linear regression and neural network regression. It is clearly shown that our prediction algorithms (RNN and LSTM) outperforms other algorithms in terms of MAE, MSE and Coefficient of Determination as shown in figure 6.

5.Conclusion

In this paper, two approaches have been proposed in order to tackle road congestion issue, one of the promising research areas is to design dynamic algorithms to control the traffic lights. With the advent of machine learning, a lot of applications with huge data used machine learning algorithms to have a data-driven decisions. These decisions would have a direct/positive impact on improving the quality of life, revenues for companies, quality of service for the services provided for the end users, etc. In this paper, we used two well-known deep learning techniques, namely, RNN and LSTM and compare them with other machine learning algorithms to perform road congestion prediction. It has been shown in the results section that our proposed algorithms outperform other machine learning algorithms in terms of convergence rate, loss values and coefficient of determination factor. Many hyper parameters have been tuned to give us the best possible results in a reasonable amount of time. In the future, we have introduced an architecture which will be responsible to find near-optimal solution for the green time assigned to each traffic light with an objective to minimize the waiting time for each user in the road network. This meta-heuristic optimization algorithm will take benefit from the output of the first proposed work, which stores the predicted congestion at each traffic light in a separate database. The usage of meta-heuristic optimization has been justified because of the complexity of the defined problem, which is considered as an NP-Hard problem.

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