Physics-guided Energy-efficient Path Selection: A Summary of Results

What is the problem? (Problem Statement)

The problem is mentioned in the title of the paper, and then explicated in the abstract. Namely, the paper addresses the Energy-efficient Path Selection (EPS) problem. This is described as finding the route between two points which uses the least amount of energy, which may be different from the shortest or fastest route. In the introduction, the authors categorize the EPS problem as a variant of the Shortest Path Selection (SPS) problem, which has a body of research literature that is detailed in the Related Works section, but which has largely ignored the energy-efficiency metric due to challenges that will be described later. The authors also decompose the EPS problem into two subtasks. The first is that of estimating total energy consumption according to vehicle properties and a path along which the vehicle can travel. The second is that of selecting the most energy-efficient path, which inherits many of its own problems from the SPS research lineage, such as choosing between edge-centric or path-centric models for estimating path cost.

Why is it important? (Problem Significance)

The importance of this problem is introduced almost immediately, in the second sentence of the abstract. Namely, world energy consumption is growing and there is increasingly urgent demand for reducing energy consumption of road transportation. The authors go into more detail in the introduction, citing current cost of transportation in the United States due to energy consumption, air pollution, and greenhouse gas emissions as reasons for government focus on reducing energy consumption. They also note that efforts so far have been subpar, and that consumption is expected to rise by 28% between 2015 and 2040.

In addition to signifying the societal impact of transportation energy costs, the authors motivate their research by claiming that path selection research up until this point has neglected energy consumption as a metric, relying on the faulty assumption that shortest paths suffice as proxies for efficient paths. This is noted in the abstract, and reiterated in the introduction, which adds that vehicle parameters such as weight are important considerations in that they determine energy consumption along any given path.

Why is it challenging?

The authors clearly note the challenges of Energy-efficient Path Selection in the abstract, saying that vehicle properties such as drivetrain efficiency on certain stretches of road (for example, regenerative braking) can result in negative road segment weights, which cause Dijkstra’s algorithm and other “greedy” classical path selection algorithms break down.

In the introduction, the authors also add that while most path selection algorithms rely on averages or distribution statistics of historical data, differences in vehicle properties make these aggregations erroneous. They propose that trajectory data should be better integrated into the selection method, which requires large historical datasets of many trip trajectories from many different vehicles. Accessing such large datasets was once challenging but has become easier.

The authors describe a more general challenge in the problem definition, stating that many factors from vehicle parameters to traffic accidents have the potential to affect energy consumption. A completely
accurate solution (one that always finds the most efficient path) is out of scope, but this work produces solutions which are not energy-inefficient.

What are the limitations of the related work? What is the novelty? (Limitations of Related Work)

As noted above, related work has focused primarily on shortest-path selection without regard to energy consumption as a cost metric. This paper is novel in that it does address the EPS problem and does so by integrating vehicle parameters such as weight, drivetrain efficiency, and front surface area into the calculation for cost, alongside vehicle motion properties such as velocity and acceleration.

In addition, what limited research into EPS that has been done has focused on edge-centric energy consumption models. Edge-centric methods lose information about the dependence between adjacent road segments, which is important when considering energy usage. For example, a vehicle’s trajectory with a left turn will have a higher energy cost after the turn due to acceleration after the stop. Decomposition of cost by edge (i.e. road segment) will be ignorant of the reason behind the extra cost on this segment, whereas a path-centric method preserves such information and results in a more accurate cost assessment for similar future trajectories. Therefore, the novelty of this approach is a path-centric method for the EPS problem.

What are the contribution methods? (Contributions, key concepts)

Two contributions of the paper are mentioned in the abstract, and they are listed in greater detail alongside a third in the introduction. First among these contributions is a path-based model for estimating energy consumption, called a Physics-guided Energy Consumption (PEC) model. The model is decomposed into a scenario-based model for calculating the cost of a “trajectory-aware path” (TAP), and a union model for joining many TAPs into a “trajectory-union path” (TUP). Furthermore, the scenario-based model involves calculating two scenario components (air resistance and vehicle motion on a road segment) and one scenario-independent scalar value known as the vehicle parameter factor. The union model prefers to join TAPs on many shared segments, in order to preserve as much dependence information.

The second of the contributions is an algorithm based on the PEC estimate which selects the most energy-efficient path. This algorithm consists of a method to extend candidate paths which is trajectory-aware, a method for estimating the cost of the extension, and a strategy for stopping early if a more efficient negative-weight path is discovered. The third contribution is a case-study which compared estimated energy costs of a route suggested by the proposed method and a route suggested by Google Maps.

What is the validation methodology? (Validation Methodology)

In validating their contributions, the authors use many different methods. Most notably, they rely on mathematical proofs for their PEC model. The model is based on a simplified powertrain energy consumption model introduced by Cappielo et. al. in 2002. They decompose this equation into the air resistance, vehicle motion, and vehicle parameter components described in the previous section. They develop equations to estimate vehicle motion and air resistance using just energy cost differences within a scenario and use these equations to propose update and assignment steps of a k-means algorithm to cluster trajectories along similar scenarios. Thus, this model leans heavily on the known validity of the k-means algorithm.
For the union model and the proposed algorithm for selecting the most energy-efficient path, the authors rely on a few lemmas and provide formal proofs to support them. These are used to show that paths can be decomposed and recomposed into and from overlapping TAPs so long as there are enough trajectories supporting the overlap across different scenarios. Equations are given to calculate the energy cost of a vehicle type along an entire path as derived from unions of TAPs.

For validating the path-selection algorithm, the authors provide pseudocode, which serves as a type of proof itself. A general path-selection framework is described, and then a novel path extension algorithm using the concepts and equations from the PEC model is described. The early-stop strategy is not given pseudocode, but its process is described in the text.

Experimental validation of the PEC model is performed by comparing energy cost estimation error produced by the PEC model against that found by a mean trajectory cost method and that found using a histogram of trajectory costs. The PEC-based path selection algorithm was evaluated by calculating PEC cost estimates for real trajectories, PEC-model based algorithmic suggestions, and open-source fastest-path selection algorithmic suggestions. Finally, a case study was presented which compared estimated energy costs of a route suggested by the proposed method and a route suggested by Google Maps.

Assumptions

This paper makes assumptions that can broadly be calculated into those that limit scope and those implicit within the methodology. As it relates to the scope of the paper, the authors focus on road transportation and so direct attention toward cars and trucks, and do not address energy efficiency issues in trains, planes, and ships, which may make up a significant portion of the rise of transportation energy costs in the next 20 years.

As it relates to their chosen methodology, the proposed method is limited by the availability of historical trajectory data, and this is noted by the authors as a point of improvement at the end of the paper. They did not address estimating energy cost along paths for which there are few or no trajectories available. In addition, the authors consider a limited number of effects on energy-efficiency. Since they lump all historical trajectory data together when estimating cost path, the model is insensitive to temporal changes in traffic patterns or in road infrastructure (e.g. construction). These effects could make the suggested paths less energy efficient, especially if the model is not updated with new trajectory data over time.

Finally, the authors use a k-means algorithm to cluster vehicles by scenario without a discussion on this choice or an analysis of clustering results. Although efficient, k-means is known to produce “globular” clusters which may not be accurate if data is not well-separated, as likely applies to vehicle parameters. K-means produces cluster classification without confidence values, and so we are unable to know the statistical significance of clusters without external validation. The authors do address k-means’ sensitivity to initial centroid choice and number of clusters.

If you were redoing it, what would you change? (Revisions)

Although this paper was published in 2018, availability of data is increasing rapidly, and we see the estimation of temporal changes in energy cost as a good place for improvement of the original paper. This revision might include creating a set of scenarios for certain times of day (i.e. “rush hour”) or by modifying the algorithm to operate on a spatiotemporal graph. As the authors note, improvements to
estimate energy cost in the absence of trajectory data are also possible, perhaps by identifying road segments with similar properties and generalizing their trajectory records.

In addition, analysis of the clustering effectiveness could be a valuable service. This could mean comparing k-means with other clustering methods such as the density-based method DBSCAN or with “soft k-means” to evaluate cluster significance. Revising this section would require careful thought about the appropriate dimensions to cluster on in order to accurately separate trajectories according to vehicle scenarios.