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Hierarchical federated learning model for traffic light management in future smart

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Abstract

The present era is marked by rapid improvement and advances in technology. Nowadays inefficient traffic light management systems can make long delays and waste energy improving the efficiency of such complex systems to save energy and reduce air pollution in future smart cities. In this paper, we propose to take real-time traffic information from the surrounding environment. Such a process, which is called profilization constantly gathers and analyses information for vehicles and pedestrians throughout smart cities in order to fairly predict their actions and behaviours. We develop an efficient multi-level traffic light control system to schedule traffic signals' duration based on a distributed profile database, which is generated by embedding sensors in streets, Vehicles and everywhere. We deploy pervasive deep learning models from the cloud to users (vehicles, bikes and pedestrians) to learn and control the traffic lights. In the cloud-level learning model, the maximum waiting time of different vehicles and pedestrians is calculated based on their profiles. The profilization process is a constant learning process throughout the whole city at the user level. Each vehicle deploys a separate learning model (decision-making) based on its average and maximum speed in a different area, waiting times at the intersections and possible trips and destinations. Such a multi-level deep learning model in the level of intersection and cloud aims to locally schedule the traffic with deadlines toward their destinations within a certain period. The results show that the proposed multi-level traffic light system can significantly improve the efficiency of the traffic system in future smart cities.

Keywords: Traffic light system, smart cities, deep learning
2010 MSC: 68Txx

1 Introduction

The world's population is growing rapidly, and as you know, a large part of this population lives in cities. The United Nations Population Fund estimates that approximately fifty-two billion people, or 64 percent of the world's population, will live in cities by 2025 [22]. The management of modern cities with existing methods creates challenges that have led to the need to achieve smart cities. In addition, it presents that this percentage will reach 68 percent by 2050, while there is an estimation that by 2030, there will be 43 mega-city in the world (over 10 million population). On another side, the ageing rate of the global population is at a significant rate of about 3 percent per year. With

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this ageing rate, there will be more than 1.4 billion older people in the world by 2030. Overall, the significant growth in the population in urban areas as well as the ageing rate of the global population will generate an urgent demand for a robust transportation system in order to transport people and required goods in a safer, more efficient, greener, and more comfortable manner [3]. Existing traffic light management systems deploy an inefficient control mechanism causing numerous problems, such as vehicular accidents, long delays for pedestrians as well as vehicles, wasting energy and worsening the air quality in smart cities [17, 9, 16]. Such inefficient traffic light control systems either deploy fixed programs without considering real-time traffic or consider the traffic to a very limited degree [19]. Currently, programs of traffic control systems are fixed or take a few inputs from some embedded sensors such as underground inductive loop detectors to indicate the existence of vehicles. New advances in wireless networks (e.g., Internet of things and smart grids) and computer science (e.g., big data [23] and artificial intelligence (AI)/machine learning (ML)) motivate us to propose a smart intersection traffic light management system for both vehicles and pedestrians which can take real-time traffic condition as input and learn how to manage the intersection [8, 4]. There are two ways to solve this problem [8]. The first solution is to develop and create transportation infrastructure, which has a high cost and related issues. An important point about this solution is that it is a temporary and short-term solution because it loses its effectiveness over time as the number of cars increases. The second solution is to use the existing infrastructure with the highest quality and in the best way and to improve their efficiency and the systems used to manage them, such as the traffic light control system. The second solution is smarter and can achieve high efficiency and maintain its efficiency in the long run. The best way to properly control traffic congestion is to use intelligent traffic light systems. In this paper, we also use the second method to provide an intelligent urban traffic system framework based on Reinforcement learning. There are two main limitations in the existing studies: (1) the traffic signals are usually split into fixed-time intervals, and the duration of green/red lights can only be a multiple of this fixed-length interval, which is not efficient in many situations; (2) the traffic signals are designed to change only based on vehicles. In this paper, we study the problem of how to control the traffic light's signal duration in a cycle based on the extracted information from vehicular networks in addition to pedestrians and bikes to help efficiently manage vehicles, pedestrians and bikes at an intersection. To the best of our knowledge, smart crowd management, which considers detailed information about the crowd (either vehicles or pedestrian), is a missing building block in smart transportation systems. Smart crowd management deploys new technologies such as the Internet of Things (IoTs) and vehicular networks to offer opportunities to smart transportation systems. Currently, both scientific and industrial communities are concentrating their research on developing connected and autonomous cars (fully or partly), electric vehicles, on-vehicle and on-the-road sensors, vehicular networking infrastructure, and smart and connected roads in order to improve the transpiration systems for future smart cities. They also have concentrated on algorithms, protocols, and architectures for data collection, processing, and analysis designed to improve contextual awareness regarding entities and events related to transportation [3, 10]. The main contribution of this paper is to use a hierarchical learning model to resolve the scalability issue of deep learning algorithms in such extensive environment. Our main idea is to use profilization based learning and decision making to manage traffic signal duration in intersections deploying the information collected from vehicular networks and pedestrians and other embedded sensors [21, 15] in surrounding environment. Deploying federated learning model [12, 2]enables our proposed model to cope with huge amounts of traffic data processing and storing requirements. The proposed learning model locally processes data and information in both node and intersection levels to transfer only learned templates not raw data and information. Such hierarchical learning model consists of three different levels of cloud, intersection and node. To implement the proposed idea, cloud-level learning model tries to guarantee source-to-destination delays (SDDs) for different vehicles such as public vehicles. This model constantly updates the maximum waiting time of vehicles in different intersections in order to keep SDD under a certain delay. In the intersection-level learning model, to improve the scalability of the system the agent utilizes the collected information in a deep reinforcement learning model to locally schedule traffic. In the vehicle/node level, a deep learning model is implemented to improve the accuracy of the profilization process. The reminder of this paper is organized as follows. Related works are reviewed in Section II. The model and problem statement are introduced in Section III. The background on reinforcement learning is introduced in Section IV. Section V shows the details in modeling an reinforcement learning model in the traffic light control system of vehicular networks. Section VI extends the reinforcement learning model into a deep learning model to handle the complex states in the system. The model is evaluated in Section VII. Finally, the paper is concluded in Section VIII.

2 Related works

Previous works have been done to dynamically control adaptive traffic lights. But due to the limited computing power and simulation tools, early studies focus on solving the problem by fuzzy logic [5], linear programming [8], etc. In these works, road traffic is modeled by limited information, which cannot be applied in large scale. Reinforcement learning was applied in traffic light control since 1990s. El-Tantawy et al. [7] summarize the methods that use reinforcement learning to control traffic light timing. The reinforcement learning techniques are limited to tabular Q learning and a linear function is normally used to estimate the Q value. Due to the technique limitation at the time in reinforcement learning, they usually make a small-size state space. The complexity in a traffic road system can not be actually presented by such limited information.When much useful relevant information is omitted in the limited states, it seems unable to act optimally in traffic light control [8, 6]. In recent years, major challenges of designing pervasive intelligent traffic systems to provide high reliable and efficient support for vehicles, bikes and pedestrians in smart cities are heterogeneous vehicles with very diverse requirements in a very dynamic environment. Moreover, future vehicles require a comprehensive traffic light management system to be able to drive in a smart city autonomously. To cope with such dynamic situation, we need to implement artificial intelligence (AI) [14]. everywhere in the system. We need to consider and involve everything in this system. Therefore, this work proposes to deploy a hierarchical deep learning model in order to improve scalability of the light management system. Moreover, it considers pedestrians' objectives and end-to-end requirements of vehicles.

3 System model and architecture

3.1 Network Model

We consider an area of a typical city with L crossroads, which every scenario with single road intersection has traffic lights to control vehicles and pedestrians. The model is shown in Figure 1 for a single crossroad. The left side shows a traffic light, where pedestrian and vehicles have their own lights. The traffic light management system first gathers street traffic information via a vehicular network [13, 1] as well as embedded sensors. The system processes the data in order to obtain the road traffic's state and reward, which has been assumed in many previous studies [7, 6, 18]. We develop a hierarchical intelligent traffic light system to schedule different vehicles with different requirements such as emergency vehicles, public transportation and pedestrians/bikers. In order to make the light system scalable in both aspect of processing and storage requirements, we deploy federated learning model on a hierarchical structure of distributed learning agents. The lowest level of such federated learning process is the level of node (e.g, vehicles/embed sensors), where the algorithm processes local behaviours. Such behaviors can be extracted from user profiles. For example, a user can regularly drives a specific route from home to office. The system does not need to gather all detail information from nodes and not send it to remote node for further processing. This learning process provides some estimation about possible routes, average speed and the priority of the vehicle. In the higher level, which is the level of intersection, a traffic light gathers all the information from the lower level learning algorithms of the vehicles in that crossroad and tries to efficiently schedule the light system based on the information from streets and the environments such as size of queue and the diversity of vehicles in each directions and also possible next routes. In the highest level of learning in the cloud, the system decides to customize some intersections to do the vehicle routing with certain delay requirements. Emergency vehicles such as police and ambulance will be forwarded immediately. We develop a delay-deterministic traffic light system for public transportation vehicles to provide a certain end-to-end (E2E) delay for them. Such vehicles require to move one point to another point in a certain time. In that sense, the E2E delay is important. Therefore, the general objective is to minimize simultaneously the waiting times of nodes with different priorities. We concentrate on public transportation vehicles, vehicles with predictable trips, pedestrians and bikers since emergency vehicles are considered to be served immediately. The system is able to distinguish the priorities of pedestrians as normal or special. In addition, trip information can be shared within a could system. The proposed system will differentiate these types of pedestrians/bikers, public vehicles and other vehicles via embedded sensors in the environment of the intersections. This system consists of L intersection, K public vehicle and a central cloud (CC) system to gather, store and process the information from vehicles and environment. In each intersection$l \in \{1, ..., L\}$, vehicles, pedestrian and bikes arrive with rates $\lambda\nu$, λp and λ_b , respectively. In the sequel, L and K denote the sets of intersections and objects(public vehicles, normal vehicles, pedestrians and bikers), respectively. Our system is developed for so called limited-latency applications in such a way that it can respond to vehicle' requests within a certain overall latency. We denote the state of each intersection l with $S_l^{<I>} = (g(V)l.(gPl).(gPl)$ where $g\{l.v\}, g\{lp\}$ and $B\{l.b\}$ represent the grids for vehicles, pedestrian and bikers in the intersection l. Each entry of these grids denotes whether a place is occupied or not. These grids presents the distributions of objects in each intersection. Therefore $V_l = \sum_{i,j} g_{i,j}\{l.\nu\}$,$P_l = \sum_{i,j} g_{i,j}\{l.p\}$ and $B_l = \sum_{i,j} g_{i,j}\{l.b\}$, denote the numbers of vehicle, pedestrian and biker,

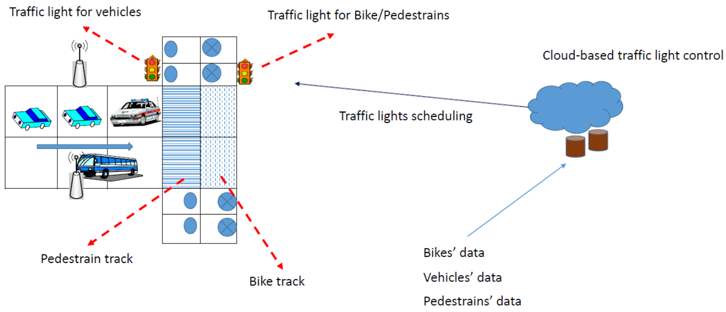

Figure 1: System Model of traffic light control

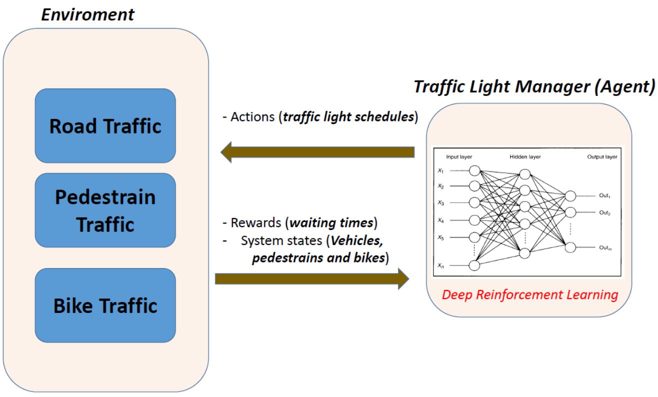

Figure 2: System Model of traffic light control

respectively. For the whole system,

$a)\quad V = \sum_{l \in L} V_l$
$b)\quad P = \sum_{l \in L} P_l$
$c)\quad B = \sum_{l \in L} B_l$
$d)\quad K = V + P + B.$

3.2 System Mode

l Every traffic light dynamically adjusts the scheduling based on both learning data (predictions) of vehicles and cloud in order to make a decision based on the current state, priorities and reward using a deep neural network shown in Figure 2. This deep learning model utilize the learning data in node and cloud level to improve accuracy and dynamics of the system. The deployed reinforcement and deep learning take into account context information with different scale in order to improve scalability of computing, communication and storage. To this end, only the process data (information) is transferred between different level of deep learning rather than transmitting raw data.

In our model, traffic lights are used to manage the traffic flows at intersections in order to provide the proper services for different vehicles. A traffic light with three signals, green, yellow and red may not be enough to manage all the vehicles when there are vehicles from multiple directions at an intersection with different type of services in addition to pedestrians and bikes. Thus, multiple traffic lights need to cooperate at a multi-direction intersection. At such an intersection, the traffic signal guides vehicles from non-conflicting directions at one time by changing the traffic lights' statuses. The time duration staying at one status is called one phase. All the phases cyclically change in a fixed sequence to guide vehicles to pass the intersections toward their destinations. All these actions can be possible by deploying a hierarchical deep learning model. In our problem, we dynamically adjust the duration in every phase at each intersection l to deal with different traffic situations and priorities at intersections. Our traffic light management system relies on IoT system and data analytic and learning models. Each public vehicle has its own schedule and profile in the cloud. Therefore, it has to be in a certain times in some predefined stations. Customer vehicles might have also some profile in the cloud based on the implemented system. For example, many customer cars regularly have very similar trips between their home and office. Such profile information can be crated by an IoT system and updated by data analytic and deep learning models. Obviously, such shadow profiles can be even created by the system for pedestrians and bikers. Here, we concentrate on the profile of vehicles. The proposed system try to keep an updated profile based on the history of every vehicle, pedestrian and bikers. Let us assume that the state of intersection l can be modeled $S_{(l.t)}^{<I>}$ in time slot t. Therefore, the whole system state can be denoted as $S_l = \{S_{1.t}^{<I>}.S_{2.t}^{<I>}.....S_{L.t}^{<I>}\}$. Each intersection l with probability α_l changes its state $S_{1.t}^{<I>}$ to $S_{1.t+1}^{<I>}$, where $\alpha_l = pr(S_{1.t+1}^{<I>}|S_{1.t}^{<I>})$ The probability α_l contains the probabilities of vehicles, pedestrians and bikers.

3.3 Profile-based Traffic Light Scheduling as Cloud Service

Our problem is defined by how to optimize the efficiency of the intersections by dynamically changing every phase's duration of a traffic light via both cloud-based and intersection based learning from historical experiences, i.e., profiles of vehicles and pedestrians. The general idea is to customize the duration for the phase that has more vehicles with critical situation in that direction. In every light management system, police and ambulance vehicles cannot be waited and they will be served instantly. For other vehicles, pedestrian and bikers we use the implemented IoT system in addition to learning models to improve the performance of the system. We use Reinforcement learning simultaneously in cloud and each intersection to learn how to control the traffic lights for different players in the traffic system, i.e., vehicles, pedestrian and bike. Cloud-based reinforcement learning model updates the maximum waiting times of different players in each intersection based on their profiles. This learning model continuously is updated and improved by instant states of the environment and any update in the profiles. This learning model can become an accurate model for the all vehicles with static or slowly profile. In the intersection level, we use a reinforcement learning to schedule traffic locally based on the current situation of intersection. In this paper, we employ the deep reinforcement learning to learn the timing strategy of vehicles in the levels of cloud and intersection to optimize the traffic management. In addition, we consider the priorities of pedestrian to learn how to manage different situations of traffics at the intersections. We will apply different levels of deep learning to improve the precision of the proposed system. Let us assume that the vehicle k should visit $l_k$intersections to reach its destination within D_k^{th}. To satisfy this condition, the cloud-level learning model proposes the following strategy for the intersections $\sum_{l\in L_k} D_{k.l} \leq D_k^{th}$ Where $D_{k.l}$ denotes the maximum waiting time in the $l-th$ intersection. These values are extracted from vehicle profiles by the cloud-level learning model. Let us assume that $d_{k.l}$ is the instant waiting time of vehicle $k$in the intersection l. Then we should have $\sum_{l\in L_k} D_{k.l} \leq D_k^{th}$ where for some vehicles based on their profile we have either

$$d_{k.l} \leq D_{k.l} \quad \forall l \in L_k$$

$$d_{k.l} > D_{k.l} \quad \exists l \in L_k.$$

In the intersection-level learning model, the traffic light system try to consider pedestrian / bikers' willing in addition to considering vehicle profile information.

3.4 Intersection Model

A traffic light cycle τ consists of three different periods : red, yellow and green denoting by T_1, T_2 and T_3, respectively. In the period of T_1, vehicles must stop since the pedestrian's light is green. In the period of T_2, both lights for pedestrian and vehicles are yellow. Here, we assume that both type of traffic (either vehicle or pedestrian/bikes) require the same period of yellow time. In the period of T_3, pedestrian/bikes must wait since the light of vehicles is green. Due to the dependency of traffic lights for different traffic flows, we can only focus on traffic light of vehicles with considering satisfactions of pedestrian/bikes. Therefore, a traffic cycle time can be calculated as $\tau = T_1 + T_2 + T_3$. We assume that τ is fixed and we only need to tune the periods T_1, T_2 and T_3. Furthermore, we eliminate the yellow light period to simplify the formulation. Let us assume that Δ is a constant, which we can add or increase from the traffic light periods. Therefore, these periods can be updated by

$$(T_1, T_2) \to (\min\{\tau, T_1 + \Delta\}, \max\{0, T_2 + \Delta\}) \to (\max\{0, T_1 + \Delta\}, \min\{\tau, T_2 + \Delta\})$$

for different scenarios. In general, the green periods for vehicles and pedestrians are T_1 and T_2, respectively. In this paper, we develop a deep learning model to adjust these periods in each cycle of traffic light based on the gathered information from sensors embedded in roads and environment.

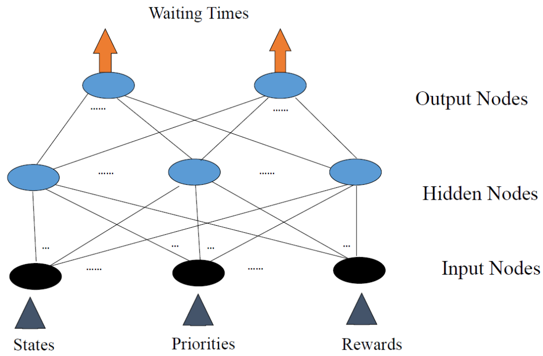

Figure 3: Neural Network Model

4 Proposed learning model

To build an adaptive traffic light control system based on learning algorithms to schedule different types of traffics, we need to define the states, actions and rewards for the system. In the following sections, these three different elements and their explanations in detail in our model. Indeed, we need to define the state of the system based on gathered data from sensors, the possible best actions and the possible rewards. In the proposed learning model, the system uses a deep learning algorithm to analyze the data from environment to determine the best actions. Then, the system takes the best action and conducts a scheduling and measure the waiting time of vehicles and pedestrian/bikes. This procedure continues until reach a optimum scheduling for T_1 and T_1, which minimizes the cumulative waiting times.

4.1 States

We define the states based on three pieces of information, position, speed priority of players (either vehicle or pedestrian) at an intersection. Through a vehicular network and Internet of Things, vehicles' position, speed and priority can be obtained. We consider two different type of priorities: 'Normal' and 'Special'. The priority 'Special' requires more attention in the scheduling algorithms. Then the traffic light can take a precise snapshot image of the current intersection. The whole intersection is divided into same-size small square-shape grids. In every grid, the state value is a three value vector ¡ position, speed, priority¿ of the inside entity. The position dimension is a binary value, which denotes whether there is an entity in the grid. If there is an entity in a grid, the value in the grid is 1; otherwise, it is 0. The speed dimension is an integer value, denoting the entity's current speed in m/s. The priority dimension is also binary, which denote the priority level of that grid. If there is a high priority entity such as police car or Elder person, the value of priority is 1; otherwise zero. Let's take Figure 3 as an example to show how these state information can be fed into the neural network to generate the different coefficient W_1 and W_2 to denote the percentages of waiting times for different traffic flows. We assume a snapshot of the traffic status at a simple one-lane four-way intersection, which is built with information in a vehicular network and IoT. The intersection is split into square-shape grids. The position matrix has the same size of the grids. In the matrix, one entry corresponds to one grid. The blank cells mean no vehicle in the corresponding grid, which are 0. The other cells with vehicles inside are set 1.0. The value in the speed dimension is built in a similar way. If there is a vehicle in the grid, the corresponding value is the vehicle's speed; otherwise, it is 0. Also, the value in the priority matrix is the same as two other matrices.

4.2 Action Space

A traffic light needs to choose an appropriate action to well guide vehicles at the intersection based on the current traffic state. In this system, the action space is defined by selecting every phase's duration in the next cycle. But if the duration changes a lot between two cycles, the system may become unstable. Thus, the legal phases' duration at the current state should smoothly change. We model the duration changes of legal phases between two neighboring cycles as a high-dimension MDP. In the model, the traffic light only changes one phase's duration in a small step. At the intersection, there are four phases, north-south green, east-northwest-south green, east-west green, and eastsouth west-north green. The other unmentioned directions are red by default. Let's omit the yellow signals here, which will be presented later. one phase in the next cycle is the current duration added or subtracted by Δ seconds. After choosing the phases' duration in the next cycle, the current duration becomes the chosen one. The traffic light can select an action in a similar way as the previous procedure. In addition, we set the max legal duration of a phase as 60 seconds and the minimal as 0 second. The MDP is a flexible model. It can be applied into a more complex intersection with more traffic lights, which needs more phases, such as an irregular intersection with five or six ways. When there are more phases at an intersection, they can be added in the MDP model as a higher-dimension value. The dimension of the circle in the MDP is equal to the number of phases at the intersection. The phases in a traffic light cyclically change in a sequence. Yellow signal is required between two neighboring phases to guarantee safety, which allows running vehicles to stop before signals become red.

4.3 Rewards

Rewards are an element that differentiates reinforcement learning from other learning algorithms. The role of rewards is to provide feedback to a reinforcement learning model about the performance of the previous actions. Thus, it is important to define the reward to correctly guide the learning process, which accordingly helps take the best action policy. In our system, the main goal is to increase the efficiency of an intersection. A main metric in the efficiency is entity' waiting time. Thus, we define the rewards as the change of the cumulative waiting time between two neighboring cycles. It means the reward is equal to the increment in cumulative waiting time between before taking the action and after the action. If the reward becomes larger than before, the waiting time increases less than before. Considering the delay is non-decreasing with time, the overall reward is always non-positive. Let us assume that the list of vehicles in the road be denoted by V, the list of pedestrian with$P$ and bikes with B. The cumulative waiting time $(CWT)X$ in the system can be calculated by $X = \sum_{i \in V \cup P \cup B}({x_i}^{Z[i]})$ where x_i and $Z[i]$ denote the waiting time and priority of entity i, respectively. The priority of entities is defined by the law and regulations of transportation system and the city. For example, an ambulance has higher priority than a police car or they can be at the same priority. A higher priority entity has higher impact in the CWT of the system. Therefore, we need to control the scheduling to minimize their waiting times. In general, the following optimization problem should be solved by the system in the intersection level:

$$Problem1 : \min_{T_1 . T_2} \sum_{i \in V \cup P \cup B} ({x_i}^{Z[i]}).$$

Table 1: The Algorithm 1 presents the proposed profilization process in the node-level

Algorithm 1 Proposed profilization	
Fist Step:	measure current parameters such as speed and location.
Second Step	create a new profile based on current measurements and results of previous predictions
Third Step:	update profile of nodes to be used by upper level process

The algorithm 1 is constantly executed in order to update the profile precisely. Also, it can be done on demand once a new measurement or profile is available. The cloud-level learning model tries to minimize the number of vehicles, pedestrian and bikes, which experience longer delay than expected. The Algorithm 3 presents the proposed federated learning model in the cloud-level In Figure 4, the proposed multi-level traffic light management system, which is based on both locally and globally learning models, is shown. In the best-case scenario, the duration of light is calculated in such a way that all vehicles and pedestrians pass the intersection with spending less than allowed time. Such scenario is possible only for those times that streets are not crowded. In more realistic scenarios, some vehicles, bikes and pedestrian have to wait longer than their expectation in the estimated profiles. The proposed multi-level model and more specially the cloud-level modeling is able to compensate such extra waiting times in the next intersections or if it is possible by offering shorter path to those vehicles

4.4 Evaluation

In this section, we explain the simulation environment and related results. Our proposed model for light management system is then evaluated via simulation, and the results are presented to show the effectiveness and efficiency of our model. We utilize and customize some typical existence data-sets [11, 20] to generate more realistic training data for each level of learning. Our main objectives in developing these sets of simulations are :1) to maximize the experienced waiting time of different players in both intersection and cloud based on their priority and their requirements.

Table 2: Samples of Times Roman Type Sizes and Styles

Algorithm 2 Proposed learning model	
Fist Step:	gather profiles (federated data) from road and environment about vehicles, pedestrian/bikes about their position, velocity and priorities. Calculate grids and state probabilities.
Second Step	: run the decision making algorithm in order to predict the best action (next state) based on current situation.
Third Step:	take the best action and measure the reward based on expected output
Forth Step: :	if result is stable for a certain time go to Final step.
fifth Step:	tune the learning algorithm based on the generated reward.

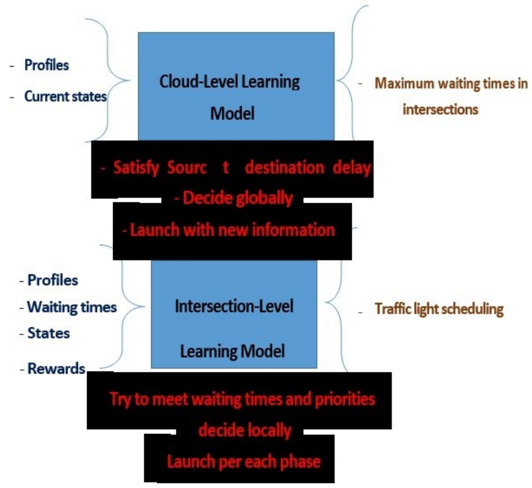

Figure 4: Multi-level traffic light management system

2) to improve the average number of vehicles which meet their requirements. These objectives are supported by the proposed reinforcement learning and deep learning models in the intersections and clouds. The constantly updating profiles in the cloud is the most important issue in measuring the performance of a traffic management system, which directly affects the players' feelings. For the both objectives, we compare the performance of the proposed model with pre-scheduled traffic signals.

4.5 Intersection-level Simulations

In Figure 5, we compare the proposed dynamic traffic light management under the conditions, which vehicles have different speed and priority. According to the generated results, the algorithm needs some iterations to converge to a specific value of waiting time for each entity (either pedestrian or vehicle). Here, we try to reduce the impact of the fast serving of vehicles on pedestrians' waiting time. The results shows only 5 percent increase in waiting time for special pedestrian if fast vehicles approach to the intersection (see Figure 6).

In order to generate more precise result and deeply learning process, we can increase the number of hidden layers of neural networks. Therefore, we analyze how much the depth of learning process can affect the performances of the proposed method.

4.6 Cloud-level Simulations

In this section, we evaluate the proposed model in the higher level, where the learning models try to adjust the maximum waiting times in the level of intersections to achieve a source-to-destination delay. These maximum waiting

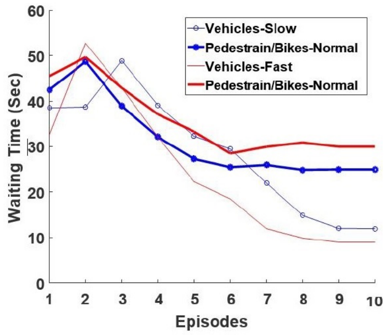

Figure 5: Normal Pedestrians/Bikes versus vehicles with different mobilities.l

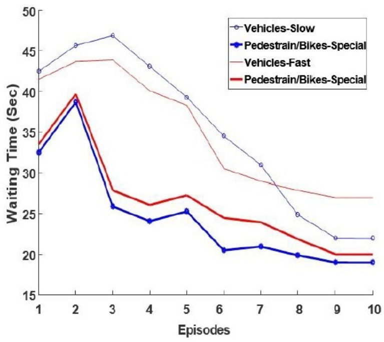

Figure 6: Special Pedestrians/Bikes versus vehicles with different mobilities

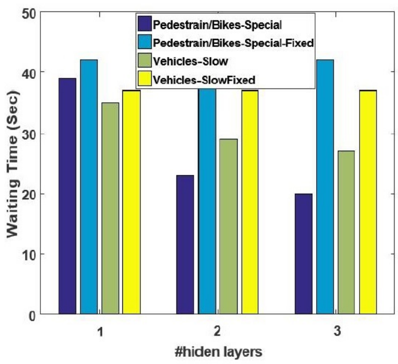

Figure 7: Proposed model with different number of hidden layers versus Fixed traffic light scheduling

Table 3: The Algorithm 1 presents the proposed profilization process in the node-level

Algorithm 1 Proposed profilization	
Fist Step:	gather profiles (federated data) from road and environment about vehicles, pedestrian/bikes about their position, velocity and priorities. Gather intersection states.
Second Step	Update the state of whole system and calculate new SDDs
Third Step:	run the learning algorithms in order to updates deadlines in each intersections for different items

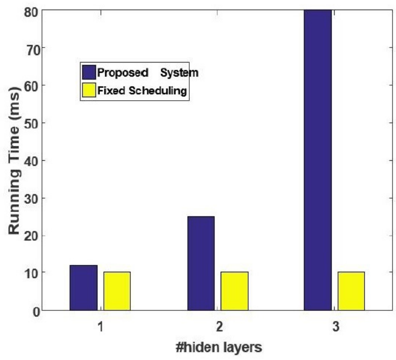

Figure 8: Proposed model with different number of hidden layers versus Fixed traffic light scheduling

time is constantly updated based on the performance of the intersection-level algorithms. In this simulation, we try to consider the scalability of the cloud-based algorithm. To this end, the number of intersections denoting the number of intersection-level algorithm is increased from 2 to 20. We want to know how many vehicles can be satisfied where the system grow significantly. According to the result shown in Figure 9, the proposed model can be applied even for a larger scenario with 20 intersection with 20 vehicles, which want to reach their destinations based on their profiles. The results show that always. more than 80 percent of vehicles will be satisfied by the proposed model. The next simulation shows the simulation time of the proposed model. According to the generated results in Figure 10, the cloud-level algorithm can quickly generate the waiting times for the intersection level algorithms.

The next simulation shows the simulation time of the proposed model. According to the generated results in Figure10, the cloud-level algorithm can quickly generate the waiting times for the intersection level algorithms.

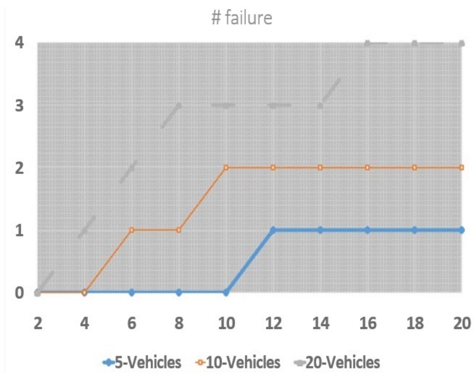

Figure 9: Failure by Cloud-level algorithm

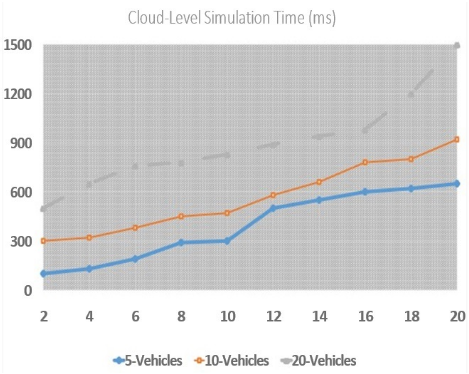

Figure 10: Simulation time of Cloud-level algorithm.

5 Conclusion

In this paper, we developed and analyzed a novel scalable traffic light system for pedestrian and vehicles based on an ubiquitous vehicular and IoT network, where every person or vehicle can participate in the sensing and data gathering process. However, such process is very challenging, but it enables us to build up a highly responsive traffic light system for the future smart cities. The proposed model employs a hierarchical deep-learning model to cope with scalability issues of the current traffic light systems. We investigate possible challenges due to different types of traffic. The proposed model uses a multi-level deep learning model to schedule different traffic flows with different priorities in such a way that their waiting time be minimized. The proposed algorithm in the cloud-level always keep an updated profile about every vehicle to generate an accurate waiting times. Such waiting time denote the maximum allowed waiting times of vehicles in each intersection. Then, the intersection-level deep learning model use this information in addition to the some other context information to locally schedule traffic toward their destinations. Based on the performance and output of the intersection-level learning algorithm, the cloud-level algorithm generate a new list of waiting time for each vehicle. We analyzed our developed algorithms under different sets of simulations to investigate the performance of the proposed learning models in both cloud and intersection levels. According to the results, applying new model can improve the service time and system efficiency and introducing deep learning model has a significant improvement in the performance. As future work, the proposed multi-level learning model can still be improved to achieve to the higher accuracy. In addition, applying the proposed model to a real scenario can be very interesting empirical research direction in this field.

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