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Deep Multi-task Learning for Smart Electrical Vehicle Charging

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Executive Summary

In response to climate change and decarbonization, electrification especially in transportation sector has grown rapidly. While the swift adoption of Electric Vehicles (EVs) contributed to Net zero emission but high charging demand introduced undesirable consequences to the power grid which requires novel solutions.

In recent years, several researchers have approached the power grid emerging challenges caused by EV charging as an optimization problem with specific constraints such as efficiency, economical aspects for both EV owners and charging station operators. In this research, Deep Multi-task learning is employed with an end to end training of a model which is supervised by a loss function. The proposed framework optimizes the performance of smart charging. The proposed model is compared with the state of the art adaptive charging algorithms as well as uncontrolled scenario for benchmarking. The result proves that while the proposed technique matches with the performance of single task method in terms of total energy delivery, it outperforms counter techniques in charging cost comparison.

Keywords: electric vehicle (EV), charging, smart, smart charging, intelligent.

1 Introduction

The global sustainability shift which was driven by the environmental challenges such as climate change and global warming led to some initiavtes like ectrification. Considering the contribution of transportation sector to the undesirable emissions [1] , the shift from Internal Combustion Engine vehicles to Electric Vehicles was inevitable. Supported by government investments globally, the trend of EV deployment is forcasted to be fast growing globally [2] as well as regionaly and in countries [3, 4].

The reliabaility and stability of power grid and micro grids are threatened with unprecedented high peak loads of EV charging demand [5]. Therefore, a careful balance between system reliability and desired user experience via EV availability should be managed.

1.1 Background and Motivation

In order to address the overwhelming charging demand to EV charging infrastructure, controlled charging method were employed. In contrast with uncontrolled charging systems which are suffering from operational challenges such as over capacity demand during peak load and inefficient resource utilization, controlled methods have proved satisfactory outcome. Moreover, some studies have shown that managed charging methods contributed to sustainability and greenhouse gas emission while reducing the power grid operation costs [6, 7].

The control methods which are used for EV charging process management can be categorized in three groups of rule based and model predictive controls (RBC) and (MPC) respectively and deep learning based control methods [8].

1.2 Related Works

Due to the disadvantages associated with RBC and MPC methods such as challenges in scalability and coputentation complexity and model sensitivity, deep learning based algorithms gained popularity in recent years. Besides the shotcomings of alternative approaches, advancements in Deep Neural Network (DNN) architectures and availability of real world equiavalnt datasets in reasonable size such as ACN-sim [9] facilitated the emerging of deep learning based algorithms.

There are some studies which studied the impact of factors such as SOC[10] or carbon emission[11] or charging station revenue[12] in adaptive charging while optimizing the decision problem. Majority of these methods are implemented using Reinforcement Learning (RL) such as introduced adaptive charging methods in [12-14].

2 Method

Mutli-task learning has shown promising results in solving problems in different fields [15]. For example in autonomous driving systems [16] and medical image processing [17].

In this study, a deep multi-task framework is proposed to overcome challenges in shallow constraint based optimization for EV charging. The multi-task learning architecture is designed to extract deep features supporting local and global optimization to produce the best outcome. The loss function is designed to guide the learning of auxulary deep features in benefit of global optimization.

The proposed model is increasing the efficiency of charging while considering energy cost and peak load effect and is named EDC-DMT-Net standing for Energy Delivered and Cost Deep Multi Task Network. This name will be used for reference to this proposed model.

2.1 Charging Model

In this study, the scope of charging model is limited to charging stations, drivers, electrical vehicles and charging sessions with their relevant constraints which are listed in this section. The EV charging is modelled with discrete time with a fix period. In our model each charging session of *s* which initiates by EV occurs in time of *t* contains related information of time of arrival to charging station and planned departure time from charging station as well as current state of charge of EV and desired state of charge in time of departure. Moreover, the EV charging constraint is provided in terms of peak charging rate of EV.

Our charging model constraints and assumptions are stated in this section.

a) Time is discrete with fixed period. $t_1$belongs to the set of time points of {1,2,3, …., T} where the distance between each to adjacent time points in this set is fixed and equal.

$$t_1 \in \{1,2,3,\dots,T\} \tag{1}$$

b) Each charging station has a peak limit of P which defines the maximum possible delivery of energy for all charging sessions of that particular charging session at any point of time.

$$\sum_{0\leq i \leq v} x_i(t) \leq P(t) \tag{2}$$

Each EV has a peak limit of CP which is enforced as a hard limit. Charging power in all charging sessions are limited to lower boudry of zero and upper boundry of EV peak limit hence the charging power can not become negative and can not exceed the maximum acceptable rate that EV accepts at any point of time.

$$0 \leq \ x_i(t) \ \leq \ CP(t) \tag{3}$$

c) The state of charge of EV can be calculated based of state of charge of EV in arrival time, previous state of charge in time and charging power of active charging sessions.

$$s_i(t) = \begin{cases} s_{i,arrival}, & t \ = 0 \\ s_i(t-1) \ + \ \alpha x_i(t) \ , & t \ \geq 1 \end{cases} \tag{4}$$

Value of α is considered as constant and known for each EV before operation. α can be calculated based on values of discretization and charging efficiency of EV battery.

d) Charging session are temporal and no charging power will be delivered for the EV which has not arrived to charging station as well as no charging power for the EV that departed from charging station.

$$x_i(t) = \begin{cases} 0, & t_{arrival} \ > t \ \ \cup \ \ t \ > \ t_{departure} \\ x_i(t) \ , & t_{arrival} \leq t \ \ \leq \ t_{departure} \end{cases} \tag{5}$$

2.2 EDC-DMT-Net Objective

While the proposed model does not suffer from the drawbacks of MPC smart charging algorithms, the proposed method is addressing the challenges of smart EV charging techniques [18].

By combining the benefits of indirectly controlled techniques with smart charging technique which is making the monetary benefits clear to EV owners and encouraging them to participate in smart charging EDC-DMT-Net addresses the drwabacks identified in EV smart charging.

EDC-DMT-Net produces two ouputs of charging rate and charging total cost. The model is trained to maximize the energy delivered during the charging sessions while the cost of charging is minimized based on time of use energy price and demand cost.

$$E = \max_x \sum_{t=1}^{T} \ \sum_{i=1}^{v} x_i(t) - \ \beta \sum_{i=1}^{v} \left| s_i(T) - \ s_{i,departure} \right| \tag{6}$$

s.t. (1), (2), (3), (4), (5)

This function aims to maximize the delivered energy to connected EVs during charging sessions by complying to all assumptions and constrained stated in charging model. This function motivates the optimal sharing of available charging power between connected EVs in order to maximize the highest delivery met demand of charging energy requests while not violating the peak limits of charging station (P) and EV peak limit (CP).

$$C = \ \min_c \sum_{t=1}^{T} \ \sum_{i=1}^{v} c_i(t) \ x_i(t) \tag{7}$$

The objective of this function is to minimize the total cost of charging for all EV charging demands in stated charging model. Total cost of charging for each EV of i at time of t is denoted as $c_i(t)$ which considers both charging cost and demand cost. The price calculation introduced in [19] is used for EV charging total cost calculations. The simplified formula of composite price which demonstrate the contributing factors in the payable price of EV charging is shown in *(8)* .

$$c_i(t) := p_t + \sum_l A_{li}\beta_{lt} + \gamma_{it} + \delta_t \tag{8}$$

$c_i(t)$ is composite price at time of t which incorporated the p_t as energy price at time of t and included the network congestion with $\sum_l A_{li}\beta_{lt}$ and charger congestion is denoted with γ_{it} while δ_t represents the demand charge.

2.3 Multi-Task Learning

As stated in EDC-DMT-Net objective, in order to output total charging cost besides the optimal charging rates for connected EVs in charging station, the multi task learning approach is chosen. The model will output the estimated total charging cost and by modified lost function, the model is encouraged to maximize the energy delivered during the charging sessions and maximize the total proportion of energy received by EVs while minimizing the payments needed from each charged EV owner.

$$L_d = (E_i - E_i^{pred})^2 \tag{9}$$

E_i denotes the energy delivered to EV of I and L_d aims to reduce the distance of E_i^{pred} to maximum possible energy delivered to connected EV.

$$L_c = (C_i - C_i^{pred})^2 \tag{10}$$

L_c represents the cost Loss which is calculated to guide model train aiming charging cost reduction by reducing the network and charger congestion. The ideal minimum total cost aims to become closer to EV charging cost.

$$L = \lambda_1 L_d + \lambda_2 L_c \tag{11}$$

Where λ_1 and λ_2 are hyper-parameters and L is combined loss function which supervises the training for multi task learning model with combination of L_d as loss of delivery and loss of charging cost that is denoted with L_c.

3 Experiment

For evaluation purpose, the simulation approach with utilizing the large EV charging dataset which is called CAN-Data [20] is used. ACN-Data has EV charging session data collected from Adaptive Charging Network (ACNs)v which includes two sites of Caltech and JPL. Multiple charging stations are operating and have delivered energy to EVs from 2016. The simulation used the data of Caltech site for the duration of one month from first March 2019 until first April 2019 and the discereet period of each simulation was chosen to 5 minutes. The Southern California Edison time of use tariff was used for pricing scheme and total cost of charging calculation. The energy delivered by EDC-DMT-Net is compared to delivered energy via single task technique and MPC technique which is optimized for earliest deadline first. As illustrated in Figure 1, EDC-DMT-Net outperforms EDF in total energy delivered comparison. However, EDC-DMT-Net energy delivery is on par with single task method. Moreover, from the figure it can be seen that when the capacity is high enough to meet the demand, EDF can reach to energy delivery of single task and EDC-DMT-Net.

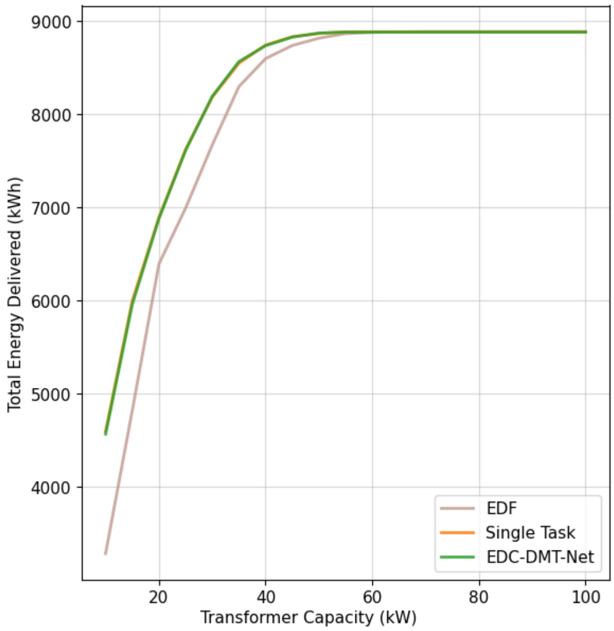

Figure 1: Total energy delivered comparison

The comparison of total cost of charging of different techniques are illustrated in Figure 2. As shown in this diagram the gap becomes wider as the available capacity grows.

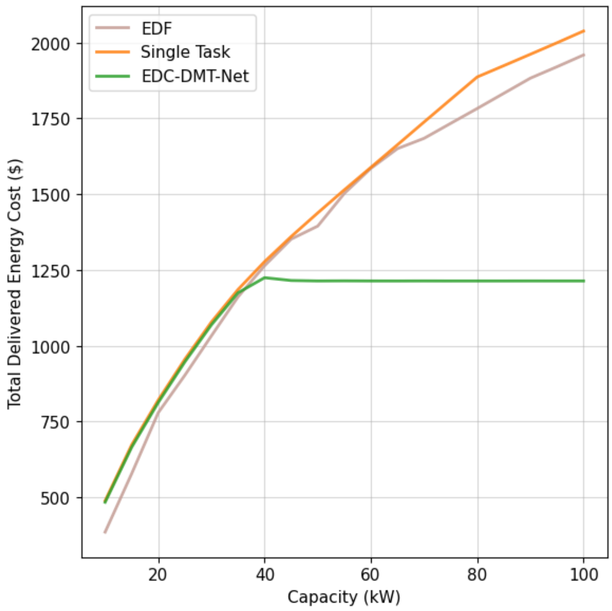

Figure 2: Total delivered energy cost comparison

The total cost of charging is a bigger differentiator factor between EDC-DMT-Net and other techniques as shown in Figure 2. The difference is shown clearly, and the gap becomes bigger when the higher demand is received, and higher capacity is available. Comparing the two diagrams, where different techniques get closer in total energy delivery, the difference in cost efficiency becomes more obvious. EDC-DMT-Net aims to make the total cost of charging closer to energy cost and minimize the demand cost.

4 Conclusion

The rapid growth of EV adoption led to increased attention to EV charging optimization and has proved the promising advantage of smart charging. However, smart charging lacks participation of EV owners and demonstrating its benefits to involved stakeholders. In this work, multi task learning approach is proposed, and EDC-DMT-Net was introduced to not only improve the EV charging efficiency but minimize the total cost of EV charging at the same time. EDC-DMT-Net produced the estimated charging cost as extra output that increases transparency of cost to EV owner and can lead to higher participation of them and incorporate the advantage of indirectly controlled techniques with smart charging. The simulation results prove outperforming performance of EDC-DMT-Net compared to single task optimized method in terms of total energy cost while maintaining the EV charging efficiency.

References

[1] Y. Van Fan, S. Perry, J. J. Klemeš, and C. T. Lee, "A review on air emissions assessment: Transportation," *Journal of cleaner production,* vol. 194, pp. 673-684, 2018.

[2] (2020, 15 November 2022). *Global EV Outlook 2020 Entering the decade of electric drive?* Available: https://www.iea.org/reports/global-ev-outlook-2020

[3] T. T. Mai *et al.*, "Electrification futures study: scenarios of electric technology adoption and power consumption for the United States," National Renewable Energy Lab.(NREL), Golden, CO (United States)2018.

[4] Y. Zheng, Z. Shao, Y. Zhang, and L. Jian, "A systematic methodology for mid-and-long term electric vehicle charging load forecasting: The case study of Shenzhen, China," *Sustainable Cities and Society,* vol. 56, p. 102084, 2020.

[5] H. Engel, R. Hensley, S. Knupfer, and S. Sahdev, "The potential impact of electric vehicles on global energy systems," *report, McKinsey Center for Future Mobility,* 2018.

[6] J. K. Szinai, C. J. Sheppard, N. Abhyankar, and A. R. Gopal, "Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management," *Energy Policy,* vol. 136, p. 111051, 2020.

[7] T. Lipman, D. Callaway, T. Peffer, and A. von Meier, "Open-Source, Open-Architecture SoftwarePlatform for Plug-InElectric Vehicle SmartCharging in California," 2020.

[8] A. Kathirgamanathan, M. De Rosa, E. Mangina, and D. P. Finn, "Data-driven predictive control for unlocking building energy flexibility: A review," *Renewable and Sustainable Energy Reviews,* vol. 135, p. 110120, 2021.

[9] Z. Lee, D. Johansson, and S. H. Low, "ACN-sim: An open-source simulator for data-driven electric vehicle charging research," in *Proceedings of the Tenth ACM International Conference on Future Energy Systems*, 2019, pp. 411-412.

[10] Y. Chen and B. Zhang, "State-of-Charge Aware EV Charging," in *2022 IEEE Power & Energy Society General Meeting (PESGM)*, 2022, pp. 1-5: IEEE.

[11] K.-W. Cheng, Y. Bian, Y. Shi, and Y. Chen, "Carbon-Aware EV Charging," *arXiv preprint arXiv:2209.12373,* 2022.

[12] S. Dimitrov and R. Lguensat, "Reinforcement learning based algorithm for the maximization of EV charging station revenue," in *2014 International Conference on Mathematics and Computers in Sciences and in Industry*, 2014, pp. 235-239: IEEE.

[13] W. Zhang *et al.*, "Intelligent electric vehicle charging recommendation based on multi-agent reinforcement learning," in *Proceedings of the Web Conference 2021*, 2021, pp. 1856-1867.

[14] Z. Zhang, Y. Jiang, Y. Shi, Y. Shi, and W. Chen, "Federated Reinforcement Learning for Real-Time Electric Vehicle Charging and Discharging Control," *arXiv preprint arXiv:2210.01452,* 2022.

[15] Y. Zhang and Q. Yang, "A survey on multi-task learning," *IEEE Transactions on Knowledge and Data Engineering,* 2021.

[16] C. Han, Q. Zhao, S. Zhang, Y. Chen, Z. Zhang, and J. Yuan, "YOLOPv2: Better, Faster, Stronger for Panoptic Driving Perception," *arXiv preprint arXiv:2208.11434,* 2022.

[17] M. Meng, B. Gu, L. Bi, S. Song, D. D. Feng, and J. Kim, "DeepMTS: deep multi-task learning for survival prediction in patients with advanced nasopharyngeal carcinoma using pretreatment PET/CT," *IEEE Journal of Biomedical and Health Informatics,* vol. 26, no. 9, pp. 4497-4507, 2022.

[18] Q. Chen and K. A. Folly, "Application of Artificial Intelligence for EV Charging and Discharging Scheduling and Dynamic Pricing: A Review," *Energies,* vol. 16, no. 1, p. 146, 2023.

[19] Z. J. Lee, J. Z. Pang, and S. H. Low, "Pricing EV charging service with demand charge," *Electric Power Systems Research,* vol. 189, p. 106694, 2020.

[20] Z. J. Lee, T. Li, and S. H. Low, "ACN-Data: Analysis and applications of an open EV charging dataset," in *Proceedings of the Tenth ACM International Conference on Future Energy Systems*, 2019, pp. 139-149.

Presenter Biography

Jafar Shayan joined ABB as Senior R&D engineer in May 2021 based in Netherlands. He currently works in ABB E-Mobility on EV charging infrasturure and happily contributes to charging up EV transition and zero emission plan.

Jafar considers himself as continuous learner and improver with high passion in software engineering and substantiality. He enjoys building high performing teams and coaching and leading them as a servant leader.

Jafar holds Master of IT management and PhD of computer science. He has more than 20 years of experience in different countries and sectors.

Besides his experience in industry, Jafar has contributed to the body of knowledge by publishing his research results and serving in technical committee of several academic conferences as reviewer.