Efficient growth strategies for bicycle network expansions

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SHORT SUMMARY

It is common practice to investigate the societal welfare performance of infrastructure projects through cost-benefit analysis. In this paper, we introduce a novel reverse geographical mapping approach where the monetary benefits are mapped back to the network. The mapping allows a more detailed geographical planning breakdown and makes it possible to apply a more stringent optimisation approach regarding the timing and prioritising of network expansions. Based on a Greedy-type optimisation heuristic we consider the case of growing a bicycle network in the Copenhagen region over a time horizon of 50 years. Although only considering travel time benefits in this study, the optimisation heuristic renders a net present value that is approximately 2 Billion DKK higher than other strategies, underlining the importance of efficient growth of networks.

Keywords: Bicycle infrastructure, cycle superhighways, geographical mapping of benefit-cost, infrastructure investment prioritisation.

1. INTRODUCTION

When investigating the performance of infrastructure investments it is common to apply cost-benefit analysis. Such analysis require that the project benefits are monetised and compared to investments and maintenance costs by expressing the different components, e.g. in net-present-value (NPV) terms. The common cost-benefit appraisal is based on bottom-up calculations from detailed route and zone-based data and consider overall project performance through such measures. However, during the bottom-up process much information is lost concerning the geographical distribution of benefits. Another related problem is that most cost-benefit applications typically apply a comparative static perspective by comparing a full scenario with a baseline in a given future year. The static perspective generally implies that everything is installed at the same time, which rule out the possibility of optimising the infrastructure according to the timing of different stages that naturally constitute large-scale investments.

While the common cost-benefit apparatus may work well for detailed and specific projects, it is a problem when considering large and generic infrastructure development plans where implementation is expected to take place over many years and constitute a bundle of separated smaller investments. In these cases it is valuable to be able to map the geographical distribution of benefits and the timing of such investments in order to pinpoint specific important corridors and thereby be able to indicate a priority of investments.

Motivated by this challenge, this study introduces a novel reverse geographical mapping where the monetary cost-benefits are transferred back to the network. This in turn allows us to track benefits at a detailed temporal and geographical level, which can be combined with dynamic optimisation schemes to optimize project performance across these detailed dimensions. In the paper we develop such optimisation heuristic, and apply the methodology to dynamically expand an entire network of cycle superhighways in the Greater Copenhagen region.

The relationship between bicycle infrastructure and bicycle use is well documented. The impact of bicycle infrastructure with respect to bicycle demand has been studied by Krizek, Barnes & Thompson (2009); Van Goeverden & Godefrooij (2011); van Goeverden et al. (2015); Zahabi et al. (2016). Increased demand often result from a mixture of elements from increased speed (Schleinitz et al., 2017; Eriksson et al., 2019) to improved traffic safety and better cycling environments, some of which have also been found important in the route choice cycling literature (Stinson & Bhat, 2003; Hunt & Abraham, 2007; Sener, Eluru & Bhat, 2009; Standen et al., 2017; Pritchard, 2018).

Only few studies examine the combined benefit-cost performance of bike infrastructure. In Denmark, the only recent relevant study is by Hallberg, Rasmussen & Rich (2021); Rich et al. (2021) who examined the cost-benefit of a large-scale cycle superhighway infrastructure. A previous more limited study on the same network is due to Incentive (2018). In all three cases, a static comparative evaluation approach was used.

Some existing studies (Guillermo et al., 2020; Schläpfer et al., 2021) deal with how to expand networks optimally based on network specific characteristics such as connectedness and directness. Specifically, they develop different Greedy algorithms to increase the network connectedness and consider how the developed network compares to the real network of different cities. While this analysis is indeed useful, it is based on a pure graph theoretical approach and does – as opposed to the methodology proposed in this paper – not consider the people that are affected nor the benefits it may result in.

2. METHODOLOGY

Consider a set of zones Ω, a set of potential segments to invest in $\mathscr{M}$, and (fixed) type specific OD-demands $x_0(i,j,t)$ for zones $i,j \in \Omega$ and types $t \in T$. Here t represents a combination of different bicycle technologies (conventional bike, e-bike, speed pedelec) and speed preferences (slow, medium, fast) as described in Hallberg, Rasmussen & Rich (2021). Additionally, let $\mathbf{v}$ be the set of road segments that has already been selected at any given point.

The aim is to expand $\mathbf{v}$ under some budget constraint in a way that maximises the total consumer surplus (see Section 2.1). This represents a dynamic optimisation problem of great complexity due to internal correlation between the different segments and non-linear demand. Therefore, instead of solving the exact problem, we establish a optimisation heuristic (Section 2.2) where network correlation is approximated from a full implementation of the network and applied under the assumption of Markov properties between investment stages.

Consumer surplus

For this study, the user benefit $UB(i,j,t)$ is calculated as the change in consumer surplus $\Delta CS(i,j,t)$ for trips between origin i and destination j by travellers of type t. By denoting the shortest path between zones i and j for type t in the full scenario (with all segments implemented) by $q_1(i,j,t)$, the formal definition is,

$$UB(i,j,t) = \Delta CS(i,j,t) = x_0(i,j,t)\left(p_0(i,j,t) - p_1(i,j,t)\right). \tag{1}$$

In Eq. (1) p_0 represents the cost matrix in the baseline scenario, while p_1 represents the cost matrix for the project scenario (full implementation). These cost matrices are based directly on the travel times of the individual links constituting the shortest path for a scenario s,

$$p_s(i,j,t) = VoT \sum_{l \in q_s(i,j,t)} \tau_{lt}, \qquad s \in \{0,1\}. \tag{2}$$

Here $q_s(i,j,t)$ is the set of links constituting the shortest path between zones i and j for type t for a given scenario s. The travel time of link l for type t denoted by τ_{lt}, involves the direct travel time (dependent on type t) as well as waiting time at intersections (independent on t), see Hallberg, Rasmussen & Rich (2021). The value-of-time that transforms the travel time into monetary units is $VoT = 91$ DKK per cycled hour.

Optimisation heuristic

The proposed heuristic relies on the consumer surplus, which are used to form a benefit matrix denoted by $\mathbf{B}$, see Eq. (3). It is constructed by assigning all entries of the consumer surplus matrix $\Delta CS(i,j,t), \forall (i,j,t) \in \Omega \times \Omega \times \mathscr{T}$, onto the segments that appear in the corresponding shortest path $q_1(i,j,t)$. The entries of the benefit matrix, b_{mn}, then contains the benefit of segment m that is also found in segment n, but subject to disaggregate weightings where a segment n is given a weight proportional to the length of n appearing in $q_1(i,j,t)$, denoted by $L_n(i,j,t)$. Formally,

$$b_{mn} = \sum_{\substack{(i,j,t) \in \Omega \times \Omega \times T: \\ m,n \in q_1(i,j,t)}} \Delta CS(i,j,t) \cdot \frac{L_n(i,j,t)}{\sum_{k \in \mathscr{M}} \mathbf{1}[k \in q_1(i,j,t)] L_k(i,j,t)}, \qquad m,n \in \mathscr{M}, \tag{3}$$

where $\mathbf{1}[k \in q_1(i,j,t)]$ is an indicator function equal to 1 when k is included in $q_1(i,j,t)$, and zero otherwise. These elements are all based on benefits and shortest paths conditional on the entire set of segments $\mathscr{M}$ being implemented. For the optimisation heuristic it is useful to approximate the benefit conditioned on only implementing a single additional segment. To do so, for any $\mathbf{v}$, we define the corresponding potential matrix as the matrix $\mathbf{P}^{\mathbf{v}}$ with elements,

$$p^{\mathbf{v}}_{mn} = \begin{cases} 0, & n \in \mathbf{v} \vee b_{mn} \leq \max\limits_{\substack{k \in \mathscr{M}: \\ k \notin \mathbf{v} \wedge k \neq n}} b_{mk} \\ b_{mn} - \max\limits_{\substack{k \in \mathscr{M}: \\ k \notin \mathbf{v} \wedge k \neq n}} b_{mk}, & \text{otherwise.} \end{cases} \tag{4}$$

There is at most one non-zero element in each row, namely at the same location as the maximum value of b_{mn} across all n's that have not yet been implemented. Here the value is positive and equal to the maximal benefit involving segment m that can be guaranteed by implementing a single additional segment. The columns that corresponds to segments that are already implemented are all zero.

To determine which segment provides the largest benefit across all segments that has not been implemented yet, we also introduce the corresponding potential vector, $\boldsymbol{\pi}^{\mathbf{v}}$, which is formed as the column sums of the potential matrix,

$$\pi_n^{\mathbf{v}} = \sum_{m \in \mathscr{M}} p_{mn}^{\mathbf{v}}, \qquad n \in M. \tag{5}$$

The value $\pi_n^{\mathbf{v}}$ thus gives an estimate of the added benefit of additionally implementing n (and only n). In each iteration, the segment that provides the highest added benefit per cost (c_n, see Section 3.1) is selected. That is, for a given potential vector, $\boldsymbol{\pi}^{\mathbf{v}}$, the additional selected segment $n_{\mathbf{v}}^*$ is,

$$n^* = \arg\max_{n \in M} \frac{\pi_n}{c_n}. \tag{6}$$

Once $n_{\mathbf{v}}^*$ has been selected, $\mathbf{v}$ is updated, i.e. $\mathbf{v} \leftarrow \mathbf{v} \cup n_{\mathbf{v}}^*$, and this cause a corresponding change in the potential matrix and potential vector. This process is repeated until the budget of the specific investment stage is exceeded, or the expected benefit $\pi_{n_{\mathbf{v}}^*}$ no longer exceeds the cost $c_{n_{\mathbf{v}}^*}$ (*Greedy: Intelligent stop*), alternatively until all segments have been selected (*Greedy: No Stop*).

3. RESULTS AND DISCUSSION

Case study

Our case study of the cycle superhighway network of Greater Copenhagen consists of 193 potential network segments (Sekretariatet for Supercykelstier, 2019), and an evaluation period of 50 years divided into 25 equally sized investment stages, each with a budget of 100 million DKK. In the first year of each investment stage, network segments can be built, as long as the total cost for the segments does not exceed the budget. The costs of each segment (c_n) includes construction costs (minus the future scrap value) as well as maintenance cost for the remainder of the evaluation period. Investment and maintenance costs are based on Incentive (2018).

Assessment of seven different investment strategies

In the following we consider seven different investment strategies as described in Table 1.

Greedy	Using the proposed optimisation strategy without a stopping criterion.
Greedy with intelligent stop	Using the optimisation strategy from Section 2.4 as long as $\frac{\pi_{n^*}}{c_{n^*}} > 1$ in eq. (6).
Longer routes first	The longest remaining segment of the longest remaining bicycle route is selected.
Shorter routes first:	The shortest remaining segment of shortest remaining bicycle route is selected.
Longer segments first	The longest remaining segment is selected.
Shorter segments first	The shortest remaining segment is selected.
Random order	A random remaining segment is selected.

Table 1: The seven investment strategies analysed in the case study.

Figure 1 illustrates the net present value for every year over the evaluation period for all of the seven investment strategies. As can be seen from Figure 1, the order of the performance rank of the different strategies largely remains unchanged in the entire period. It means that irrespectively of

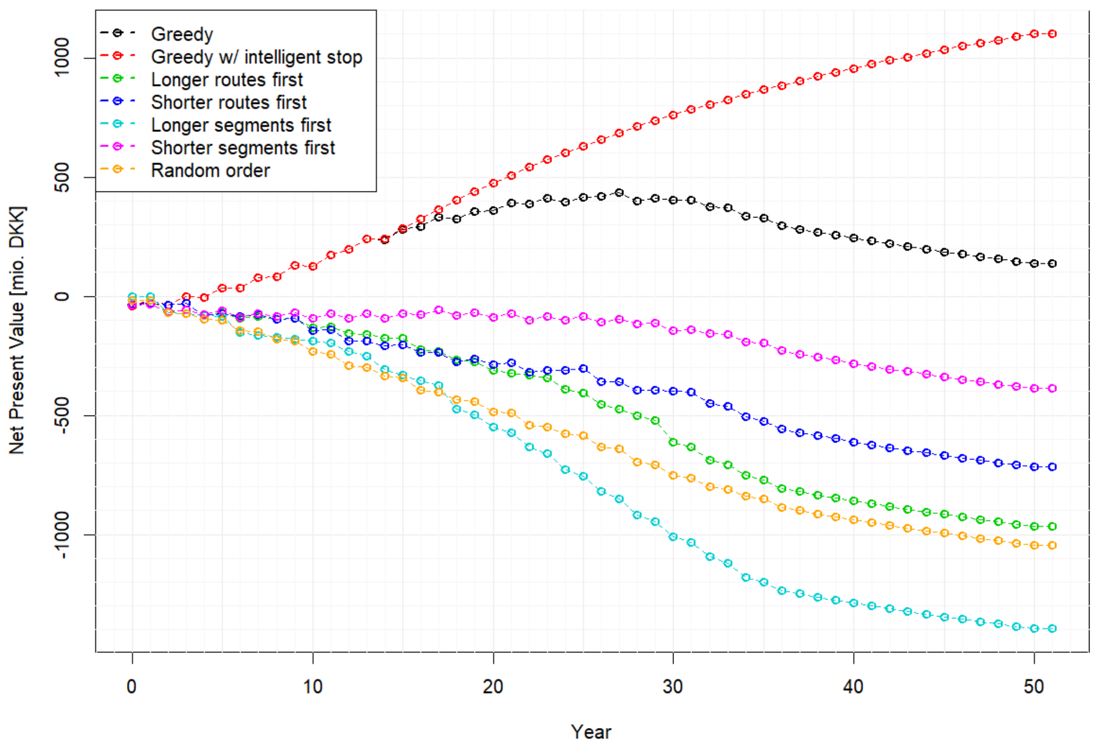
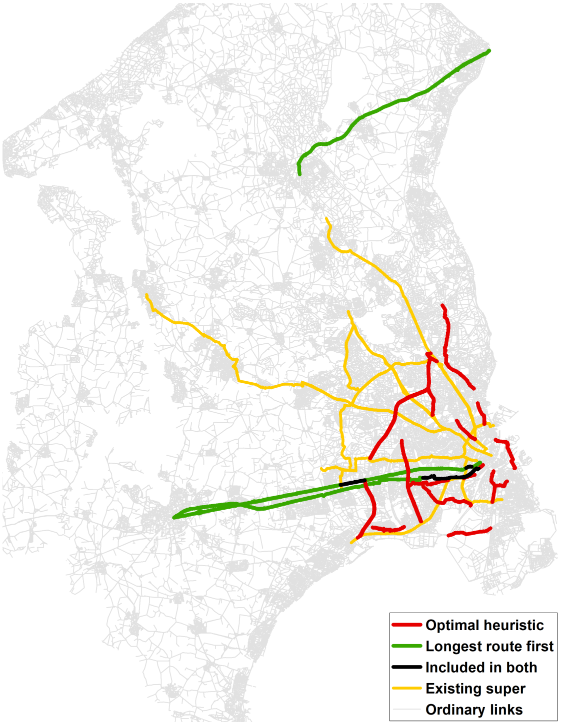


Figure 1: Net present value in every year of the evaluation period for each of the seven investment strategies

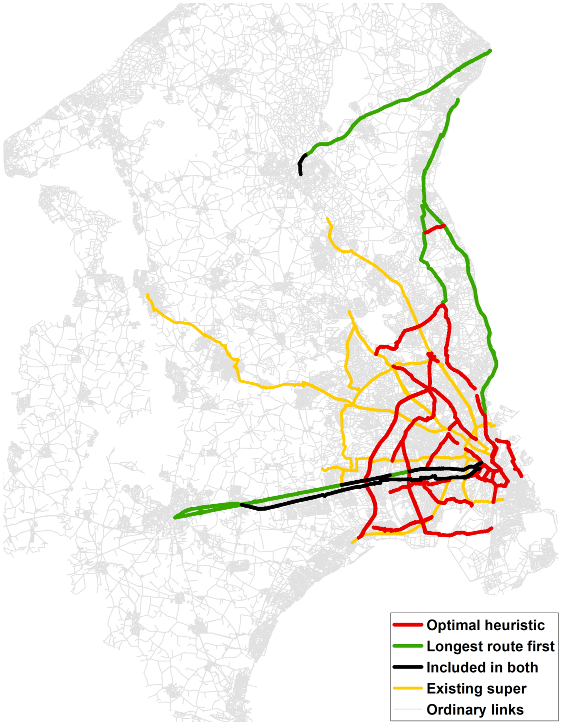
the historical investments up to a given year, for the investment strategy that follows in proceeding years, it is important to apply a model-based selection of investments. It is also clearly shown that the greedy algorithm, both with and without intelligent stop, outperforms the remaining five strategies

The suggested investment scheme for the two greedy algorithms are very similar until year 14, after which the strategy with the intelligent stop presents itself as the best strategy. The 'intelligent-stop' strategy prevent investments that are no longer beneficial after a certain point and 'harvest' from this point and out, the accumulated benefits from the first investments. The difference in net present value is almost one billion Danish kroner, indicating that a lot of the proposed network segments are not worthwhile building under the assumptions in this case study. However, it should be noticed that only direct network-related benefits are included in this study, why the total benefits are largely underestimated (Rich et al., 2021), meaning that many projects after year 14 are likely to be beneficial as well. Hence, the main take-away of the presented results is that we can expect a massive difference in the accumulated benefits depending on the investment strategy.

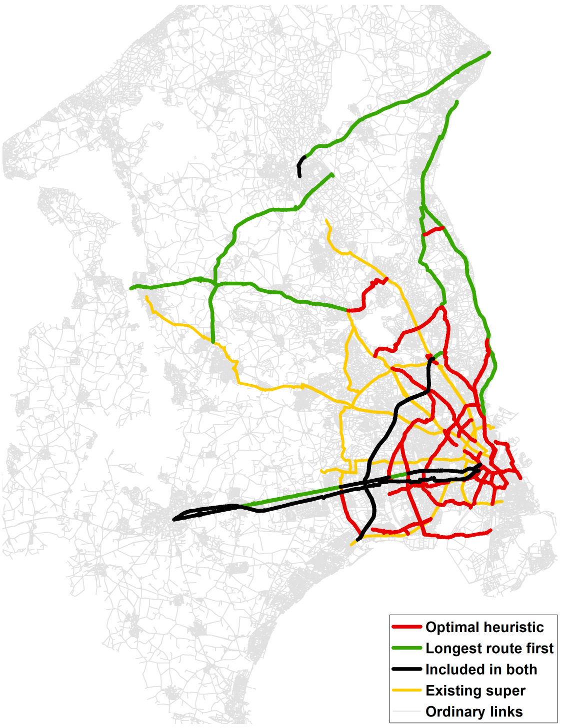
In Figure 2 we illustrate different investment stages geographically for two different investment strategies. Needless to say, from the perspective of the society, this information is vital as it suggest where to start the investments and equally important, where investments should be postponed. The suggested network extension in Figure 6 reveals several things. Firstly, it suggest that connectedness to the existing cycle superhighways is important. Secondly, it is also shown that investments in denser urban areas closer to the city centre, tend to be better investments compared to investments in rural areas or in less densely populated suburbs. This is not surprising and raises and important discussion concerning the regional and geographical distribution of investments.



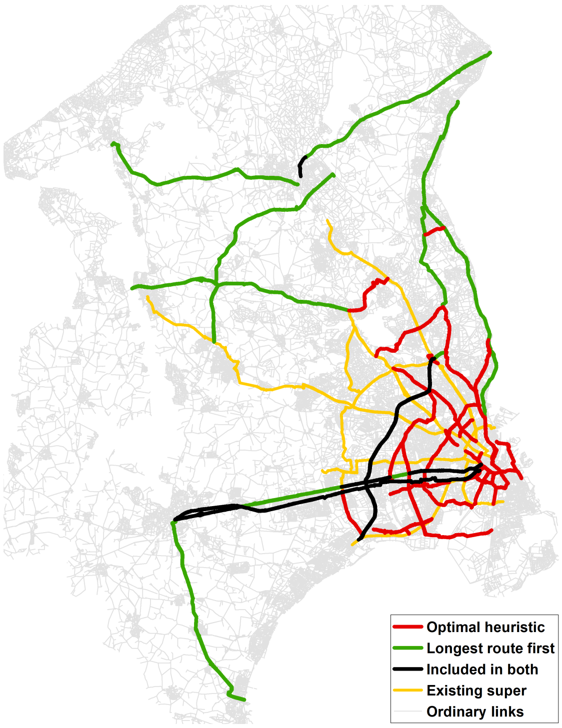
(a) Year 4, cumulative budget of 300 mill. DKK



(b) Year 10, cumulative budget of 600 mill. DKK



(c) Year 16, cumulative budget of 900 mill. DKK



(d) Year 22, cumulative budget of 1,200 mill. DKK

Figure 2: The extent of the super cycle highway network at the end of various years for the optimisation heuristic and implementation by longest route first, respectively

Table 2 presents selected key performance indicators for the different investment strategies. The 'Intelligent Stop' algorithm renders a lower investment as it stops investing when the investments are no longer beneficial for society. The resulting scrap value as well as the maintenance costs largely follows the amounts of investments, see Rich et al. (2021) for further details. Time benefits are all positive and reflect that whenever infrastructure is improved users are always better off. However, the results very clearly suggest that benefits are outweighed by costs for scenarios where

Table 2: Investment key-performance indicators represented in Mill. DKK.

	Greedy: No stop	Greedy: Intelligent stop	Longest route first	Shortest route first	Longest segment first	Shortest segment first	Random order
Construction costs	903.6	357.6	847.0	882.3	820.2	877.8	881.7
Scrap value	336.1	78.0	336.1	336.1	336.1	336.1	336.1
Maintenance costs	1,403.2	542.2	1,446.7	1,407.9	1,475.3	1,413.9	1,417.4
Time benefits	2,107.4	1,904.9	991.8	1,236.1	564.7	1,567.0	917.8
Net present value	136.8	1,101.1	-965.8	-718.1	-1,394.6	-388.5	-1,045.2

optimisation is not used. The effect of intelligent investments is very large, corresponding to a difference in net present value of up to more than 2 billion DKK.

4. CONCLUSIONS

In the paper we consider cycle investments in a dynamic perspective and develop methods to achieve an efficient allocation of investments geographically as well as temporally. We do this by considering the development of a large-scale network of cycle superhighways in Copenhagen over a period of 50 years. By bundling investment budgets every second years, we model which investments to consider for every two year period and where these investments should be located geographically. Hence, we answer the important question of 'where' and 'when' to invest and derived the accumulated societal benefits that result from the different investment strategies. We find that our proposed Greedy strategies are superior, yielding net present values that outperform the the other considered strategies by at least half a billion DKK in net present value.

In the paper we deliberately present an analysis where we focus on direct travel time savings that result from changes to the network. Hence, we restrict the analysis from other demand effects that could arise because of mode- and destination substitution or induced demand. However, the integration of such effects is an interesting future topic, particularly relevant as health benefits arising from increased bicycle use has previously been found to dominate socioeconomic benefits of large bicycle infrastructure investments (Rich et al., 2021). Hence, this study represents a natural lower bound for what can likely be achieved if all combined demand effects were integrated in the surplus calculation, underlining the importance of proper prioritisation even further.

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