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Delivery Route Based ERS Network Optimization

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Summary

The provision of decision support for- and knowledge about which parts of the road network to electrify to maximize the network's charging utility (in terms of transport efficiency, environmental impact and logistics operations) ***given*** the present and future (real or simulated) freight routes is crucial in successful large scale ERS implementations. Charging utility of segments in a network are not independent of one another but largely depend on which part of the routes include the segments. Therefore, advanced route analytics, combinatorial network optimizations and macro- and micro simulations of transport and logistics are proposed to find an optimal ERS network.

1 Introduction and Research Questions

There are many aspects to consider for ERS network infrastructure development. Some of the most important aspects include: technologies, trends, and interaction between vehicles, powertrain, and infrastructure [1, 8, 7]; current and future transport demand [1, 2, 7]; energy systems and production [5, 9-11]; logistics operations [6], environmental impacts and business models and policies [4, 14].

ERS network infrastructure development is costly. Current cost range between 1km electric road 400 to 800 thousand Euros. Selecting the "right" segments to electrify is important. Current methods try to optimize the ERS network infrastructure based on the amount of tours / routes that include a road segment / link [7] based on *select link analysis* which, based on network assignment models / assumptions, provides information of where traffic comes from and goes to at selected links, i.e., it provides the spatial distribution and origin–destination (O-D) pair composition of aggregate link flows [2].

In comparison, the present paper argues that it is not enough to know the delivery route / tour based aggregate link flows [7] or the spatial distribution of O-D pairs that give rise to the aggregate links flows [2] and that it is essential to know *how* traffic comes from and goes to selected links, i.e., one must consider the exact spatial descriptions of and topological relations between delivery routes / tours. Furthermore, the paper argues that *charging utility of segments / links in a network are not independent of one another but largely depend on which part of the routes include the segments*.

The corresponding research questions are as follows:

- How to estimate the utility of a segment in a partially electrified ERS network for routes of various vehicles having various powertrains and carrying various loads?
- How to find a partial ERS network that maximizes the utility for a given ERS infrastructure investment budget?
- What is the impact of the partial ERS on transport efficiency, environment and logistics?

Consequently, the aim of the outlined research is to develop decision support for- and knowledge about which parts of the road network to electrify to maximize the network's charging utility (in terms of transport efficiency, environmental impact and logistics operations) ***given*** the present and future (real or simulated) freight routes. This paper proposes the use of advanced route analytics, combinatorial network optimizations and macro- and micro simulations of transport and logistics to achieve this aim.

2 Methodology

2.1 Motivation and challenge for route based ERS charging utility estimation

The charging utility $u(s)$ of a ERS segment s depends on a number of things. Specifically, $u(s)$ depends on:

- the charging and discharging (energy use) characteristics of Vehicle-Load-Powertrain (VLP) and ERS technology configurations,
- the number and duration of traversals of VLP configurations on s,
- the battery state of the VLP configurations that reach and leave s,
- the length and spatial distribution of the routes of VLP configurations that reach, leave, or pass through s, and finally
- the spatial and topological relationships between s and other ERS segments in an ERS network.

Some of these dependencies are illustrated in a simplified situation in Figure 1. Figure 1(a) shows a number of VLP configurations or VLPs for short (illustrated by the line width) that reach the segment in the center via different routes. As the battery states of the VLPs after traversing the center segment is zero percent (illustrated by the black line) the VLPs either have to complete their remaining routes off-battery via an alternative energy / fuel source or have to stop and charge. In Figure 1(b), segment s is electrified which allows the VLPs to be charged during the traversal of s and allows the VLPs to complete a larger fraction of their routes using Battery Electric (BE) operation. For simplicity, the new segments traversals that the VLPs can complete on BE operation can be called the *charging utility* of segment s. In Figure 1(c), in addition to s, s1 and s2 are also electrified. Because of the topological relationship between the routes and the electrified segments, due to the electrification of s_1, the VLPs entering approaching from the south east can be charged on both s_1 and s and continue their routes north east. Note that the electrification of s_1 has increased the charging utility of s and s could charge additional VLPs. The electrification on s_2 also affects the charging utility of s or vice versa as VLPs could can complete a larger fraction of their routes using BE operation. Note however, that due to the maximum battery capacity constraints the charging utility of segments are also constrained, specifically the batteries of VLPs traversing both s and s_2 could not be charged to 120% capacity. Collectively, Figure 1 illustrates that charging utility of segments in an ERS network are not independent of one another, but largely depend on which part of the routes include the electrified segments.

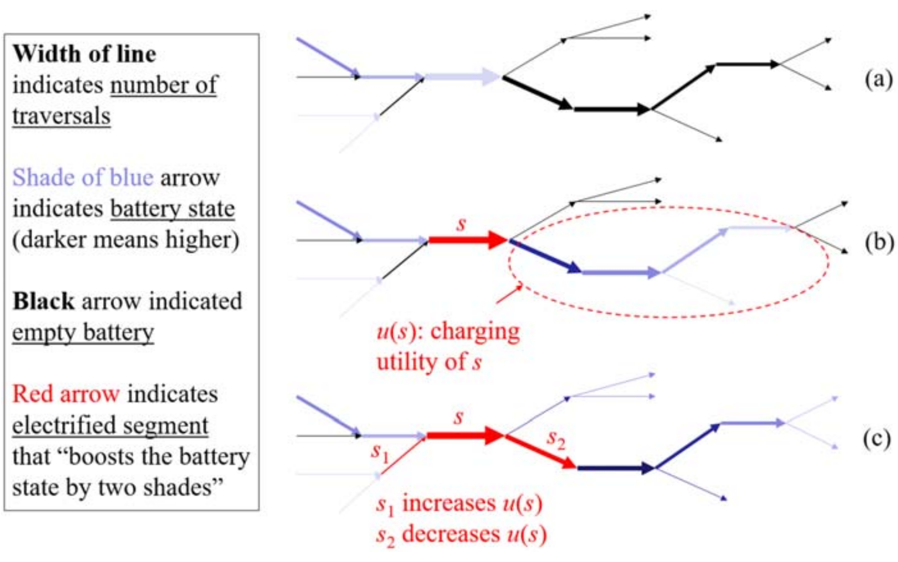

Figure 1: Illustration of concept of route based charging utility of segments.

Route based charging utility estimation and subsequent combinatorial ERS network optimizations are challenging for at least the following four reasons.

- **Big Data**: The 200 thousand trucks in Sweden, for a location sampling frequency of every 1-60 seconds, produce 12 million – 0.72 billion (150MB – 10GB) measurements per operating hour.
- **Exponential number of routes**: Theoretically there are at least $2*N*2^m$ possible routes that are composed of *m* segments. Typically, a larger, real life transport network has 100K-10M routes.
- **Complex optimizations**: Routes are composed of sub-routes through which they form complex spatial / topological relationships. As the charging utility segments is not independent, combinatorial network optimizations become increasingly complex.
- **Lack of support for data processing**: Calculating route based utility requires data processing and queries that are not supported by current Big Data tools.

2.2 Estimation of route based charging utility of segments and ERS network optimization

As this paper report on work in progress, this section only briefly outlines a methodology for estimating route based charging utility of segments and finding and optimal partial ERS network that maximizes the charging utility for a given infrastructure investment budget (e.g., *N* number or km of electrified segments). Interested readers are referred to the cited publications.

1 Map match and interpolate raw trajectories to obtain routes as sequences of segments [12].
2 Insert all the routes in an FP-tree *T*, thereby essentially creating partitions for routes in branches of *T*, where the same routes fall in the same branch of *T*. Maintain the count and other relevant route statistics (e.g. load) at each node in *T*. Use the header table of *T* as a dictionary to look up all routes that pass through a given segment [13].
3 Using a vehicle energy consumption model *M* [11], for every top *K**N* frequent segment *s* estimate the total charging utility of *s* by identifying *s* in the routes in *T* and *applying M* to the parts of the routes that include *s* and that follow it.
4 Using the sum of charging utilities of the segments with the top *N* charging utility as an upper bound on the maximum charging utility achievable within the infrastructure budget *N*, apply a greedy, heuristic-based guided search algorithm like A* [3] to find the optimal partial ERS network that maximizes the charging utility for a given infrastructure investment budget.

2.3 System-level research methodology

The proposed methodology, as Figure 2 illustrates, can be incorporated in a larger optimization framework that also takes into consideration future transport demands as well as of changes of transport and logistics operations due to ERS implementation.

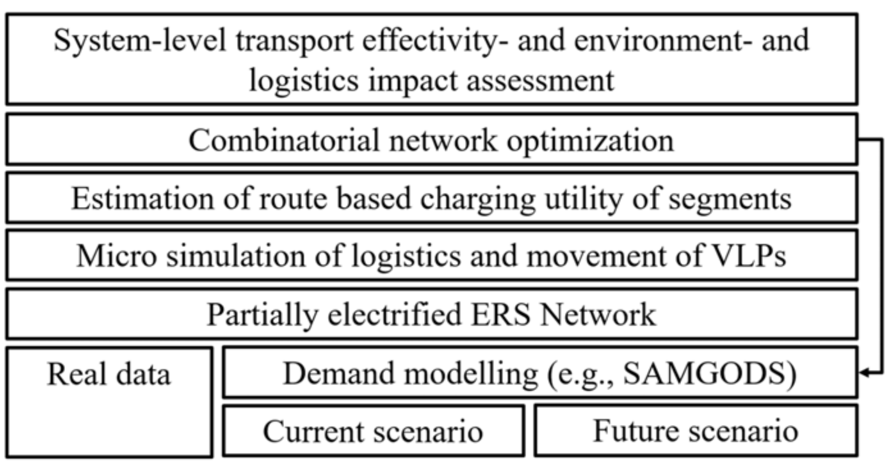

Figure 2: System-level ERS network optimization framework with dynamic feedback.

3 Preliminary Results

As evidence to justify the herein proposed route based ERS network optimization proposed, in the following preliminary results are presented to test the following hypothesis: *Route based charging utility is significantly different from segment based charging utility.*

To test the hypothesis, approximately 600 thousand, one-month worth of-, on average 5km long trip trajectories of 15000 taxis in Stockholm have been studied. First, the trajectories have been map matched [12] and interpolated using the road network of Stockholm, resulting in trajectory / route representations that consist on average a sequence of 30 road network segments. Then, for the 100 segments with the most number of routes that pass the given segment, the number of routes (referred to as *support* in Figure 3 (left)) and the frequency weighted average length of the routes (referred to as *average length* in Figure 3 (right)) that contain the given segment as the start and end of the route have been calculated. The variety of starting and ending route characteristics is apparent in Figure 3.

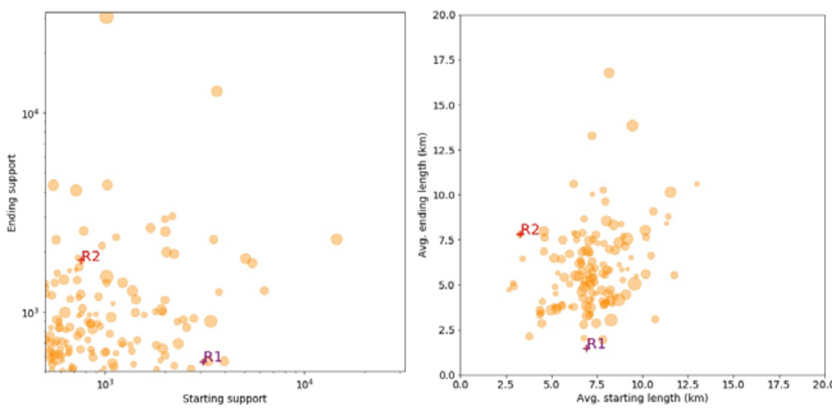

Figure 3: Variability of the number of routes (left) and the frequency weighted average length (right) of routes that start and end at top segments.

A map of the routes that start (green) and end (blue) at segments R1 and R2 as shown in Figure 4. While R1 and R2 are roughly equally frequent in routes and therefore could be falsely assumed to have similar charging utilities, the green routes reveal that the *individual* charging utility of R1 is potentially larger than that of R2.

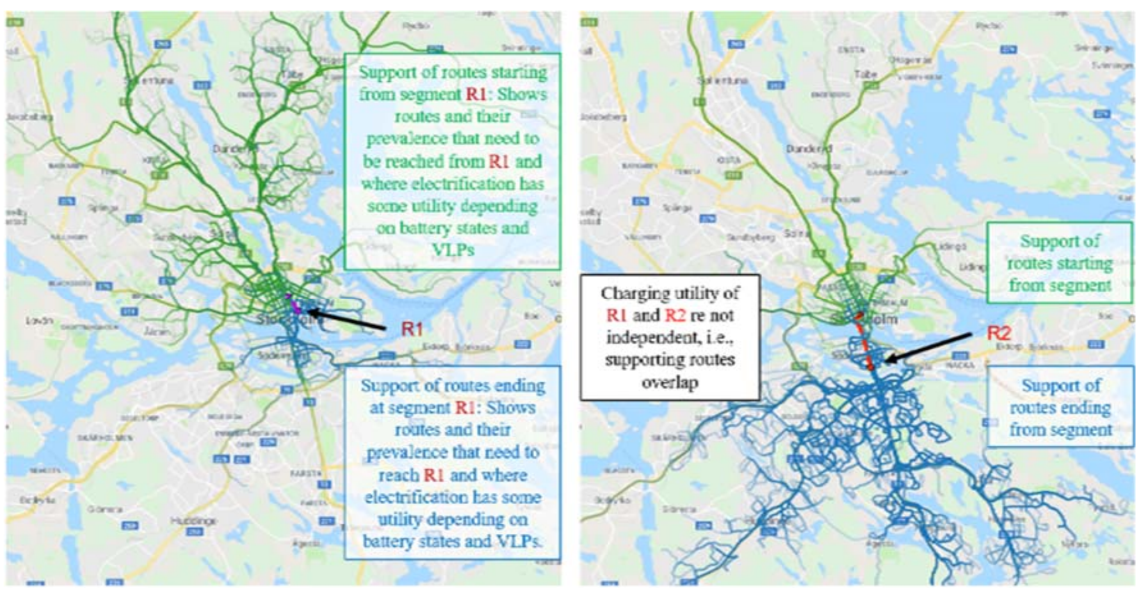

Figure 4: Largely differing spatial characteristics and prevalence of routes that start (green) and end (blue) at segments R1 (left) and R2 (right) which are roughly equally frequent in routes.

Acknowledgments

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References

[1] R. Balieu, F. Chen and N Kringos. *Infrastructural aspect of electrified road systems: Long-term performance prediction by Finite Elements integrated into a Life Cycle Assessment.* 2nd Electric Road Systems Conference, 2018.

[2] T. Bernecker, J. Boysen, M. Schubert and G. Nebauer. *Development of a core network for the use of overhead line heavy duty vehicles on the German motorway network.* 2nd Electric Road Systems Conference, 2018.

[3] 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 SSC4, 4(2):100–107, 1968. (A*)

[4] B. Hasselgren. *Industrial dynamics and path dependency – the case of implementing ERR-systems in Sweden.* 2nd Electric Road Systems Conference, 2018.

[5] D. Jelica, M. Taljegard, L. Thorson and F. Johnsson. *What is the hourly electricity demand when implementing ERS?* 2nd Electric Road Systems Conference, 2018.

[6] J. Jöhrens, J. Rücker and H. Helms. *Logistical Constraints on Commercial Applications for ERS*. 2nd Electric Road Systems Conference, 2018.

[7] J. Jöhrens, J. Rücker, H. Helms and V. Waßmuth. *Identification of economically viable ERS routes in Germany*. 2nd Electric Road Systems Conference, 2018.

[8] S. Kühnel and F. Hacker. *Benefits and system design of ERS in the context of falling battery costs*. 2nd Electric Road Systems Conference, 2018.

[9] A. Malmquist and J.A.A Ramos. *Energy system model for electric roads.* 2nd Electric Road Systems Conference, 2018.

[10] M. Taljegard, L. Göransson, M. Odenberger and F. Johnsson. *Impact of electric road systems on the Swedish-German electricity mix*. 2nd Electric Road Systems Conference, 2018.

[11] M. Taljegard, L. Göransson, M. Odenberger and F. Johnsson. *Spacial and dynamic energy demand of the E39 highway – Implications on electrification options*. Applied Energy 195:681-692, 2017.

[12] C. Yang and G. Gidofalvi. *Fast map matching, an algorithm integrating hidden Markov model with precomputation.* International Journal of Geographical Information Science, 31(3):547-579, 2017.

[13] C. Yang and G. Gidofalvi. *Mining and visual exploration of closed contiguous sequential patterns in trajectories.* International Journal of Geographical Information Science, 24p., 2017.

[14] Q. Wang and D. Berlin. *Stakeholder Assessment Tool from the ERS Engineering Toolbox; The Case of eRoadArlanda.* 2nd Electric Road Systems Conference, 2018.

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