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A Time and Energy Consumption Efficient Routing Approach for Electric Vehicles in Real-World Conditions

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ABSTRACT: Limited driving range remains one of the barriers for widespread adoption of electric vehicles (EVs). To address the problem of range anxiety, this paper presents an energy consumption prediction method for EVs, designed for energy-efficient routing. This data-driven methodology combines real-world measured driving data with geographical and weather data to predict the consumption over any given road in a road network. The driving data are linked to the road network using geographic information system software that allows to separate trips into segments with similar road characteristics. The proposed strategy is tried on an arrangement of information assembled in the Warrigal venture, which gives genuine vehicle state data. Since the devoured vitality information are not accessible in this dataset, a point by point EV show is received to evaluate the vitality utilization. The obtained results verify the effectiveness of the proposed routing algorithm in locating the time and/or energy efficient routes. This method allows for prediction of energy consumption over any route in the road network prior to departure, and enables cost-optimization algorithms to calculate energy efficient routes. The data-driven approach has the advantage that the model can easily be updated over time with changing conditions.

KEYWORDS: Electric vehicle (EV), efficient routing, travel time, energy consumption, data mining, Particle Swarm Optimization, A star time Module.

I. INTRODUCTION

Most research on vehicle energy efficiency relies on predefined drive cycles as benchmark tests. Although this approach provides repeatable results and allows for easy comparisons, it ignores the relationships between the driver, the vehicle controller, and the environment. This paper illustrates an approach that links the mapping and navigation service ADAS RP and the advanced vehicle simulation tool Autonomie. The goal is to predict the amount of energy consumed on a user-specified route. An added benefit is that the approach creates an innovative framework for various research topics that rely on real-world trips: "green" routing, hybrid control optimization, fleet management, etc. Applications of the approach could be especially significant in the case of hybrid electric vehicles (HEVs). The added degree of freedom from a second source of power allows for greater flexibility in the design of the controller. For example, several studies show that the reduction in fuel consumption by HEVs can be higher on roads with slopes if future road information is made available to the controller. The main challenge in this study is to create a speed and grade profile for a trip when those data are limited. The challenge is very similar to the online future-trip prediction problem.

According to [1] this analysis, the problem at hand is formulated as an instantiation of the famous shortest path problem. Several efficient algorithms have been proposed for solving this problem; thus, the present paper does not envision to work on altering these algorithms. Instead, this paper's contribution is about a new approach in estimating the energy consumption costs that are associated with the road segments of a route under investigation. The proposed approach intends to take into account all factors that affect the energy cost associated with a road segment, by integrating the influence of both expected and unexpected factors. By being able to reliably predict the total energy costs of individual road segments, it is then possible to find the optimal route based on existing shortest path algorithms (e.g., Dijkstra, Bellman-Ford).

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The number of studies of energy-efficient routing of EVs remains minimal. Sachenbacher et al. [8] presented an A* search that considers regenerative energy and the battery parameters which yields a consistent heuristic function of complexity problem. Furthermore, the authors developed the routing algorithm claiming that it expands each node once at most. The presented algorithm adjusted for the battery limits by modifying the weight function that the authors presented, where the weight function is generated by the potential energy and the vehicle propulsion energy loss. On the other hand, this paper did not consider traffic cost, time delay in longer paths, and it assumed that the map is a perfect environment with the vehicle traveling from the source to the destination with no interruptions. Finally, the implemented algorithm grows at a rate which can be computationally demanding on embedded computers especially with the huge number of route nodes that is usually made available to the drivers.
Artmeier et al. [1], [9] studied energy-efficient routing for an EV from a graph theory context. They developed a generic shortest path algorithm to solve the problem. The authors analyzed the shortest path problem and adapted the method to fit the specific EV characteristics. Furthermore, they identified hard constraints which enforce that the battery cannot be discharged below its limits and soft constraints which enforce that the battery cannot store more energy than its maximum capacity. The developed algorithm had a worst case complexity of (n^3).
Sweda and Klabjan [10] studied the problem of finding the minimum cost path of an EV, when the EV has a target destination but not enough battery capacity or charge to get there. Two methods were studied, the backward recursion approach and the approximate dynamic programming algorithm. However, the authors in this paper did not consider the regenerative energy ability of the EV.
Salehinejad et al. [11] studied route selection using ACO and they also considered the availability of traffic information by using an online/offline mode. But the developed algorithm was implemented on a conventional fossil fuel vehicle.
Siddiqi et al. studied the route optimization problem for EV using PSO [12] but the authors did not consider regenerative braking, furthermore they also considered the total recharging time and cost. The work presented in this paper uses ACO and PSO. These meta heuristic optimization methods are applied to the EV example in order to find the most energy-efficient route between two points on a given predefined map.
In a previous work we applied the ACO on a simulated [13] and a real-world [14] scenario. In [15] we applied PSO on a simulated EV routing problem. The significance of this paper is to wrap up the work that was done earlier and at the same time tackle the EV routing problem from a different perspective. It also addresses the concerns and reasons of why traditional routing problems fail to produce good results.

II. LITERATURE SURVEY

Masikos, Michail, et al. [1], presented paper “Machine-learning methodology for energy efficient routing” describes, Eco-driving assistance systems encourage economical driving behaviour and support the driver in optimizing his/her driving style to achieve fuel economy and, consequently, emission reductions. Energy efficiency is also one of the most pertinent issues related to the autonomy of Fully Electric Vehicles (FEVs). This paper introduces a novel methodology for energy efficient routing, based on the realization of dependable energy consumption predictions for the various road segments constituting an actual or potential vehicle route, performed mainly by means of machine-learning (ML) functionality. This proposed innovative methodology, the functional architecture implementing it, as well as demonstrative experimental results are presented in this paper.

Abousleiman, Rami, and Osamah Rawashdeh [2], presented paper “Electric vehicle modelling and energy-efficient routing using particle swarm optimization” covers, Vehicle routing is traditionally based on Dijkstra or Dijkstra-like algorithms. These algorithms worked well for fossil fuel vehicles. The increase in pollution levels, government regulations, and pressure from environmental groups have caused an increase in electric vehicles (EVs) production and use. EVs are capable of regenerating energy which creates negative weights in search graphs that traditional algorithms are incapable of handling without some modifications. This study presents a model that characterizes the energy consumption of an electric vehicle. Most passive and active factors are presented and applied in the formulation. The presented model is verified against 306 kilometers of driven data and proved to have 1.3% absolute error difference between the real vehicle’s consumed energy versus the predicted energy consumption as generated by the model. The model is then used with a particle swarm optimization algorithm to solve the single constraint optimization problem of

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finding the most energy efficient route between 2 points on a map. Simulation and real-world test results demonstrate savings in the energy consumption of the electric vehicle. Results showed more than 9.2% reductions in the energy consumption of the electric vehicle when driven on the developed algorithms' suggested routes rather than the ones generated by Google Maps and MapQuest.

Abou sleiman, Rami, and Osamah Rawashdeh [3], presented paper "Energy-efficient routing for electric vehicles using metaheuristic optimization frameworks" describes, Electric vehicles are gaining an increased market share. People are becoming more acceptable of this new technology as it continues to gain momentum especially in the North American and European markets. The main reasons behind this trend are the growing concerns about the environment, energy dependency, and the unstable fuel prices. Traditional source-to-destination routing problems are designed for conventional fossil-fuel vehicles. These routing methods are based on Dijkstra or Dijkstra-like algorithms and they either optimize the traveled time or the traveled distance. These optimizers will most likely not yield an energy efficient route selection for an electric vehicle. Electric vehicles might regenerate energy causing negative edge costs that deem Dijkstra or Dijkstra-like algorithms not useful for this application (at least without some modifications). In this paper, we present examples of why traditional routing algorithms would not work for electric vehicles. A meta heuristic study of the energy-efficient routing problem is presented. Ant Colony Optimization and Particle Swarm Optimization are then used to solve the energy efficient routing problem for electric vehicles. The 2 meta heuristic methods are analyzed and studied; the results and performance of each are then compared and contrasted.

Storandt, Sabine [4], presented "Quick and energy-efficient routes: computing constrained shortest paths for electric vehicles" shows, In this paper we study multi-criteria routing problems related to Electric Vehicles (EVs). Because EVs still suffer from a rather small cruising range restricted by the battery's capacity, and loading stations are sparse and reloading is time intensive, previous work focused on computing the most energy-efficient routes efficiently. Unfortunately these approaches do not guarantee anything in terms of distance or travel time. But even a very eco-friendly driver might not be willing to accept a tour three times as long as the quickest one to save some energy. Therefore we present new types of queries considering energy-consumption and distance or travel time and reloading effort, e.g. computing the shortest or quickest path on which the EV does not run out of energy while requiring at most k recharging events (with k being an input parameter). The respective optimization problems are instances of the constrained shortest path problem, which is NP-hard. Nevertheless we will provide preprocessing techniques that allow for fast query answering even in large street graphs.

Zhang, Shuwei, Yugong Luo, and Keqiang Li [5], presented "Multi-objective route search for electric vehicles using ant colony optimization." Describes, In this paper, a temporal multi-objective ant colony optimization (ACO) algorithm is proposed to generate the routing plan for electric vehicles to fulfill the various requirements of drivers under a time-dependent stochastic traffic environment. The algorithm optimizes the route length, traveling time, energy, battery recycling lifetime and cabin temperature integrally, and meets constraints on arrival time and state of charge limitation. Simulation experiments are conducted and three different evaluation indexes are adopted. The performance of the algorithm is compared with two other multi-objective ACO methods. The proposed algorithm is proven to process higher convergence performance, and the solutions are also widely distributed, which suggests the effectiveness of this newly presented algorithm.

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III. SYSTEM ARCHITECTURE AND METHODOLOGY

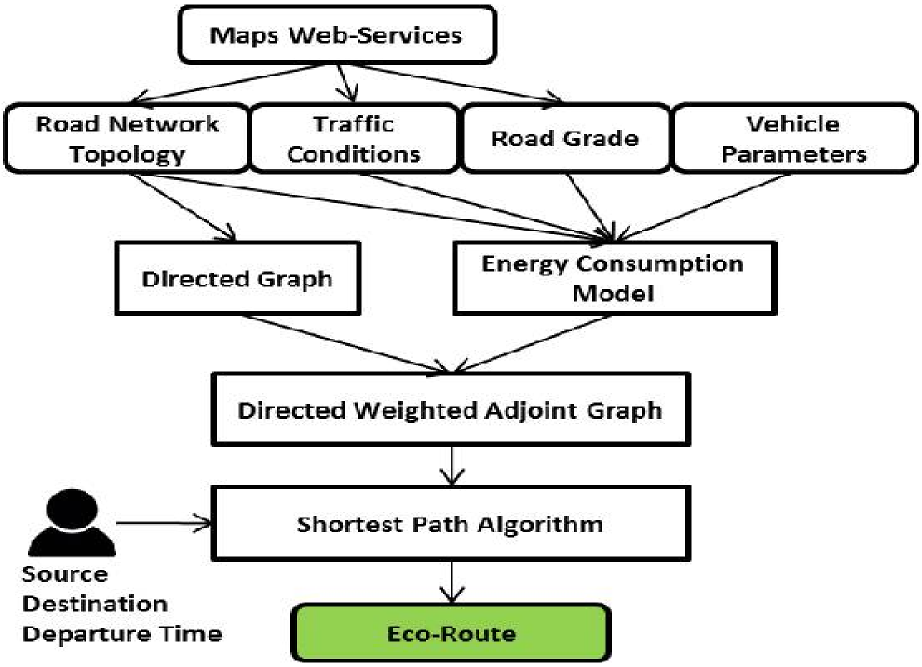

Figure 1: Proposed System Architecture

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The number of developed meta heuristic optimizations have grown. As of today there exist a vast number of meta heuristic algorithms most commonly, Particle Swarm Optimization, Genetic Algorithms, Simulated Annealing, Tabu Search, Harmony Search, Bee Algorithms, Ant Colony Optimization, Firefly Algorithms, and many more. The solution to a problem that is generated using a metaheuristic will be produced without any concerns about its optimality [17]. Most of the times, the complexity of the problem is too big, that it makes it impossible to search every possible solution. Thus meta heuristic methods trade-off concerns such as precision, quality, and accuracy in favor of computational effort (space and time efficiency).

A. Ant Colony Optimization

ACO is a branch of swarm intelligence that is constituted of meta heuristic optimizations which is generally used to find solutions to hard combinatorial optimization problems. ACO as first introduced by Marco Dorigo in his PhD thesis in 1992 [19]. ACO is inspired by ants and their foraging behavior [20]. Ants deposit chemicals on the ground called pheromones; these chemical traces are then used by the entire ant colony members to help navigate either towards their nest or towards a food source. Ants' navigational behavior is based on autocatalysis, this behavior helps the ants to find the shortest path between a food source and their nest [21]. Deneu bourg et al. investigated the ant's behavior [22] and their work was the benchmark for the different ACO algorithms that were proposed in the early 1990's. Deneubourg's experiment, also known as the "double bridge," features a nest of Argentine ants that were put by the edge of 2 different bridges. Each ant has the option of selecting either one of the bridges' side.

B. Particle Swarm Optimization

Particle swarm optimization is a branch of swarm intelligence, it is a population-based stochastic algorithm that is used to solve continuous non-linear optimization problems. It is an evolutionary computation technique that was developed by James Kennedy (a social psychologist) and Russell Eberhart (an electrical engineer) in 1995 [23]. This algorithm

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and as the name suggests was based on swarm particles and how these particles interact with each other. Humans, insects, birds, and fish have a defined social behavior that allows individuals to benefit from the findings of the group. Individuals learn from one another and use some stochastic behavior to ultimately benefit the whole group. PSO revolves around a very simple notion, it requires primitive mathematical operators, it is computationally inexpensive, it requires very few parameters to be adjusted, and finally it can be implemented with few lines of code. PSO can be used to solve many different kinds of problems. The original paper submission [23] included an example where PSO was used to train the weights of an artificial neural network. Kennedy and Eberhart's proposed algorithm relied on two elements: the nearest-neighbor velocity and a random factor they called "craziness". Each of the agents of the flock was randomly initialized with a position and with a velocity vector. In each loop each agent attempted to match the velocity of its nearest neighbor. To avoid unanimous and unchanging direction of the agents' behavior from occurring, the "craziness" factor was introduced. The result was a lifelike simulation of the agents representing the behavior of the bird flock. PSO is similar to a genetic algorithm (GA) in that the agents are initialized with some random "solutions" [24] but unlike a GA, solutions are never discarded as the survival of the fittest principle is not applied. The algorithm searches the solution space by adjusting the trajectories of the individual agents that form piecewise paths in a quasi-stochastic manner.

C. Time Mode A-Star Algorithm

The Time Mode A-Star Algorithm compute the optimal path in terms of travel-time cost. Working on stochastic networks with weights representing travel-time costs, the algorithm is modified to tackle the battery constraints. The focus in this algorithm is to compute the optimal path in terms of travel-time cost; however, the battery constraints must be satisfied along the path so that the driver is ensured not to be stranded. Therefore, a path with less travel-time cost cannot be used if it does not satisfy the battery constraints. Any path with an energy cost that is greater than the battery charge level is excluded from the search process by turning its travel-time cost into infinity.

IV. RESULT AND DISCUSSION

The 2 implemented algorithms were applied on a virtual map with 10 nodes and 13 routes. Both algorithms converged fast to the optimal solution as was shown in [13 - 15]. ACO algorithm was straightforward to implement as ants optimize for the shortest path in nature. A conversion between the shortest path to the energy optimized path had to be done. PSO on the other hand, had more modifications from the original formulation and was more tedious to formulate. Nevertheless, good results were achieved in both algorithms. PSO was able to solve for the solution in less than 400 milliseconds, while ACO took close to 1.8 seconds to analyze the same problem. This is in fact based on the simplicity of the PSO logic.

V. CONCLUSION

A calculation for EV effective directing that outcomes in either least vitality utilization or least travel time is proposed. The calculation utilizes information mining methods to acquire a proficient course in light of authentic driving information. It is presumed that the most limited time course isn't really the vitality proficient way and diverse factors, for example, roadway conditions and driving style have critical impact on the vitality utilization. Not at all like the current directing strategies in which the connection speed and incline are viewed as steady, a proficient speed profile is considered in the proposed steering calculation. Another noteworthy preferred standpoint of the proposed strategy is that since roadway conditions and activity level are inalienably installed in the verifiable driving information, the got comes about because of the proposed calculation mirror those conditions. Moreover, by constant chronicle of exceptional information, the latest changes in the driving conditions, for example, speed breaking points or movement level, will be naturally reflected in the accumulated information and there will be no compelling reason to refresh those conditions in the directing calculation.

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VI. FUTURE WORK

Some key improvements to this method will be made in the future. More road information will be factored in the computation of the speed target (e.g., slower speed targets when a turning manoeuvre is identified). Another major improvement will be the introduction of more variance to currently constant speed sections, in order to more accurately mimic stop-and-go traffic, natural speed oscillations, obstacles, etc. We will also emphasize validating the modeled speed profiles with real-world driving data

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