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Optimal Path Planning for Electric Vehicles through Speed and Time

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ABSTRACT

As a new, upcoming technology in the transportation andpowersectors, electric vehicles offermany environmental and economic benefits. In contrast to conventional routing systems, which determine the optimal route to a destination, this work designs a route planning specifically for electric vehicles that considers both time and speed factors simultaneously. A physical model of the electric vehicle's energy consumption is used to model the road network as a network of nodes, with weighted edges, in order to apply anoptimal path algorithm that finds the route with the lowest edge cost.An optimized optimum path algorithm seeks to find the optimal path with the least amount of edge costs. In this case the edge costs are speed and time.The prototype route choice algorithm has been developed based on the improved Dijkstra algorithm. This algorithm employs both the optimal distance path and the optimum travel time path function.

Keywords – *time, Electrical vehicle,network,optimal path,speed*

I. INTRODUCTION

Electric Vehicles are transportation vehicles that use an electric motor or motors for propulsion. They can be powered by extravehicular sources of electricity or by batteries in autonomous mode.At the beginning of the 20th century, electric vehicles were considered a viable method of propulsion, providing a level of comfort and ease of operation that wasn't possible with gasoline-powered vehicles. Electric vehicles (EVs) have seen resurgence in popularity in the 21st century because of technological innovations, as well as increased focus on renewable energy and the lessening of transportation's impact on climate change, air pollution, and other environmental issues. Due to rising pollution, along with the depleting crude oil reserves, electric vehicles have received considerable attention from international leaders. When driving an electric vehicle on freeways, there are two main problems to contend with: first, the battery life of the vehicle, and second, the length of time required charging it.Depending on the path taken, energy consumption can vary greatly. Based on the special characteristics of electric vehicles, this study goes into the optimal route planning to a destination. Currently, efforts are being made to maximize battery life, minimize energy consumption, and improve journey time.The aim of this work is to find a route that uses the least amount of energy to go from one point to another. In addition, the best route to maximize battery life can be determined as well as the optimum journey time. To solve the optimization problem in a network with nodes, edges, and edge costs, optimal path algorithms are used. The algorithms provide a method for finding the optimum edge cost path from one node to another.An electric vehicle model that describes the physics of different driving modes is used to estimate the energy consumption and travel time. An optimization algorithm weighs factors based on these three variables: (i) Energy consumption: The vehicle should arrive at its destination with the maximum possible battery charge (ii) Time: The journey should take the least amount of time possible (iii) Battery life. It is crucial to minimize the cumulated energy flow in order to maximize the battery lifespan of electric vehicles. It is our intention to include the drivers' preferences in a very flexible manner in this paper.

II. RELATED WORK

The vehicle starts at a specified origin, stops and refuels at refueling vertices on the way and arrives at a specified destination. Its algorithm is a two-stage optimum path computation: constructing a new network that is composed of all the optimum paths between all pairs of refueling vertices and finding the optimum path between the origin and the destination in the new network. The well-known Dijkstra's algorithm is applied to solve the problem. Lawler considered the same problem but regarded the travel time instead of the length as the cost of the arc. He developed two polynomial algorithms by applying the Bellman-Ford method and the Floyd-Warshall method. However, both objective functions neglect the impact of refueling operations. This may result in vehicles refueling more often than necessary or refueling even when the energy level is high. To limit the number of stops for refueling, the two-stage optimum path problem (SP) of EVs was modified. Two scenarios (the maximum number of stops for refueling was specified versus not specified) are studied to identify a more reasonable path in the electric vehicle optimum walk problem (EV-SWP). The paper also provides polynomial algorithms. The EV-SWP has been frequently reviewed and compared by other studies. However, the maximum number of stops for charging instead of the impact of refueling operations is considered. The value of the maximum number is difficult to determine and may affect the solution.

The optimal routing problem with limited fuel is equivalent to the weight-constrained optimum path problem (WCSP) if the weight (fuel consumption) and the cost of each arc are not related and vehicles cannot refuel. Therefore, modified WCSPs were presented in other studies. The WCSP with refueling and presented new algorithms that exploit the inter-replenishment path structure. Thus, author focused on the processing method, the algorithm presentation, and the result comparison instead of the problem definition. The cost of the optimal path in the studies that are discussed above is the travel time or length. The objective of the routing problem of EVs is to find energy-efficient paths rather than short or fast paths due to the limited battery capacity. They formalized the energy-optimal routing problem as a special case of the WCSP: the energy value may be negative, which corresponds to energy recuperation. A prefix-bounded optimum path tree with respect to function absorp is computed to solve the problem. The energy consumptions are constant among arcs and are unrelated to the arc length and the traffic state. However, in practice, EVs may become more fuel efficient as the average speed increases. In this paper, we assume that the energy (electricity) consumption of an EV that is traversing a link is related to the distance and to the average travel speed. Many methods are available for estimating the average travel time and travel speed using automatic number plate recognition data. Many other studies about urban road transportation, which include queue length estimation, traffic demand estimation, and saturation degree estimation, are also based on such information. Consequently, ANPR data are utilized in this paper for average travel time and travel speed estimation.

III. PROPOSED ALGORITHM

The multi-objective optimization is solved by applying anoptimum path algorithm. Optimum path algorithms use networks made of nodes and edges. The goal of optimum path algorithms is to find the path with the least amount of edge costs. By minimizing the sum of weights of the edges of a graph, the optimum path algorithm finds the path between two vertices.It is proposed to define travel time as the dynamic weight of the road according to an improved Dijkstra algorithm. To determine the optimum path between two points, the data for the road network is preloaded into memory during Step 1 (initialization). To index related roads, a searching rectangle is constructed in Step 2 (searching). To solve the optimum path problem, Dijkstra's algorithm is employed in Step 3 (optimum path calculation).

IV. EXPERIMENTAL RESULT AND DISCUSSION

By definition, the optimum path problem is to determine a path between two vertices (or nodes) in a graph such that the total edge weights are as low as possible.In optimum path problems, the choice of the route optimum in travel time is considered.It is the edge weight that determines the travel time.With the dynamic edge weight, the shortest path problem differs from the traditional one.In order to construct the network, new information about the nodes and edges will have to be collected.

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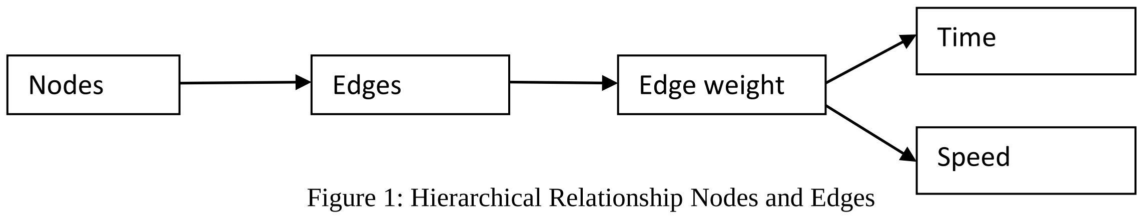

Figure 1: Hierarchical Relationship Nodes and Edges

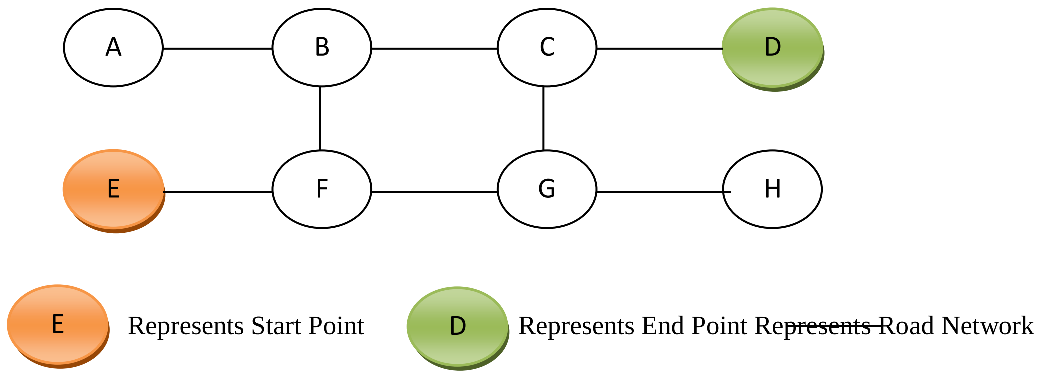

Figure 2: An analysis of optimum travel times

Table 1: The process of traveling the shortest distance

Destination	The path and the arrival time from Source to other nodes					
A	α	α	α	E, F,G,A	E,F,B.A	E,F,B.A
B	α	E, F, B	E, F, B	-	-	-
C	α	α	E, F,G, C	E, F,C	-	-
D	α	α	α	α	E,F,G,C,D	E,F,G,C,D
F	E, F	-	-	-	-	-
G	α	E, F,G	-	-	-	-
H	α	α	E, F,G, H	E, F,G, H	E, F,G, H	-
E (Source)	E, F	E, F,G	E, F,G, B	E, F,G, B,C	E, F,G,B,C, H	E, F,G,B,C, H,D

Table 1 depicts the original point and the destination point is established first. Next, the minimum time cost of edge E and F. Thirdly, there is the minimum weight of the edge compared to the other points. Fourth, update the edges weight if the path passes G and gets closer to the original point. Fifth, add the point until you reach the destination point by selecting the next minimum weight edge. We then find the path with the shortest travel time between the original point and the destination point. Taking the path of E, F, G, C, and D from E to D takes a short amount of time

V. CONCLUSION AND FUTURE ENHANCEMENT

The proposed algorithm for shortest travel time is evaluated using distance factor and time factor. Separate units are used to measure the distance and time cost. According to the results of the comparison, shortest travel time routes take less time than shortest distance paths. The future study will also analyze multiple sources of data to determine the traffic condition.

REFERENCES

[1] R. W. Floyd, "Algorithm 97: shortest path," Communications of the ACM, vol. 5, no. 6, p. 345, 1962.

[2] P. E. Hart, N. J. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," IEEE Transactions on Systems Science and Cybernetics, vol. 4, no. 2, pp. 100–107, 1968.

[3] D. Pfoser, S. Brakatsoulas, P. Brosch, M. Umlauft, N. Tryfona, and G. Tsironis, "Dynamic travel time provision for road net- works," in *Proceedings of the 16th ACM SIGSPATIAL Inter- national Conference on Advances in Geographic Information Systems (ACM GIS '08)*, pp. 475–478, Irvine, Calif, USA, November 2008..

[4] H. Bar-Gera, "Evaluation of a cellular phone-based system for measurements of traffic speeds and travel times: a case study from Israel," *Transportation Research Part C: Emerging Technologies*, vol. 15, no. 6, pp. 380–391,2007.

[5] A. Kesting and M. Treiber, "Online traffic state estimation based on floating car data," in *Proceedings of the Traffic and Granular Flow (TGF '09)*, pp. 1–11, Shanghai, China, June 2009.

[6] S. Brakatsoulas, D. Pfoser, R. Salas, and C. Wenk, "On map- matching vehicle tracking data," in *Proceedings of the 31st International Conference on Very Large Data Bases (VLDB '05)*, pp. 853–864, Trondheim, Norway, September 2005.

[7] H. Shimizu, M. Kobayashi, and Y. Yonezawa, "Analysis of mean link travel time for urban traffic networks," in *Proceedings of the 51st Vehicular Technology Conference (VTC '00)*, pp. 318–322, Tokyo, Japan, May 2000..

[8] J. F. Ehmke, S. Meise, and D. C. Mattfeld, "Floating car data based analysis of urban travel times for the provision of traffic quality," *International Series in Operations Research & Manage- ment Science*, vol. 144, pp. 129–149,2010.

[9] X. Liu, S. Chien, and K. Kim, "Evaluation of floating car tech- nologies for travel time estimation," Journal of Modern Trans- portation, vol. 20, no. 1, pp. 49–56, 2012.

[10] Y. Zhao, J. Liu, R. Chen et al., "A new method of road network updating based on floating car data," in Proceedings of the 2011 IEEE International Geoscience and Remote Sensing Symposium (IGARSS '11), pp. 1878–1881, Melbourne, Australia, July 2011.

[11] Q. Li, Z. Zeng, T. Zhang, J. Li, and Z. Wu, "Path-finding through flexible hierarchical road networks: an experiential approach using taxi trajectory data," *International Journal of Applied Earth Observation and Geoinformation*, vol. 13, no. 1, pp. 110–119, 2011.

[12] R. Zhang and E. Yao, "Electric vehicles' energy consumption estimation with real driving condition data," *Transportation Research Part D: Transport and Environment*, vol. 41, pp. 177–187, 2015.

[13] C. De Cauwer, J. Van Mierlo, and T. Coosemans, "Energy consumption prediction for electric vehicles based on real- world data," *Energies*, vol. 8, no. 8, pp. 8573–8593, 2015.

[14] A. I. Croce, G. Musolino, C. Rindone, and A. Vitetta, "Energy consumption of electric vehicles: models' estimation using big data (FCD)," *Transportation Research Procedia*, vol. 47, pp. 211–218, 2020.

[15] F. Wu and R. Sioshansi, "A stochastic flow-capturing model to optimize the location of fast-charging stations with uncertain electric vehicle flows," *Transportation Research Part D: Transport and Environment*, vol. 53, pp. 354–376, 2017.

[16] J. He, H. Yang, T.-Q. Tang, and H.-J. Huang, "An optimal charging station location model with the consideration of electric vehicle's driving range," *Transportation Research Part C: Emerging Technologies*, vol. 86, pp. 641–654, 2018.

[17] F. He, Y. Yin, and J. Zhou, "Deploying public charging stations for electric vehicles on urban road networks,"*Transportation Research Part C: Emerging Technologies*, vol. 60, pp. 227–240, 2015.

[18] M. Kchaou Boujelben and C. Gicquel, "Efficient solution approaches for locating electric vehicle fast charging stations under driving range uncertainty," *Computers & Operations Research*, vol. 109, pp. 288–299, 2019.

[19] R. Chen, X. Qian, and L. Miao, "Optimal charging facility location and capacity for electric vehicles considering route choice and charging time equilibrium[J]," *Computers & Operations Research*, vol. 113, 2020.

[20] W. Kong, Y. Luo, and G. Feng, "Optimal location planning method of fast charging station for electric vehicles consid- ering operators, drivers, vehicles, traffic flow and power grid," *Energy*, vol. 186, 2019.

[21] M. Schu¨cking, P. Jochem, W. Fichtner, O. Wollersheim, andK. Stella, "Charging strategies for economic operations of electric vehicles in commercial applications," *Transportation Research Part D: Transport and Environment*, vol. 51, pp. 173–189, 2017.

[22] X. Dong, Y. Mu, X. Xu et al., "A charging pricing strategy of electric vehicle fast charging stations for the voltage control of electricity distribution networks," *Applied Energy*, vol. 225, pp. 857–868, 2018.

[23] Z. Yi and M. Shirk, "Data-driven optimal charging decision making for connected and automated electric vehicles: a personal usage scenario," *Transportation Research Part C: Emerging Technologies*, vol. 86, pp. 37–58, 2018.

[24] M. Elgarej, M. Khalifa, and M. Youssfi, “Optimized path planning for electric vehicle routing and charging station navigation systems,” *International Journal of Applied Meta- heuristic Computing*, vol. 11, no. 3, pp. 58–78, 2020.

[25] F. Guo, Z. H. Huang, and W. L. Huang, “Integrated location and routing planning of electric vehicle service stations based on users’ differentiated perception under a time-sharing leasing mode,” *Journal of Cleaner Production*, vol. 277, p. 22, 2020.

[26] C. Wang, F. He, X. Lin, Z.-J. M. Shen, and M. Li, “Designing locations and capacities for charging stations to support in- tercity travel of electric vehicles: an expanded network ap- proach,” *Transportation Research Part C: Emerging Technologies*, vol. 102, pp. 210–232, 2019.

[27] H. Liu, W. Yin, and X. Yuan, “Reserving charging decision- making model and route plan for electric vehicles considering information of traffic and charging station,” *Sustainability*, vol. 10, no. 5, 2018.

[28] Z. Li, K. Dey, M. Chowdhury, and P. Bhavsar, “Connectivity supporteddynamic routing of electric vehicles in an induc- tively coupled power transfer environment,” *IET Intelligent Transport Systems*, vol. 10, no. 5, pp. 370–377, 2016.

[29] Y. Wang, J. Bi, and C. Lu, “Route guidance strategies for electric vehicles by considering stochastic charging demands in a time-varying road network,” *Energies*, vol. 13, no. 9, 2020.

[30] R. Galvin, “Energy consumption effects of speed and accel- eration in electric vehicles: laboratory case studies and im- plications for drivers and policymakers,” *Transportation Research Part D: Transport and Environment*, vol. 53, pp. 234–248, 2017.