Optimization of Secured Cluster Based Charging Dynamics and Scheduling of EV Using Deep RNN

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Abstract. In the near future, Electric Vehicles (EVs) are anticipated to develop into fantastic modes of transportation. Due to their limited range and under powered batteries, EVs are crucial for lowering the use of conventional fuel. When the battery charge is about to reach a critical level, it is essential to be aware of local Charging Stations (CS). As a result, we could spot two issues: (1) Secured Cluster based CS allocation and routing to CS (2) Scheduling vehicle at CS based on delay prediction. First, a Cluster based Vacant charging slot is searched in clustered charging stations using cloud and Vehicular Adhoc Network (VANET) model, along with evolutionary Social Ski Driven (SSD) optimized algorithm using Deep Recurrent Neural Network (DRNN) as a new optimal routing for EVs to reach CS based on established fitness function computing distance, battery power and traffic congestion. Second, at CS, vehicle time scheduling is done using the DRNN approach, considering delay-based distance computation. When compared to the stochastic Particle Swarm Optimization (PSO) algorithm for routing, the proposed DRNN-SSD routing algorithm optimizes delay and traffic congestion significantly achieving better successful allocation rate of CS during On-peak and Off-peak hours.

Keywords: CS · DRNN · DRNN-SSD · DRNN-PSO

1 Introduction

The usage of vehicles has dramatically expanded in recent years due to quickly expanding infrastructures and urban modernisation, which has resulted in pollution and global warming difficulties, as well as the lack of supplies and their high floating costs, managing traditional fuels has become more challenging, which has led to the modernization of the automobile industry is looking for affordable and environmentally friendly transportation. In coming days electric vehicles

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have become a great form of transportation in the near future. However, EVs' insufficient battery capacity necessitate regular recharging for travelling over long distances. Many EV manufacturers are building their vehicles with massive battery capacity to go longer distances that weigh between 50 and 400 kgs due to a lack of CS or awareness of its availability and to reduce the time necessary to charge. In the long term, the durability of EVs will be impacted by modest commercial vehicle loads and passenger loads since EVs cannot be instantly recharged like traditional fuels can in emergency situations. In this research work, a cloud assisted VANET model for cluster based vacant charging slot detection is proposed to raise awareness of CS and with the help of a nature-inspired evolutionary optimized SSD routing algorithm, EVs receive assistance to reach CS at its closest proximity based on EV battery power, distance to charging station and traffic congestion across lanes as well as vehicle time scheduling mechanism that is performed using DRNN and made known to EVs using VANET-cloud. In accordance with the utilisation of the requested power configuration at charging stations, EVs are assigned to the vacant charging slots based on priority, notably high for emergency vehicles like ambulances, fire trucks, etc., medium, and low for standard EVs at CS.

2 Motivation

Collaboration of Cloud computing and VANET supports wide variety of applications and in present days finding the CS is a tedious task and reaching to it with minimum battery power are highly needed and also number of CS available for charging EVs are fewer in contrast to the number of EVs that exist and unskillful charging can cause a grievous stress on the power grid and hence, To handle scheduling of time for EV charging to get connected to the required power configurations at CS has become equally essential. A motivation from past research studies led us to introduce A cloud-assisted VANET model uses DRNN that schedules EVs to the vacant slots of CS based on priority option to select high, moderate or low power configurations, and using DRNN-SSD routing algorithm is proposed to select minimum congested route using DRNN based traffic congestion and delay based distance computation.

3 Literature Survey

Due to its affordability and environmental benefits, EV adoption has greatly increased in recent years [1]. Because EVs are being integrated into the power distribution network on such a large scale, the implementation of approved charging schemes is crucial. Decentralized and centralised solutions make up the bulk of the charge control options. While the centralised strategies use a centralised authority to directly regulate the charging process of EVs, the decentralised schemes allow the EVs to conduct regulating of the charging process themselves. Both Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communication are supported by VANETs, which [2–4] enable efficient data gathering from surrounding vehicle nodes and then communicate traffic changes to the Road-Side Units (RSUs) and nearby vehicle nodes. Consequently, real-time traffic-based data may be utilised to administer traffic flow [6]. Many studies have been conducted to develop effective charging scheduling algorithms for EVs in order to suit a variety of needs, including queue time reduction [7], trip energy use reduction [8], overall elapsed time reduction [9]. Due to the costs and limitations of variable rate chargers (VRC) and charging methods, electric vehicles (EVs) are often charged using discrete rate charging (DRC), in which the chargers store a variety of rates, such as binary rates like off/on. DRC reorganises the process of modulating power over a constrained range of rates in general. Therefore, it is important for actual operating conditions [10] that an EV charging approach be compatible with VRC and DRC. The author of [11] proposes SSD routing algorithm for EVs. The author of [12] discusses about efficient routing for EVs using SSD combined with fractional calculus and authors in [13] discusses about cluster based searching for parking also presents a DRL approach for handling user requests for parking.

4 Cluster Based CS Allocation Using VANET- Cloud

VANET is the state-of-the-art in the field of wireless networks where the objective of VANET is to exchange the information or message transfer between the resources. It can be achieved in various ways such as Vehicles to Vehicle (V2V), Vehicle to Infrastructure (V2I) and Vehicle to Road Side Units (RSU) and these RSU's are connected to the cloud platform to form a Cloud-assisted VANET networks that bring forth wide variety of application services. In addition Cloud platform provides storage and computing facilities. Hence, the structural system design of cluster based CS allocation for EV charging using cloud-assisted VANET is presented in Fig. 1. Whenever an EV requests for charging slot using web interface applications gets connected to VANET-cloud the request

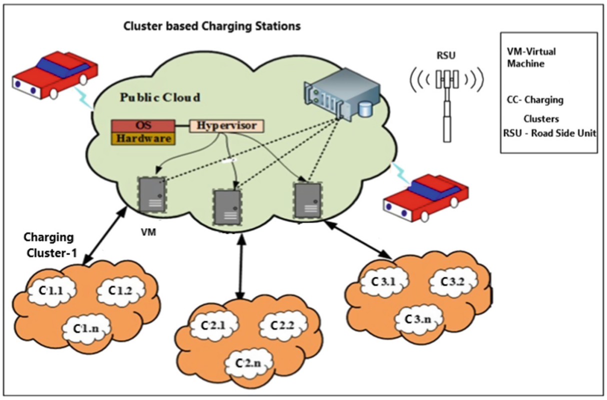

Fig. 1. Cluster based CS allocation for EV Charging

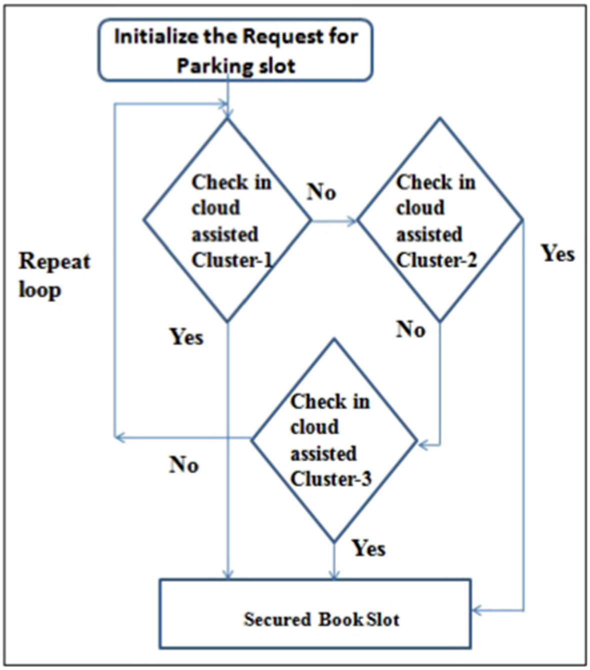

Fig. 2. Workflow of secured Cluster based CS allocation for EV Charging

is searched in multiple clusters consisting of CS are located near to the EV in the range of 1000 m. charging clusters-1 consists of number of CS represented by C1.1 to C1.n, similarly for Charging cluster-2 are C2.1 to C2.n and charging cluster-3 are C3.1 to C3.n. The following flowchart shown in Fig. 2 explains about the searching of vacant slot in cluster based CS allocation model. All clusters having CS consisting of charging ports of high, moderate and low power configurations they gets synchronized with VANET-cloud every 30 min and updates the available vacant charging slots at CS in their respective clusters which helps in determining the vacant charging slots by checking in each nearest cluster from the distance of EV and then second nearest cluster and so on until vacant slot is available then the routing of the EV is done using Social Ski driver routing algorithm.

5 Routing and Scheduling Using DRNN Based System Model

VANET uses V2V and V2I communication to distribute messages. In order to take advantage of the resource management in a specific region, RSU connects with a cloud server and other roadside units in this situation [14, 15]. The data acquired through wireless or cable transmission is processed by the VANET cloud server. Through the cloud, information is acquired from RSU and vehicle units. The cloud then performs centralised calculation and broadcasts the results to the application users.

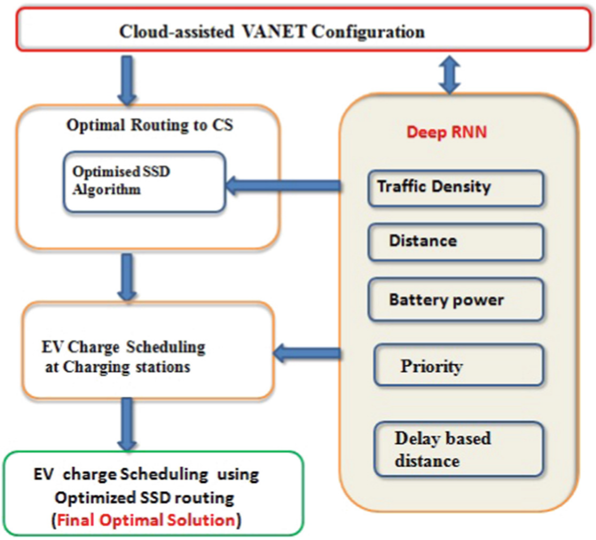

Fig. 3. Routing and Scheduling using DRNN

First, the Proposed Model communicates with electric CS about vacant slots through a cloud interface. The first time an EV requests charging, it sends its vehicle identification number and password to the VANET-cloud model. The corresponding vehicle's private key (V_{pkey}) is generated by the cloud server. To choose the best, quickest, and least congested route for EVs, a cloud server executes the suggested optimised SSD algorithm. To determine the route with the least amount of congestion, Deep RNN is used together with distance, battery power, and traffic density. In the charging station, EVs are secondarily scheduled for charging based on *Priority and delay-based distance prediction* using DRNN. The conceptual diagram is shown in Fig. 3.

5.1 Deep RNN Based Fitness Function Computation

Deep RNN has an infinite number of recurrent concealed levels in its network architecture, and as a result, there is a recurrent relationship between all of these hidden layers [24]. The traffic density, status of EV battery power and distance to CS is given as input because Deep RNN is more adept at managing inputs of various lengths and as a result of continuing to iterate with the data from concealed states, the outcome of the previous state condition is used as input to the subsequent state condition. The output sequences are then mapped using the hidden states that Deep RNN created by drawing the input series to them. Traffic Density signifies number of EVs present in the road lanes of a particular area and is given by

$$T_j = \left[\frac{n + 1}{(S_0)\,c}\right] \tag{1}$$

where, c represents the count of road lanes, S_0 signifies the sample road lane length and n specifies count of electric vehicle. Battery status of charge B_s is evaluated using Coulomb's counting method that defines status of charging and discharging current of the battery by integrating values over time is given by

$$B_s = B_s(t-1) + \frac{i(t)}{B_c}\theta\mathrm{t} \tag{2}$$

where $B_s(t-1)$ represents initial stage of charge at time '$(t-1)$' and $i(t)$ is the battery current at instant 't' B_c is the battery capacity in ampere hours and θt refers step time.

Hence, The fitness values includes traffic density, battery power and distance is given by

$$f = \frac{1}{2}\left[T_j + \frac{1}{2N}\sum_{m=1}^{N}(1-B_s) + D_k + (1-P_i)\right] \tag{3}$$

where T_j represents traffic density at j^{th} time, D_k provides distance travelled by k^{th} EV and B_s refers to battery power of s^{th} EV, P_i refers to priority opted by i^{th} EV and N denotes number of EVs. Hence, optimised DRNN based SSD routing is found by considering the minimum values of fitness function that is given by

$$min(f) \tag{4}$$

5.2 EV Routing Using SSD Algorithm

Numerous metamorphic techniques used to determine the best values for feature selection [25] and also in support vector machines [26] have inspired the social ski driven algorithm [5]. Through a series of collective simulation rounds or iterations, SSD's primary objective is to identify the area where the best possible optimum solutions may be attained from the records of prior data. The mean global solution is produced by averaging all fitness values calculated using Eq. (3). Updated EV positions are obtained by adding the velocity represented as

$$Z_n^{0+1} = Z_n^0 - V_n^0 \tag{5}$$

where Z_n^0 signifies current position of EVs and V_n^0 represents velocity of n^{th}EV at 0^{th} iteration.

$$Z_n^0 = \begin{bmatrix} KSin(\eta 1)(X) + Sin(\gamma 1)(Y); & \text{if}\eta 2 \leq 0.5 \\ KCos(\eta 1)(X) + Cos(\gamma 1)(Y); & \text{if}\eta 2 > 0.5 \end{bmatrix} \tag{6}$$

where

$$X = (A_i^0 - B_i^0) Y = (C_i^0 - B_i^0)$$

where K denotes parameter to stabilizes exploration and exploitation, η_1 and η_2 represents uniformly distributed arbitrary numbers in the range [0, 1]. X and Y parameters consists of A_i^0 denotes finest solution of i^{th} EV at 0^{th} iteration, B_i^0 represents current position of i^{th} EV at 0^{th} iteration and C_i^0 denotes mean global solution at 0^{th} iteration for all EVs. To choose optimum charging station to route the EVs is obtained using DRNN based Fitness function to obtain optimal route.

6 Deep RNN Based Vehicle Time Scheduling for Charging

Time scheduling for charging is done by taking into account the fitness function using EV Priority and delay-based distance prediction using Deep RNN to reach the final best solution. Each electric vehicle's request for a charging station is illustrated in the charge station encoding as shown in Fig. 4, which has three charging ports designated as CP1, CP2 and CP3. Here, CP1 are high power with High Priority charging ports that permits speedy recharging at high cost and least time is used for recharging high priority vehicles and for those in need of quick charging service depending on vacancies, etc. Similarly CP2 is having moderate priority and CP3 with Low Priority configurations with moderate and low powers respectively are utilized to charge the EVs at different charging rate, cost and time.

6.1 CS Encoding

An optimized time scheduling of EVs for charging at CS is performed by considering priority, delay prediction using DRNN to reach CS and charging time of EV is based on charging port used by EV and allocation to charging ports defines the response time of EV at CS upon arrival. Emergency vehicles such as ambulances, fire engines, etc. have high priority and routed to CP1 having x slots and other normal EVs requested to get charged are distributed and routed to CP2 and CP3 lines having y and z slots respectively based on their opted charging priorities respectively.

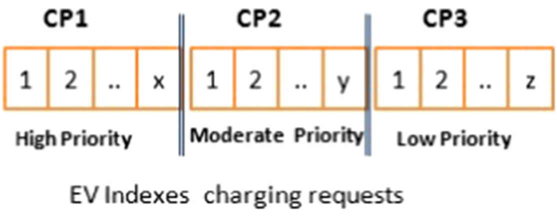

Fig. 4. Deep RNN based fitness computation

6.2 EV Time Scheduling for Charging Computation Using DRNN

Priority of charging is opted by EV user such as high, moderate and low based on requirements. The Fig. 5 shows diagram of DRNN the outcome of the previous state condition of traffic data set is used as input to the subsequent state condition. The output sequences are then mapped using the hidden states that Deep RNN created by drawing the input series to them. The optimized fitness function uses minimization function for EV time scheduling to evaluate for delay prediction based on distance considering traffic congestion computation using DRNNis given below.

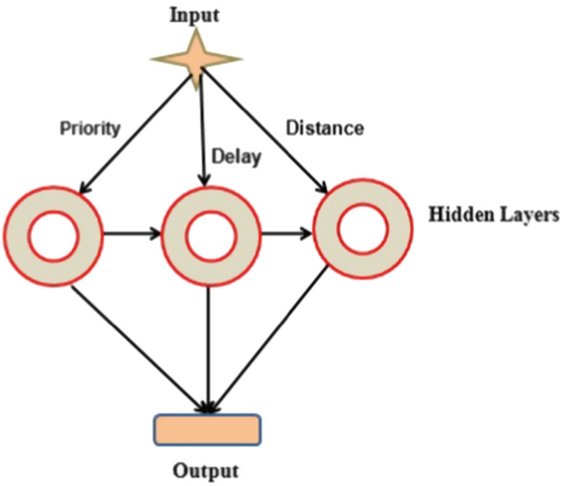

Fig. 5. Deep RNN based fitness computation

$$(min)F_{TS} = \frac{\sum_{m=1}^{N}\left[D_t + R_{(i)}\right]}{2} \tag{7}$$

where N stands for the total number of electric cars that will be charged, D_t stands for time delay $R_{(i)}$ stands for the i^{th} EVs minimal response time.

6.3 Delay

Delay is defined as the expected charging time period required based on current EV power available to get charged at CS. minimum delay is considered and computed by Eq. (8).

$$D_t = \left(\frac{EV_{max}.(1 - B_a)}{(CP)_{Pow}}\right) \tag{8}$$

where B_a is the EV's available battery power, $(CP)_{Pow}$ is the charging line power and EV_{max} is the maximum battery capacity of an EV. Response time can be defined as minimum time duration taken by charging station to respond to a request and it is computed using below equation.

$$R_{(i)} = \frac{D_t}{T} \tag{9}$$

where $R_{(i)}$ is the response time and T is the whole time period. Consequently, EVs time scheduling for charging and routing utilising DRNN-SSD Algorithm operates in a cloud server. Where the cloud server initially utilises the EV ID (V_{pkey}) for communication through constant synchronisation, after which all EVs' current locations and velocities are uploaded to assess the most optimal routing and support EV users using Google Maps. As a result, the cloud server assigns the appropriate EV to a vacant charging line according to priority after determining the minimal fitness values based on minimum delay and response time.

7 Results and Discussion

The Performance metrics for EVs time scheduling for charging and routing using optimized DRNN-SSD algorithm are evaluated in percentage for traffic congestion, delay, successful allocation rate for On peak and off peak hours.

7.1 Experimental Setup

The execution of optimized DRNN-SSD routing and time scheduling for charging EVs is performed using windows 10 OS using Intel core i5 processor 6GB Ram and simulated using PYTHON tool. Here, Particle Swarm Optimization (PSO) algorithm is one of the bio-inspired that uses stochastic optimization technique based on the movement and intelligence of swarms is considered as a routing algorithm for comparison with proposed optimized DRNN-SSD routing algorithm.

7.2 % of Traffic Congestion

The proportion of congestion per lane during off-peak hours is seen in Fig. 6. After 50 initial rounds of simulation, the proposed DRNN-SSD is used to calculate traffic congestion, taking previous iterations data into account it yields 31.4%, compared to 33.0% for PSO making 1.6% optimization. After 100 simulation rounds, the proposed DRNN-SSD performs better than PSO, with 25.4% and 28.8%, respectively with 3.4% optimization. The same was true at On peak hours, as seen in Fig. 7. After 50 rounds, the DRNN-SSD and PSO produce 61.4% and 65% percent of congestion, respectively. Finally, after 100 rounds of simulation, DRNN-SSD performs better when picking lanes with the lowest density than PSO, which produces 54.5% and 60.1% of congestion, respectively. Finally making 5.6% optimization in congestion.

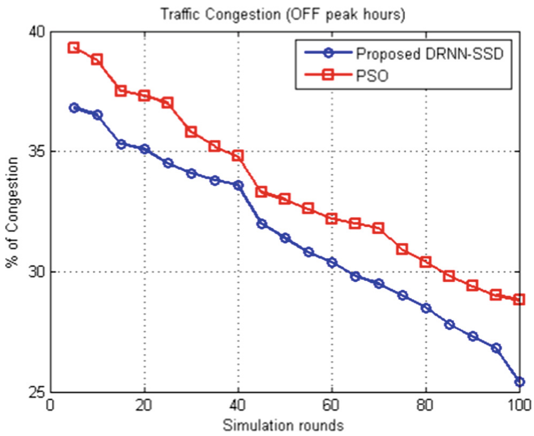

Fig. 6. % of Congestion (Off peak hours)

7.3 % of Delay Prediction to Reach CS

Figure 8 displays the proportion of EV charging delays at CS during on-peak times. The proposed DRNN-SSD outperforms PSO suggesting least delay of 19.2% over 24.1% of PSO after completion of the initial 50 rounds of simulation thereby optimizing delay of 4.9%. This is done in order to compute the delay for expected charging time of EVs at CS while taking previous iterations data into account. PSO gives a result of 29.6% while the proposed DRNN-SSD gives 25.4% after 100 rounds of simulation making a delay optimization of 4.2%. Similar results were obtained during off-peak hours, as shown in Fig. 9. After

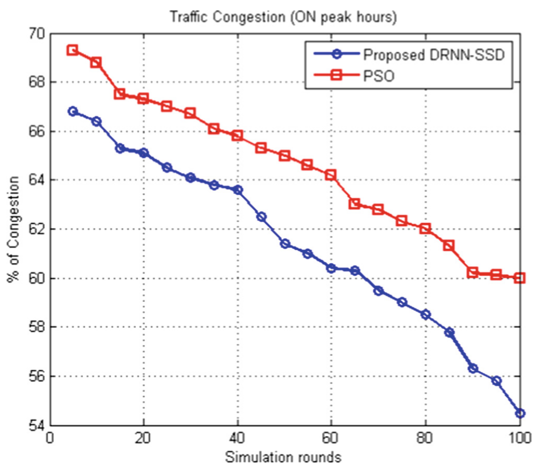

Fig. 7. % of Congestion (On peak hours)

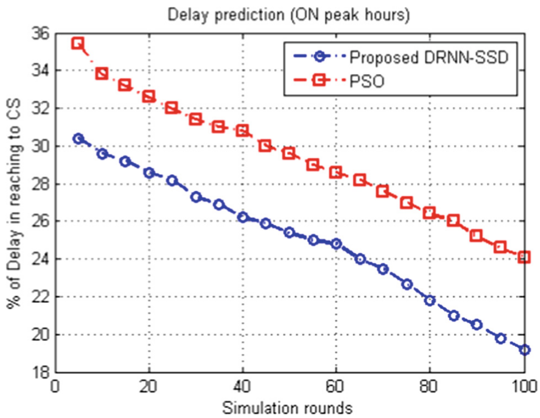

Fig. 8. % of delay (On peak hours)

50 rounds, DRNN-SSD and PSO provided 11.7% and 14.1% with 2.4% optimization in delay, respectively and eventually, after 100 rounds of simulation, DRNN-SSD outperformed PSO, providing 7.2% and 10.3%, respectively making 3.1% of optimization in delay.

7.4 % of Successful Allocation of EVs to CS

The percentage of EVs successfully allocated during On-peak hours is shown in Fig. 10. Unoccupied slots are provided via a cloud-assisted VANET model, and EVs are routed to CS using the DRNN-SSD routing algorithm while taking

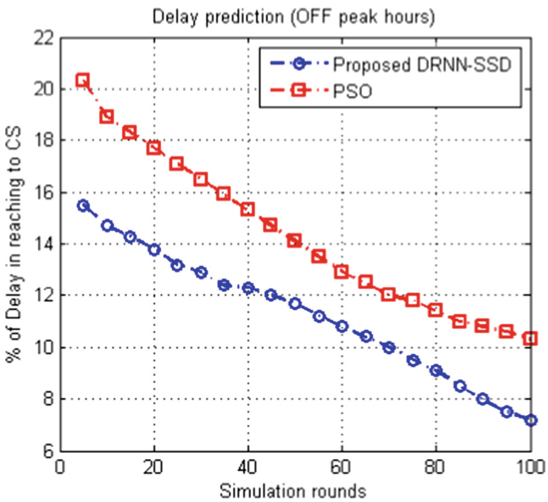

Fig. 9. % of delay (Off peak hours)

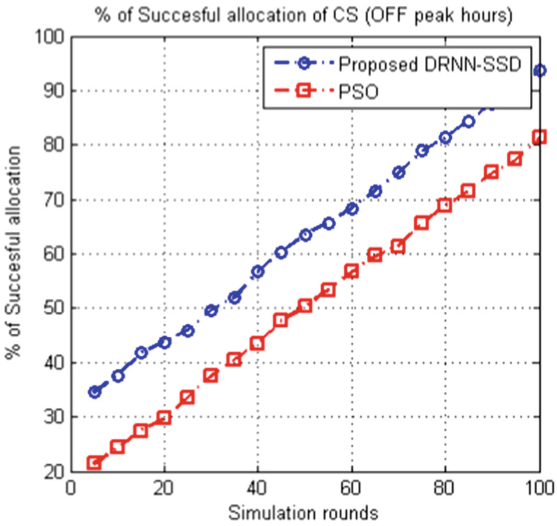

Fig. 10. % of Successful allocation (Off peak hours)

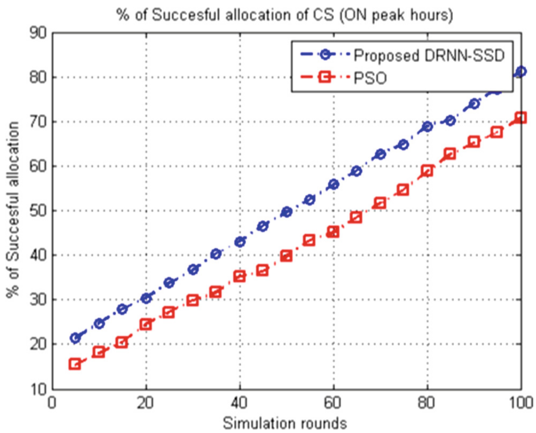

Fig. 11. % of Successful allocation (Off peak hours)

into account the fitness function with minimal delay and least traffic congestion. The recommended solution uses recurrent synchronizations to determine whether slots are available in nearby CS. The suggested DRNN-SSD takes into account an improved fitness function computing with least congested route to reach CS faster than PSO and provides a high success rate for allocating EVs to charging slots at CS. After the first 50 rounds of simulation, the proposed DRNN-SSD beats PSO with a score of 49.7% compared to 39.7% after 100 rounds, with scores of 81.3% and 70.7% respectively. During Off peak hours depicted in Fig. 11, after 50 rounds of simulation, DRNN-SSD and PSO yield

63.6% and 50.3% respectively and eventually, after 100 rounds of simulation, DRNN-SSD outperforms PSO with 93.8% and 81.3% respectively. Hence, The overall simulation results shows better optimization using DRNN approach in choosing minimum percentages of Congestion per lane, delay and maximum successful allocation rate when compared to bio-inspired PSO routing algorithm. With DRNN approach, during off peak hours after 100 rounds of simulations the percentage of optimized delay and congestion is 3.1% and 3.6% leading to increased successful allocation rate by 13.3%. Similarly, during On peak hours after 100 rounds of simulations the percentage of optimized delay and congestion is 4.9% and 3.4% leading to increased successful allocation rate by 10%.

8 Conclusion and Future Work

This study proposed a novel approach that uses a cluster based CS allocation using cloud-assisted VANET model made up of RSUs and EV units as a communication interface to a cloud server to provide vacant slot for charging and evaluation of optimised routing using a nature-inspired evolutionary SSD algorithm while taking into account the minimum fitness values like battery power, distance and the traffic congestion. Additionally, a vehicle time scheduling mechanism based on fitness function is carried out at CS for EVs. Delay prediction and traffic congestion computation is performed using DRNN technique with optimized delays and traffic congestion choosing the route with the least amount of congestion shown the better percentage of EVs successfully allocating to CS during On-peak and Off-peak hours. Here, PSO is outperformed by the proposed DRNN-SSD in terms of performance. In future, further bandwidth parameter has to be considered and comparative performance analysis must be performed with other optimized routing strategies.

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