Prototyping Design and Optimization of Smart Electric Vehicles/Stations System using

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Abstract:

This paper demonstrates an experimental attempt to prototype electric vehicle charging station's (EVCS) decision-making unit, using artificial neural network (ANN) algorithm. The algorithm acts to minimize the queuing delay in the station, with respect to the vehicle state of charge (SOC), and the expected arrival time. A simplified circuit model has been used to prototype the proposed algorithm, to minimize the overall queuing delay. Herein, the worst-case scenario is considered by having number of electric vehicles arriving to the station at the same time greater than the charging points available in the station side. Accordingly, the optimization technique was applied to reduce the mean charging time of the vehicles and minimize queuing delay. Results showed that this model can help in reducing the queuing delay by around 20% of the mean charging time of the station, while referring to a bare model without ANN algorithm as a reference.

Keywords: Real-time algorithms, Physical realization, Electric vehicles stations, Queuing delay optimization, Artificial neural network (ANN) algorithm.

1. Introduction

In today's rapidly evolving business environment, automated systems in warehousing are critical for meeting increasing customer demands, especially with the rise of e-commerce. One such system that has garnered significant attention is the **Shuttle-Based Storage and Retrieval System (SBSRS)**, an automated warehousing system that utilizes robotic shuttles for high-efficiency picking and storing of products. SBSRS is primarily deployed in mini-load retailer warehouses to streamline operations and improve system performance.

The traditional SBSRS features shuttles operating on fixed tiers, leading to lower utilization of shuttles due to the non-flexible design, which may contribute to inefficiencies in cost and sustainability. To address this, a more **flexible SBSRS design** has been developed where shuttles can traverse multiple tiers, facilitated by additional lift mechanisms. While this flexible design potentially increases shuttle utilization, it introduces new challenges in transaction processing and shuttle scheduling.

This study addresses these challenges by investigating the impact of **Priority Assignment Rules (PARs)** and real-time data tracking in optimizing transaction processing for flexible SBSRS designs. By using **agent-based modeling**, we aim to evaluate multi-objective performance metrics, including **Average Flow Time (AFT)**, **Maximum Flow Time (MFT)**, and the **Standard Deviation (SD)** of flow times, to provide a more comprehensive view of the system's efficiency.

1. INTRODUCTION

Is the Electric Vehicles (EVs) market a booming market? Various studies have demonstrated such a question [1-4]. The electric vehicles deployment rate has recently risen worldwide and has become the conventional transportation for the cities as it reduces air pollution and fuel dependency [5]. Accordingly, queuing delay and charging cost problems appear, and many researchers tried to solve them using different optimization techniques. Previous works were investigated to reduce the charging cost for EVs, either by introducing new charg-ing schemes, integrating renewable energy sources, or utilizing decentralized in-door charging [6-10]. The current study focuses more on the other problem, queuing delay. One of the solutions to minimize queuing delay is by increasing charging points with respect to electric vehicles demand in each zone [11]. Reducing electric vehicle charging time and queuing delay will enhance the usage of electric vehicles globally. As the increases in electric vehicle usage may lead to congestion in the electric vehicle charging stations (EVCS). Accordingly, optimization of high priority vehicles needs to be established, which will lead to rearrangement of vehicles entering the station simultaneously [12,13]. Fast charging modes like constant current constant voltage (CCCV) and multistage constant current (MSCC) may lead to a decrease in charging time, but also as the charging duration is longer than fueling time so that congestion may happen, and queuing delay will occur [14].

Another factor affecting the queuing delay is the state of charge (SOC) upon arriving at the station. The lower the SOC, the higher the charging priority. The battery management system is the primary key in controlling the SOC, as it contains many accurate algorithms that control the functional status of the battery [15]. Previous literature demonstrates various attempts to provide intelligent battery management systems in vehicles, seeking optimum charging, either time or cost. The work in [16] provided an attempt to utilize fuzzy logic to control a vehicle's battery management system. Another trial based on vehicle-to-vehicle technology was conducted in [17]. Moreover, the charging swapping methodology was utilized as in [18]. Alternatively, the integration of self-controlling and renewable resources were investigated [19].

Integrating machine learning models in optimization problems has attracted various researchers' attention. A study of mathematical optimization methods and machine learning to estimate optimized solutions by being trained on previously optimized solutions shows that the machine learning model is more accurate and efficient in obtaining the value of the optimized instances [20]. In [21], global solar radiation is required to design a proper energy conversion system due to the high cost of measurement several mathematical models are used linear and nonlinear in parallel with a machine learning model; result conducts that machine learning accuracy compared by actual reading shows more accurate results as error percentage at some time reaches less than 2%. In [22], scientists used artificial neural network (ANN) for medical purposes, and they faced some problems regarding feeding the network with data from a real-world, determination of the best structure as it needs many trials, eccentric network behavior as ANN has some limitations regarding providing clue how results are obtained when it providesa probe solution to specific problem and duration of the network is un-expectable beside to is an unknown clue. Overall, it can be concluded from previous work that ANN is more practicable, applicable, and accurate than conventional mathematical optimization models.

On the other hand, ANN has limitations regarding time, unknown behavior, feeding data translation, and hardware dependency. ANN's advantages outweigh its disadvantages as ANN are developing rapidly, and scientists are eliminating its disadvantage one by one, which shows a great perspective in the future. Provided all these attempts to effectively optimize the charging process of vehicles, in both dimensions cost and time, the physical realization and prototyping of such an intelligent system are still missing in the literature.

This paper proposes an accurate prototyped model implemented using an embedded system controller to emulate electric vehicles that communicate with electric vehicle stations. 12 EVs nodes (Figure 1) were fabricated with scaling down the EV battery by two 3-V batteries, the controlling unit is implemented using an Arduino controller, and the data is demonstrated using an LCD screen (cf. Figure 2). The intelligent point is considered in the Arduino kit with the ANN model running to minimize the queuing delay on the EV station side. Again, LCDs are mounted in the EV stations to demonstrate the predicted queuing delay for each arriving vehicle. A real-time energy management model is deployed on the Arduino kit for estimating the SOC and the expected charging time, with the aid of the Al model. The model pretends to estimate the queuing delay using the developed ANN model. A series of experimental measurements were recorded and compared with theoretical expectations.

2. PROTOTYPE DESIGN METHODOLOGY

As a prototype, 12 electric vehicles are assumed to arrive per two stations, with three charging points in each station (c.f. Figure 1). For the sake of decisionmaking on the station side, estimating the battery's state of charge (SOC) is an essential task. Our proposed prototype is a scaled-down model with two 3-V batteries connected in series for each EV, while Arduino is acting as a control unit [23, 24].

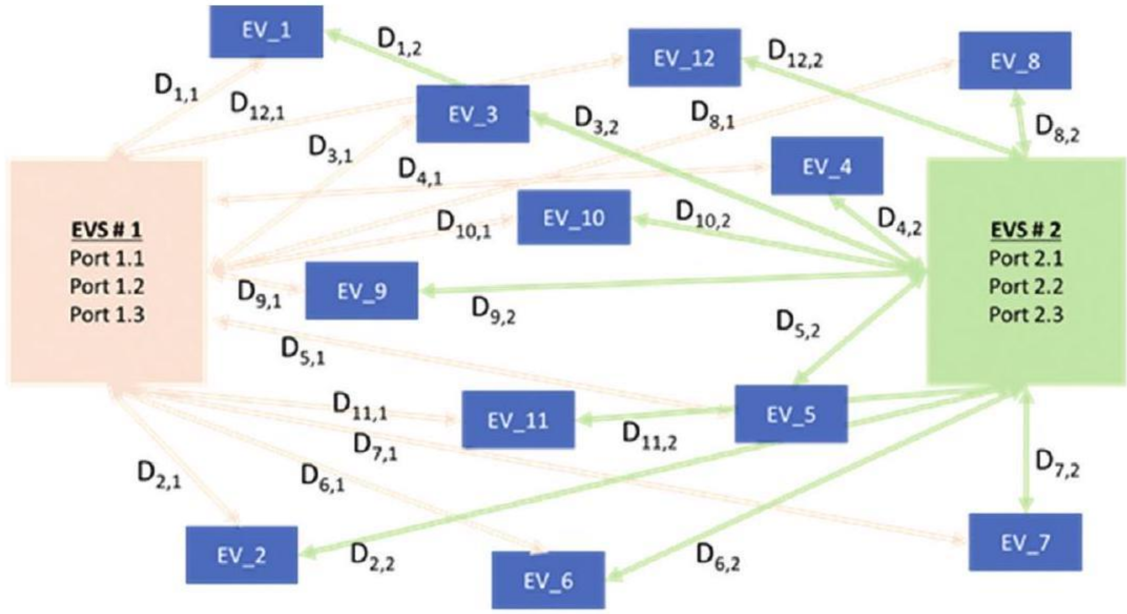

Fig. 1. Schematic diagram for the EVs scenario with two available EV stations. The distance between EV and EV station is denoted as Dm, n, where m is the EV number and n is the EV station (EVS) number.

Levenberg-Marquardt has been chosen in this work as it showed the highest validation among other algorithms, including Bayesian regularization and scaled conjugate gradient, as reported in [25].

A generated dataset of 12,234 point was developed, while utilizing our database of EVs, published in [12] (cf. table 1). To ensure the suitability of the chosen ANN model with respect to the optimization problem under test, the generated dataset was tested. The dataset has been divided into three subsets: training, validation, and testing [25, 26]. A 70% of the dataset was included as a training data, where the model learning process is conducted. Another 15% of the dataset are used for validating the data in terms of the data range under test. Finally, the remaining 15% are seeded as new input to the system to examine the prediction capabilities of the learning process implemented with the first 70% of the dataset. The accuracy of the validation process showed around 93%, while 91% and 71% were observed for the validation and testing process, respectively. As an overall accuracy performance indication, 89% accuracy was recorded for the suggested ANN model. We consider this output as an acceptable accuracy for the model to be used in the current study, with the possibility for further improvement in the future work by limiting the relatively high variation in accuracy (71% to 93%).

As time-series app helps in utilizing the inputs and outputs to continuously predict the minimum expected EVs queuing delay, a real-time autoregressive nonlinear optimization algorithm [26] is used to rank EVs according to the SOC at the station, as well as the expected arrival time as a function in the distance to the station D_(m,n). The model is considering a possibility for a queuing delay whenever the number of arriving vehicles is more than the available charging points at the station side, assumed to be three points per station.

As mentioned earlier, the illustrated model was deployed on the Arduino kit for physical realization. The Arduino kit supplies the circuit by 5 volts, the LCD is supplied by 10 volts total, and the data wires are connected to (8,9,10,11,12,13) digital pins with (RS, E, D4, D5, D6, D7). LEDA is connected to the positive side to provide better vision, and the batteries are connected to a potentiometer to vary the output voltage controlling the SOC, as shown in Figure 4.

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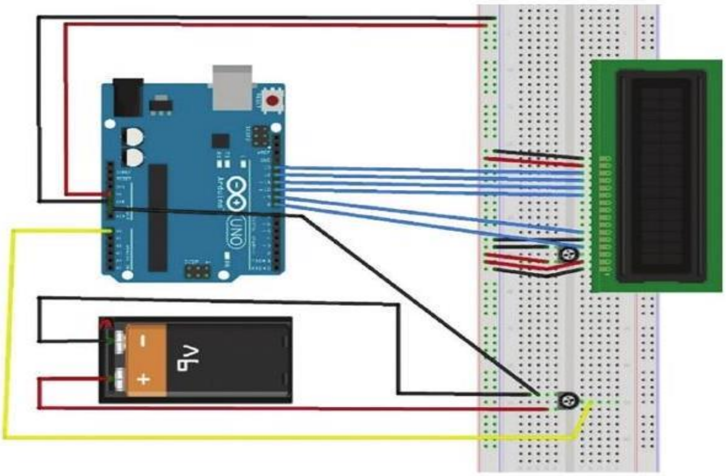
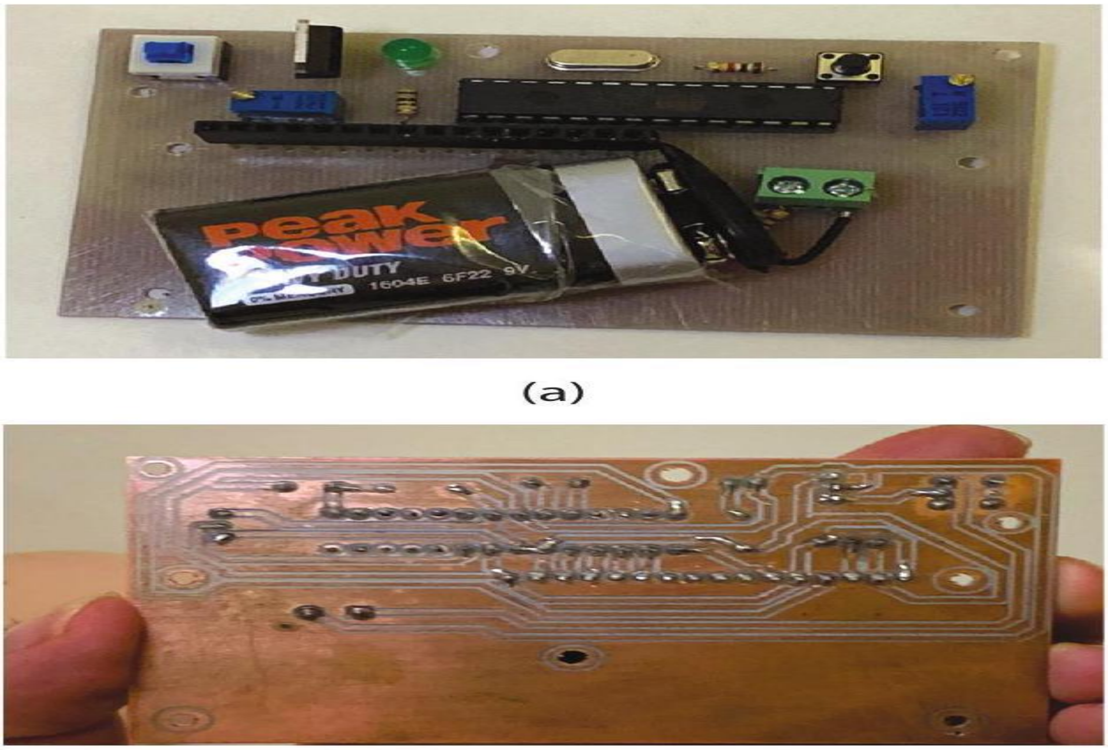


Fig. 4. Wiring diagram for the EV node

Consequently, the actual circuit realization is shown in Figures 5-a and b.



(a)

(b)

Fig. 5. (a) and (b) demonstrates the actual circuit model for the EV node.

3. RESULTS AND DISCUSSIONS

The hardware system described in section two is then utilized in capturing actual data concerning the change of the queuing delay with the SOC variation following the ANN model prediction. The model depends upon scaling down the vehicle battery, Fiat 500 Model 2018, with a battery capacity of 42 KW.hr, to a small battery used with a small capacity, as described in section two. This model helped show the SOC's effect on the charging time and queuing delay.

As mentioned in Figure 1, 12 EVs were prototyped to communicate with two EVs. The EV decides which EVCS to access based on the SOC recorded at the EV node, the distance between the EV node and EVCS node, and the queuing delay expected at EVCS based on the traffic. The conducted experiment is implemented by fixing all EVs in terms of distance to stations, as (Dm,n), while one EV is kept with variable SOC. Accordingly, the SOC variation can influence the decision taken and reflect the expected queuing delay.

Figure 6 shows that the queuing delay is directly proportional to the SOC, while the charging time is inversely proportional. The experiment is conducted so that a group of vehicles enters the charging stations when all vehicles' SOC remains static while one vehicle SOC varies in our prototype to show how the change in SOC affects the charging time and queuing delay problem.

It was observed that the queuing delay could be predicted only if the number of EVs arriving at the station exceeds the number of available charging points at the station. Herein, all vehicles were charged based on the DC constant current constant voltage (DC-CCCV) charging mode, despite any congestion in stations that may occur.

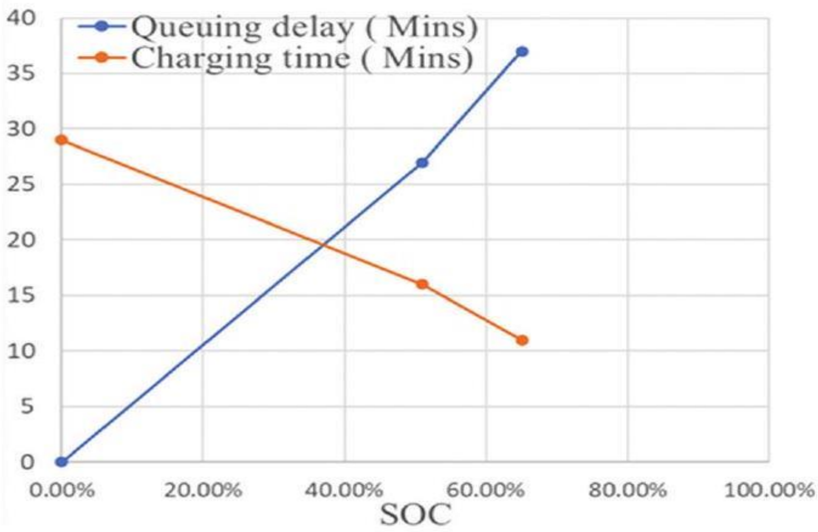


Fig. 6. Charging time and queuing delay variation against SOC for the worst-case scenario, including 12 arriving EVs, to two EV stations.

Conceptually, the optimization technique used in this paper is driven by arranging the vehicles with the highest charging time in descending order, as this technique will minimize the total mean charging time, which will decrease the mean charging time along the way day.

Screenshots for the recorded SOC and queuing delay are demonstrated in Figure 7, all data are listed in Table 1. The figure illustrates three randomly selected EVs, showing the EV node side with the SOC, and the EV station side with charging time and queuing delay. The same 12 EVs scenario was run without performing the ANNN decision model on the EVs side to test the model's utility. The average queuing delay was calculated with and without the ANN model in both cases. It was shown that the average queuing delay with applying the ANN model is reduced by 20%, with respect to the bare case (24.5 mins to 29.2 mins, respectively).

The model shows that the queuing delay is directly proportional to the SOC as when the SOC increases, the queuing delay increases. This means that the optimization algorithm identifies the high-priority vehicles with the lowest SOC to minimize the queuing delay for those vehicles as it reaches zero. In contrast, vehicles with high SOC will have the longest queuing delay time even though they have the shortest charging time. Overall, the average mean charging time, including the queuing delay with applying optimization technique for those vehicles, will be less than the average mean charging time without applying this technique as calculated earlier. Based on the above, the proposed prototype validates the utility of the selected ANN model to minimize the queuing delay at rush hours. The model can be extended to include more EVs as well as EVCS. We considered such extension as a part of the future work.

Fig. 7. Recorded SOC, charging time, and queuing delay for three samples out of the 12 EV prototyped (a) EV # 1, (b) EV # 5, and EV # 8.

EV_# Initial SOC
(%) Estimated SOC at
Station Predicted Charging Time
(mins) Dm,1 (m) Dm,2 (m) Queuing delay
(mins)

EV_1	12	9.57545117	29.13756525	0.618588	1.42121	0
EV_2	30	33.56969084	21.50423098	4.98713	5.19231	11.59742
EV_3	40	28.32280701	36.57449544	4.17398	2.78219	18.55471
EV_4	50	37.58541729	16.86148293	2.90895	4.98562	0
EV_5	51	36.38462651	16.33263482	3.84365	4.25879	27.58459
EV_6	60	43.85077205	16.42789885	4.77989	3.51666	0
EV_7	70	74.27270927	21.07815914	1.001587	1.875104	9.54214
EV_8	65	27.53896209	11.536542497	4.14293	4.35069	37.65812
EV_9	80	78.63664373	3.808792758	1.316519	1.989016	0
EV_10	25	21.94191819	24.03313005	0.877803	2.09306	0
EV_11	35	26.22420666	38.30491932	1.64114	3.37592	7.11244
EV_12	45	45.82565932	11.6138407	0.786987	1.854612	0

Table. 1. Recorded SOC, charging time, distance to stations and queuing delay for three samples out of the 12 EV prototyped. Selected station is underlined per EV

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