A novel technology in freight transportation for improvement of the environmental impact

Politecnico di Bari

LIBERATORIA PER L'ARCHIVIAZIONE DELLA TESI DI DOTTORATO

Al Magnifico Rettore
del Politecnico di Bari

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iscritto al 3° anno di Corso di Dottorato di Ricerca in **Rischio, Sviluppo Ambientale, Territoriale ed Edilizio (DICATECH)** ciclo **33**
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Una tecnologia innovativa per il miglioramento dell'impatto ambientale per il trasporto merci

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Polytechnic University of Bari

02

Doctor of Philosophy in Risk and Environmental, Territorial and Building

2020

Coordinator:
Prof. Michele Mossa

XXXIII CYCLE
ICAR/05 – Transportation

DICATECh - Department of Civil, Environmental, Land, Building Engineering and Chemistry

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POLITECNICO DI BARI

02

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2020

Coordinatore:
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XXXIII CICLO
ICAR/05 – Trasporti

DICATECh
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Dedication

I dedicate this Phd thesis to my parents Rada and Radenko, sister Nevena, and aunt Nada for all of their love and support during all of my life.

Ову докторску дисертацију посвећујем родитељима Ради и Раденку, сестри Невени и тетки Нади за сву њихову љубав и подршку током целог мог живота.

Title: A novel technology in freight transportation for improvement of the environmental impact

EXTENDED ABSTRACT (Eng.)

New technological innovations of eco-friendly vehicles combined with the usage of renewable energy sources showed significant results in mitigating emissions. In this thesis, we consider the eHighway system, a recent technology based on electrified roads. It is designed to supply new hybrid trucks, i.e. electric overhead catenary (OC) trucks, which are connected to overhead power lines through a pantograph positioned at the top of the vehicle. The eHighway implementation can result in lower emission vehicles' rate since the vehicles are operating with electric mode. Therefore, in this thesis, we present a single-level multi-objective network design model and a bi-level multi-objective network design model considering a novel technology, the eHighway system. The proposed models investigate the opportunities of adopting eHighways and evaluating its environmental benefits considering limited budget resources for infrastructure electrification. Additionally, the models could be considered as useful tools for decision-makers in eHighway network planning and design.

For developing both models, a simulation model presented in the literature was used to calculate the number of traction substations needed for arc electrification according to hybrid trucks flows. As a first approach, in the case of the single-level multi-objective network design model, we propose a formulation including three objectives: minimisation of infrastructure and environmental costs, maximisation of average traffic density of OC hybrid trucks on electrified arcs. The Pareto optimisation approach is considered for a comprehensive analysis of all possible solutions according to different criteria weights. This model served as a basis to construct a bi-level multi-objective network design model that also considers the possibility of increasing the capacity of electrified arcs to improve overall network performances. Thus, in the case of the bi-level network design model we considered four objectives in the upper level related to the minimisation of the total Overhead Catenary (OC) hybrid trucks' travel time, infrastructure and environmental costs and maximisation of average traffic density of OC hybrid trucks on electrified arcs. The decision of the upper level depends on the output of the lower level which is formulated as a Stochastic Users Equilibrium traffic assignment based on a fixed-point problem. Moreover, the proposed bi-level network design model deals not only with finding the set of the arcs to be electrified but also with the capacity expansion of the electrified arcs for improving the performance of the overall system. Additionally, genetic algorithms were used as a solution approach, which demonstrated the effectiveness in finding the near-optimal results in a reasonable computation time. The proposed models have been tested on a medium-sized network and the Sioux-Falls network. In particular, we analysed the Pareto front obtained from the single-level model, where non-dominant solutions are identified according to the three considered criteria. Moreover, a sensitivity analysis is carried out for the bi-level problem in terms of criteria weights and the percentage of hybrid vehicles using the eHighway system. Numerical results quantified the environmental improvement we can obtain by using the eHighway system in both models, which can be a basis for making decisions regarding the adoption of this new technology.

key words

eHighway system, environmental impact, network design, Pareto optimisation, Genetic Algorithm, capacity expansion

Titolo: Una tecnologia innovativa per il miglioramento dell'impatto ambientale per il trasporto merci

EXTENDED ABSTRACT (ita)

Le nuove innovazioni tecnologiche riguardanti veicoli eco-compatibili combinate con l'utilizzo di fonti energetiche rinnovabili hanno mostrato risultati significativi nella mitigazione delle emissioni. In questa tesi, abbiamo considerato il sistema eHighway, una recente tecnologia basata su strade elettrificate (autostrade elettriche). Questo sistema è progettato per fornire energia elettrica a nuovi veicoli pesanti ibridi, ossia veicoli pesanti elettrici via catenaria (Overhead Catenary trucks), che sono collegati alle linee elettriche aeree attraverso un pantografo posizionato sulla parte superiore del veicolo. L'implementazione delle eHighway può portare ad una riduzione del tasso di emissioni dei veicoli, dato che i veicoli funzionano in modalità elettrica lungo le strade elettrificate. Pertanto, in questa tesi, viene proposto un modello multi-obiettivo di progettazione della rete a singolo livello e un modello multi-obiettivo di progettazione della rete bi-livello considerando questa nuova tecnologia. I modelli proposti indagano le opportunità di adottare le eHighways e valutarne i benefici ambientali considerando limitate risorse di budget per l'elettrificazione dell'infrastruttura. Inoltre, i modelli potrebbero essere considerati uno strumento utile per i decisori nella progettazione delle reti eHighway.

Per lo sviluppo di entrambi i modelli è stato utilizzato un modello di simulazione presente in letteratura per calcolare il numero di sottostazioni di trazione necessarie per l'elettrificazione di ciascun arco sulla base dei flussi di mezzi ibridi. Come primo approccio, nel caso del modello di progettazione della rete multi-obiettivo a singolo livello, viene proposta una formulazione che comprende tre obiettivi: minimizzazione dei costi infrastrutturali e ambientali, massimizzazione del flusso di traffico elettrificato. È stato utilizzato l'approccio di

ottimizzazione di Pareto per un'analisi completa di tutte le possibili soluzioni in base a diversi pesi associati ai criteri. Nel modello bi-livello abbiamo considerato quattro obiettivi nel livello superiore relativi alla minimizzazione del tempo di viaggio totale dei mezzi pesanti ibridi, dell'infrastruttura e dei costi ambientali e alla massimizzazione del numero totale di veicoli nella rete. La soluzione del livello superiore dipende dall'output del livello inferiore che è formulato come un problema di assegnazione del traffico SUE a punto fisso. Inoltre, il modello proposto di progettazione di rete bi-livello si occupa non solo di trovare l'insieme degli archi da elettrificare ma anche l’espansione della capacità degli archi elettrificati per migliorare le prestazioni del sistema complessivo. Inoltre, gli algoritmi genetici sono stato utilizzati come approccio risolutivo, che ha mostrato efficacia nell’individuare soluzioni quasi ottimali in tempi di calcolo ragionevoli. I modelli proposti sono stati testati su una rete di medie dimensioni e sulla rete di Sioux-Falls. In particolare, è stato analizzato il fronte di Pareto ottenuto dal modello a singolo livello, dove le soluzioni non dominanti sono state identificate secondo i tre criteri considerati. Inoltre, è stata effettuata un'analisi di sensitività per il problema bi-livello in termini di pesi dei criteri e di percentuale di veicoli ibridi che utilizzano il sistema eHighway. I risultati numerici hanno quantificato il miglioramento ambientale che si può ottenere utilizzando il sistema eHighway in entrambi i modelli, che possono essere considerati una base di valutazione per prendere decisioni in merito all'adozione di questa nuova tecnologia e alla progettazione della rete stradale elettrificata.

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List of Acronyms

Overhead Catenary	OC
Electric Road System	ERS
Network Design Problem	NDP
Electric Vehicles	EVs
Hybrid Electric Vehicles	HEVs
Plug-in Hybrid Electric Vehicles	PHEVs
Continuous Network Design Problem	CNDP
Discrete Network Design Problem	DNDP
The Mixed Network Design Problem	MNDP

1. INTRODUCTION

Since the last decade, greenhouse gas (GHG) emissions from transportation are acknowledged as one of the main issues for the sustainable development of urban and extra-urban areas. For example, in 2014 the road transport accounted for more than 70% of all GHG emissions (European Commission, 2019). The expansion of cities and the presence of higher pollutions and emissions, such as carbon dioxide (CO_2), nitrogen oxides (NOx), sulfur dioxide (SO_2), particulate matter (PM10, PM2.5), etc., are having a high impact on people's life and health. Therefore, the concept of sustainable development is concerned with creating better life opportunities for people and future generations living in cities by taking into account the population growth of urban areas due to economic and social factors. The transportation sector remains one of the main issues considering the negative environmental impact and the GHG emissions in the urban areas caused by the higher traffic and transportation volumes, traffic jams and congestions, air pollution, etc. Also, one of the common problems in cities is related to traffic congestion, parking, and spatial inaccessibility mostly in historical areas. However, freight transportation has been posing the highest difficulties, considering that urban freight transport accounts for 25% of total CO_2 emissions and 30-50% of other pollutants such as particulate matters, NOx, etc. (ERTRAC & ALICE, 2015). In the European Union, heavy-duty vehicles are responsible for 5%, while light-duty vehicles are responsible for 15% of total GHG emissions (European Commission, 2019). Moreover, according to (Civitas, 2015), around 20-25% of freight vehicle kilometres are related to extra-urban areas, while 40-50% are accountable for urban freight distribution.

An increase in freight flows and satisfaction of customer service in a long-time period requires the management of all freight processes and facilities, and collaboration of transportation companies and public authorities, as well as technological innovations. As a result, transportation sustainable development provided a set of regulations regarding the interest of public authorities focusing on the traffic safety and environmental well-being of cities, and private companies concerned with the customers' satisfaction and economic benefits. The European Commission provided the set of climate change strategies, transportation policies, and emission targets e.g. 15% reduction of cars and vans from 2025, 37.5% reduction of cars, and 31% reduction of vans from 2030 (European Commission, 2020). The predictions for 2030 could lead to a 22% reduction of CO_2 emissions considering the 68 gco_2/km as a target for new cars in 2025 (ICCT, 2016). To meet these targets, the transportation sector faced many challenges in developing an emission-free environment considering the promotion of eco-friendly vehicles, and the usage of renewable energy sources. The European Commission Climate & Energy Framework provided a framework regarding the targets such as 40% reduction of GHG emissions, 32% share of renewable energy, and 32.5% improvement in energy efficiency by 2030 (European Commission (Climate Action), 2020). Also, the average emission targets are set as 175 g CO_2/km for 2017, and 147 g CO_2/km by 2020 (Environmental European Agency, 2019).

In the last years, the governments are supporting the installation of charging infrastructure for electric and hybrid vehicles by offering a various incentive for buying zero-emission vehicles such as purchase grants, exemption, or the reduction of fees related to the vehicles' registration tax, pollution tax, road tax, etc. New technological innovations in designing zero-emission vehicles together with the usage of renewable energy sources showed a significant contribution in mitigating emissions in extra and inter urban areas. For example, one of the evolving technologies for environmentally friendly transport in inter-urban areas are electric cargo bikes and electric vans. These vehicles introduce many advantages such as environmental benefits and lower operating costs, higher flexibility, the reduction of time needed for loading/unloading operations and the manipulation from one to another mode of transport, parking flexibility, accessibility to historical and/or zones with traffic limitations, etc. However, in the extra-urban areas, the zero-emission technologies, such as hybrid and electric trucks have longer operativity and flexibility outside the urban areas due to the capacity of the battery and the number of recharging at the charging stations. These vehicles are encouraging solutions for the public authorities, as well as for transportation companies, regarding the emissions reduction, and the decrease of vehicle's maintenance and operative costs, respectively. Furthermore, the promotion of zero-emission vehicles contributes to the steady growth of vehicles' market share and, according to the prediction, it could grow up to 23% in 2030 (European Parliament, 2019).

1.1. The motivation

This thesis encourages the promotion of the above-mentioned zero-emission technologies for the extra-urban areas, as well as government emission initiatives for implementing sustainable freight transportation solutions which could contribute to the overall environmental and economic benefits in the long-term period. To meet these goals, some projects investigated the possibilities for the emissions reduction through the Electric Road System (ERS) implementation in which the electrification of the road segments provides continuous electricity supply to electrified vehicles while driving on these sections and allow having less-sized batteries (Grahn et al, 2009). Beside the high-level investment cost for building ERS infrastructure, the reduction of battery size could decrease total vehicle cost and affect the demand' increment for such vehicles (Jelica et al., 2018). The variations between different ERS approaches are due to the power transfer from the power grid to the vehicles. The ERS technology can operate with two different approaches, via overhead catenary wires and via conductive rail in the road. The first solution is demonstrated to be more convenient considering that the second solution is giving higher vulnerability and less effectiveness due to higher safety requirements, infrastructure maintenance, and investment costs, (Andersson et al, 2018).

Therefore, this thesis proposed the novel optimisation transportation network design models for the eHighway system adoption. In general, the eHighway system is designed to supply Overhead Catenary (OC) trucks with electric energy, through the pantograph connected to the overhead power lines (Volkswagen, 2019). The pantograph is positioned at the top of the OC vehicles and allows the automatic connection/disconnection from the overhead wires, which leads to the simultaneous usage of electric and diesel power modes. The implementation of the eHighway system gives the possibility for lower emission vehicles' rate since OC vehicles are operating with the electric mode on the electrified sections. Additionally, when are not connected to the eHighway system, the OC vehicles' batteries can operate on a driving range up to 3km and save energy on a lower distance. Moreover, despite the higher initial costs, the usage of OC vehicles could lead to lower maintenance and operational costs for a transportation company in a long-term period.

Recently, some countries investigated the opportunities for the eHighway system implementation with the test projects on a part of the road segment on the highway network with a small number of OC trucks. The first eHighway project supported by the Swedish Government was implemented in the city of Gävle. The test project was launched on the E16 highway road with 2 km of distance (Siemens, 2016). The case study of Swedish eHighway system implementation on a route E4 required higher energy demand of 5GWh/day considering average weekend peaks, but at the same time, the electrification of the 4% of total traffic volume resulted in the reduction of 5.3% of the CO_2 emissions (Jelica et al, 2017). The second project was developed in Germany, "Trucks for German eHighways" and it was tested in Lübeck, Frankfurt on the B462 road in Baden-Württemberg (Road traffic technology, 2019). The implementation of the eHighway system and the electrification of vehicles could lead to savings for transportation companies of around 20000 € over 100 000 km, regarding fuel costs. Another result of testing the eHighway system in Carson (California) demonstrated the effectiveness of OC trucks and zero-emission miles up to 20% more than plug-in hybrid electric trucks, (Lehmann, 2018). Recently, the A35 Brebemi highway company in Italy started the adoption of the eHighway system in the north of Italy (Green Car Congress, 2019). The pilot project focuses on developing 3 km in both directions of the eHighway system in the region of Lombardy (connecting Brescia, Bergamo, and Milan), with the objectives of achieving sustainable and economic benefits (Melis & Rigoni, 2019).

1.2. The aim and objectives

The idea of this thesis is to propose a novel optimisation model for the eHighway system considering the characteristics of this technology. According to European emission targets, i.e. the use of renewable energy sources and the advancement of OC trucks, eHighways are a promising solution for sustainable freight transportation. Therefore, this thesis aims to solve the single-level multi-objective network design problem (NDP) and the bi-level multi-objective NDP for the eHighway system adoption considering OC hybrid trucks, in which emission model was used for evaluating the environmental benefits of the eHighway technology, while the traction substation simulation model was used for evaluating the minimum number of the traction substations needed for each electrified arc.

The first one, the single-level multi-objective NDP model, aims to investigate the influence of the different criteria in the eHighway system considering the interests of public authorities and transportation companies. The multi-objective NDP model is developed as a single-level model, where the assignment of the traffic flow is fixed. The model aims to find the optimal set of arcs to be electrified as a result of the multi-objective optimisation in which different criteria weights are given to the objective functions, expressed as the minimisation of the infrastructure and environmental costs and the maximisation of the average traffic density of OC hybrid trucks on the electrified arcs. Therefore, the Pareto optimisation approach is used for finding all possible solutions according to different criteria weights. Moreover, the single-level multi-objective NDP model considers the environmental awareness and the interest of the transportation planners regarding the total costs and the maximisation of the number of OC vehicles on electrified arcs in the eHighway system.

The second one, the bi-level multi-objective NDP model, aims to find the set of arcs to be electrified through the minimisation of total travel time in the eHighway system, the minimisation of the eHighway system's costs expressed as the environmental and infrastructure costs and the maximisation of the average traffic density of OC hybrid trucks on the electrified arcs. The proposed model is formulated as a bi-level model, where the decision of the upper-level problem depends on the fixed-point lower level problem. The upper level aims to minimise the costs of the eHighway system and find the set of arcs to be electrified considering available budget resources, while the traffic flow assignment is obtained through the lower level problem. Additionally, the model deals with the capacity expansion of some of the electrified arcs in the upper level considering available expansions' budget resources Since the design of the bi-level model is correlated with the longer time period usage, the capacity expansion of the electrified arcs is justifiable considering that the attraction of the eHighway system and the traffic demand regarding OC hybrid trucks could increase in the future period. Moreover, the added lanes on the electrified links could be dedicated only to OC hybrid vehicles. However, in the case of the single-level multi-objective NDP model we used the Pareto optimisation since we obtained optimal solution, but in the case of the bi-level multi-objective NDP model that is not guaranteed.

1.3. The overview of the thesis

The structure of the thesis is given as follows. In Chapter 2 are presented the literature and the contribution of the thesis. In Chapter 3 are described the main characteristics of the eHighway system, while in Chapter 4 is given the problem description of the developed models and corresponding mathematical formulations. In Chapter 5 are described solution approaches e.g. exact approach for single, and genetic algorithm for the bi-level multi-objective NDP, respectively. Chapter 6 is related to the obtained results of the proposed models, tested on the numerical application of a medium-sized and the Sioux-Falls network. Moreover, in Chapter 6 is reported the sensitivity analysis related to the bi-level NDP regarding the percentage of the OC hybrid trucks using eHighways system and the different weight coefficients related to the objective functions. In Chapter 7 are described the conclusions and further developments.

1.4. The contribution

To date, after a thorough examination of the literature review, there are hardly any papers that investigated the eHighway system from the transportation point of view. Most of the previous studies showed the potential of the eHighway system, but they are limited to technical and energy system modelling. Hence, this thesis investigates the opportunities for the eHighway system implementation on the existing highway networks focusing on transportation network modelling. Alongside the needed energy demand generations and the power supplies' costs of the eHighway system, the importance of transportation question in the eHighway system implementation is essential for understanding and predicting the travel behaviour, the vehicles' emissions, and traffic demand of the whole transportation system.

This thesis gives an insight of the impact of the eHighway system and aims to optimise the number of electrified arcs in transportation network modelling considering the imitated budget resources for the eHighway system implementation. Additionally, the contribution and objectives of this thesis are given as follows:

- To give an insight into the assessment of the eHighway system technology in the transportation network design modelling;
- To evaluate the environmental benefits of the eHighway system implementation;
- To propose the novel transportation network design models for eHighway system adoption, a single and a bi-level multi-objective NDP model, which aim to optimise the performance of the whole transportation network considering the implementation of the eHighway system.
- In the case of the single level multi-objective NDP model it evaluates the criteria related to the environment, infrastructure, and users' requirements;
- The bi-level NDP is developed as an extension of the single-level multi-objective NDP model, where the capacity expansion is considered in the upper level, while the traffic flow assignment is obtained from the lower-level fixed problem;
- The developed models could benefit authorities who are making long-term decisions since the advantages could be achieved for a long period;
- A sensitivity analysis was carried out to evaluate network design problem solutions according to different criteria that could help decision-makers in choosing the best alternative.

2. LITERATURE REVIEW

This Chapter presents the studies regarding some zero-emission technologies' applications of interest for the proposed transportation network design models, as well as the literature background of the eHighway system. The first part of the literature review regards environmentally friendly vehicles, and in particular, the application and advantage of the hybrid and plug-in hybrid electric vehicles in various case studies. The second part covers the background of the studies related to the transportation network design problems, while the third part is related to the background of the eHighway system application.

2.1. The eco-friendly hybrid technologies

Eco-friendly vehicles include various types of different technologies e.g. Electric Vehicles (EVs), Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs), Battery Electric Vehicles. They all tend to be more energy efficient, compared to the conventional ones, with the possibility of using a renewable energy source and energy recovery while braking (Fiori & Marzano, 2018). Initially, electric mobility has been devoted to EV considering the environmental impact from individual trips, while in recent years GHG emissions from trucks have been adding attention. The results from New York City Cycle showed that electric trucks consume 28% less energy, emits 38% less GHG emissions, and have 35% lower maintenance costs than diesel trucks (e.g. depending on the class of vehicle, road gradient and slope, type of internal combustion engine (ICE) for diesel trucks, the payload, traffic conditions, etc.), (Lee et al., 2013).

Some studies investigated the environmental contribution and main technical performance regarding power-to-weight ratio, the performance, and opportunities of different powertrain vehicles' technologies in freight transportation, as well as the life cycle (Lajevardi et al. 2019). One of the main investigations is the function of the range level and battery cost, according to traversed distance (Falcao et al., 2017; Pelencia et al., 2017; Chong et al. 2018). Guerrero de la Peña et al. (2020) proposed the Mixed Integer Linear Programming (MILP) model for supporting the usage of novel powertrain technologies considering the total costs of ownership, the CO_2 emissions, the infrastructure, economic factors, etc. The study showed the opportunities for displacing diesel vehicles and a potential CO_2 emission reduction of 20%. Lombardi et al. (2020) analysed energy performances and the environmental impact of ICE diesel vehicles, PHEVs, BEV, and Plug-in Fuel Cell Vehicle (PFCV) powertrain technologies. The BEV and PFCV technologies showed lower energy consumption, while the GHG emissions of 3.5 t diesel truck resulted in the highest emissions of 270 gCO_2/km/kg.

2.1.1. The Hybrid Electric Vehicles (HEVs)

Since EVs have been showing limited autonomy in traversed distance due to the battery duration, which leads to more charging stations and, therefore, the increase in total travel time, the HEVs offered the possibility for overcoming this issue. The study proposed by Mancini, (2017) demonstrated better results for HEVs in terms of the total travelled distance, compared with EVs, due to the number of limited recharging stations as well as and the autonomy of HEV to switch to the fuel propulsion mode when the battery has been recharged. The combination of ICE with an electric motor allows the lower fuel consumption and emissions, better energy efficiency, and energy recovery through regenerative braking. HEV vehicles have been acknowledged to give the most promising result in terms of emissions, operational and maintenance costs on smaller and long-haul distance, depending on the type of hybrid electric powertrain technology e.g. serial, parallel and serial-parallel technology (Borthakur et al. 2018; Zhuang et al. 2020). Serial HEVs are considered for the urban traffic and stop-and-go conditions, while parallel HEVs are suitable for a longer distance (Jyotheeswara et al. 2018; Anselma et al. 2020; Cipek et al. 2020). Borthakur et al. (2018) compared the performance of serial PHEVs and serial HEVs for heavy-duty trucks on Indian highways. The results of the comparison showed the advantage of serial PHEV powertrain technology both for vehicles' components and vehicles' performance regarding acceleration, maximal longitudinal speed, and fuel economy. Another classification of HEVs was devoted to the micro, mild, full HEVs, and PHEVs considering the type of electrification level. Mild HEVs have larger electric motors compared with micro HEVs, which allows them better energy savings, while the technology of full HEVs is convenient for urban areas, Zhuang et al. (2020).

2.1.2. The Plug-in Hybrid Electric Vehicles (PHEVs)

The PHEVs have similar characteristics as full HEVs, with the possibility of charging the battery by plugging into the grid which allows longer duration performances, Zhuang et al. (2020). For example, Hiermann et al. (2019) considered three classes of vehicles (conventional ICE vehicles, PHEVs, and EV). The mixed fleet consideration resulted in decreasing operational costs of around 7% compared with a homogenous fleet. On the one side, the application of PHEVs demonstrated higher energy usage, but on the other side, the ability to use ICE and electric engine resulted in lower operational costs. Additionally, Liu et al. (2018) introduced a robust dynamic charging line deployment for plug-in hybrid electric routes considering a mixed fleet of passenger cars and trucks. The results of optimal charging lines showed the reduction of emissions and total cost comprising travel time and fuel cost for drivers.

Plötz et al. (2018) investigated fuel economy and CO_2 emissions of PHEVs based on daily and annual driving behaviour. The results of using renewable energy sources for PHEVs indicate the CO_2 emissions of 37gCO_2/km and saving of

57 kt CO_2 emissions, compared to ICE vehicles. Also, Salazar et al. (2019) proposed strategies for PHEV considering environmental and energy criteria. The model, tested on the Eastern Massachusetts highway network, demonstrated the fuel savings of around 50% and a slight incense of travel time regarding eco routes, while the shortest travel time-optimal solution resulted in the highest fuel consumption.

Vora et al. (2017) analysed the powertrain simulation and battery degradation model for the series PHEVs to predict fuel consumption, energy consumption, and battery replacements. Additionally, Li et al. (2020) developed a MILP considering the advantages of PHEVs in the terms of travelled distance and the efficiency of battery's capacity and charging related to electric and fuel stations. Nejad et al. (2017) proposed an energy-efficient routing problem for PHEVs to minimise fuel consumption and choose a suitable operation strategy for energy minimization and emission reduction. The model was tested on the Southeast Michigan road network and resulted in around 25 % fuel economy improvement. Arslan et al. (2015) aimed to find the minimal cost path for PHEVs referring to the costs of electricity, fuel, and battery degradation. The results showed the advantages of PHEVs regarding the availability of charging infrastructure and usage of more refuelling/charging stations when the costs of electricity are lower than gasoline.

Another group of authors proposed different algorithms for solving the PHEV routing problem, Jahangir et al. (2020). Murakami (2018) proposed three algorithms - the LAB, THP, and improved THP algorithm for solving PHEV routing and scheduling problems. The algorithms resulted in the optimal solution for most of the instances where the performance of the LAB algorithm was better for small-instance problems, while the performance of THP and improved THP algorithm showed advantages even for bigger-sized problems. Yu et al. (2017) proposed a simulated annealing heuristic with a restart strategy (SA_RSBF and SA_RSCF) for PHEVs. The SA_RSCF resulted in better performance, while the average difference between the strategies was around 0.08%. Sun et al. (2016)

proposed a routing design for PHEVs considering the lowest fuel costs and different energy consumption depending on the fuel operation mode. Their proposal was a cost-optimal algorithm, which resulted in energy cost savings of around 48 %.

2.2. The transportation road network design problems

The development of urban areas and the expansion of city mobility has been tackling with many issues related in the road traffic, such as e.g. the increment of traffic jams and congestions, emissions, as well as the necessity for extending road capacities and transportation resources as a result of the growing transportation and travel demand. The main challenge is the optimisation of the overall road system, travel behaviour management, travellers' path choice, and minimisation of the total cost considering addition and capacity enhancement of new arcs on road. In the literature, this problem has been the subject of the transportation Network Design Problems (NDPs) regarding the optimisation, management, design, and planning of road network areas. During the last decades, numerous authors have been providing overviews of the methodology, method, solution approach, algorithm and mathematical contribution related to transportation NDPs (Yang et al. (1998); Farahani et al. (2013); Kepaptsoglou et al. (2009); Iliopoulou et al. (2019); Jia et al. (2019); Xu et al. (2016); Magnanti et al. (1984); Migdalas (1995)). Generally, network design models are refereeing to the optimisation of the decision variables in the network through the maximisation or minimization of the objective function, often seen as the minimisation of the overall costs or the maximisation of the revenues, considering problem's constraints. Beside the decision variables, the objective function depends on the link traffic flow which is often represented as a function of the origin-destination matrix, network characteristics (links, paths, number of nodes), and the path choice probability. Mostly, transportation network design models are expressed as bi-level optimisation problems, where the result of the first-level optimisation problem (main problem) depends on the solution of the second-level optimisation problem (e.g. traffic flow assignment model), Cascetta (2009). In general, transportation NDPs are divided in two categories – continuous and discrete network design problem; Continuous Network Design Problem (CNDP) are focusing on capacity expansion of the existing arcs in the road network, while Discrete Network Design Problem (DNDP) are dealing with the addition of the number of arcs in road network design, (Yang et al. 1998). The combination of CNDP and DNDP is formulated as the Mixed Network Design Problem (MNDP). The literature review regarding the application of the CNDP, DNP and MNDP models is described in the further.

2.2.1. The Continuous Network Design Problem (CNDP)

As previously mentioned, CNDP aims to optimise transportation network performance through the expansion of the road capacity, expressed as the addition of the total number of lanes on the links in road network. In general, CNDP is formulated as bi-level problem in which the upper level focuses on capacity expansion, while the second level determine the travellers' path choice behaviour, usually determined by the deterministic user equilibrium traffic assignment or the stochastic user equilibrium traffic assignment. Additionally, CNDP is formulated as a non-convex optimisation problem, and various heuristics or metaheuristic algorithms were developed for solving CNDP (Gao et al. (2007); Angulo et al. (2014); Li et al. (2012)). For example, the paper proposed by Gairing et al. (2017) demonstrated the complexity and approximation of the CNDP.

The paper proposed by Sun (2016) focused on bi-level CNDP where the upper-level minimised the total investment costs and impedance in a traffic network, while the lower-level considered demand uncertainty in the user-equilibrium (UE) assignment model. Also, Changzhi et al. (2009) proposed bi-level CNDP to minimize the weighted sum of expected values related to the demand and capacity uncertainty. Several papers focused on the using heuristics algorithms for finding the solution of CNDP (Suwansirikul et al. (1987); Msigwa et al. (2020)). The paper proposed by Gao et al. (2007) developed the globally convergent algorithm for solving single-level convex programming problem of CNDP and made the comparison with widely used heuristic algorithms. Other authors proposed metaheuristic approaches such as evolutionary algorithms and particle swarm optimisation (PSO). For example, Cao et al. (2013) considered demand and cost uncertainty in developing bi-level CNDP and used genetic algorithm as a solution approach. Başkan et al. (2018) introduced an enhanced differential evolution algorithm based on the multiple improvement strategies for solving CNDP, which demonstrated a good-quality solution, especially with high demand requests. Another group of authors demonstrated the effectiveness of using PSO as a solution approach for CNDP (Angulo et al. (2014); Sun et al. (2014)). The paper proposed by Xu et al. (2010) provided the sensitivity analysis related to the different parameter settings for PSO using the one-at-a-time designs method, where the swarm size of around 20 resulted in the near-optimal solution. Angulo et al. (2014) proposed a continuous bi-level location model for expanding highway network and PSO as a solution approach, where the first level optimisation problem choose the locations of highway corridors, while the second level optimisation problem was related to the users' behaviour in choosing a route in the highway network. The objective function of the first-level optimisation model aimed to minimize the travel time of the existing Castilla–La Mancha highway network and to find the location of the additional highway links. Another paper proposed by Sun et al. (2014) used PSO for optimising links' capacity expansion on a road network using bi-level CNDP for maximizing the reliability of total travel time in the first and minimizing the driver's travel time uncertainty in the second level optimisation problem. The application of the Advanced Traveller Information System was used to increase the users' perception in choosing route paths.

2.2.2. The Discrete Network Design Problem (DNDP)

The DNDP is dealing with the expansion of the road network expressed through the addition of the new links to improve transportation network performance. It can be formulated as a bi-level problem in which the upper level is dealing with the addition of the new links on the road network where the decision variable related to the link's addition can take 0-1 values, while the lower level is seen as the traffic assignment problem. In other cases, the upper level problem variable can take a series of integers instead of 0-1 values, as proposed in Quo & Haibo (2013).

Various solution approach algorithms have been used for solving DNDP i.e. exact, heuristic and metaheuristic, (Rey, 2020; Poorzahedy & Turnquist, 1982). For example, Farvaresh & Sepehri (2013) proposed a Branch and Bound Algorithm which was able to find a global optimal solution for bi-level DNDP. Additionally, Wang et al. (2013) proposed the global optimisation method for the DNDP considering the relation between UE and system optimal assignment. Hosseininasab & Shetab-Boushehri (2015) developed three models regarding the time-dependent DNDP using the two-phase simplex method, Frank-Wolfe algorithm, and genetic algorithm as a solution approach. Wang et al. (2019) proposed a bi-level DNDP focusing on the relationship between land use and transportation mode accessibility measurement. The study was tested on a numerical example of a Sioux-falls network which demonstrated the improvement of the accessibility of traffic zones by using genetic algorithm as a solution approach. The study proposed by Wang et al. (2017) proposed the active set approach for solving a bi-level DNDP to expand and modify road networks, where the increment of capacity and infrastructure costs were related to the number of lanes in the existing road network. Additionally, Divsalar et al. (2016) developed a mixed-integer nonlinear nonconvex problem for solving DNDP to find the global optimal solution for adding new links to the existing road network. Another study proposed by Juan et al. (2012) used a genetic algorithm for multiuser DNDP where the upper-level aimed to minimise total travel time under stochastic demand conditions, while the lower-level used multiuser traffic equilibrium assignment for assigning demand to the network. The numerical example of Nguyen Dupuis network showed the importance of the heterogeneity and demand uncertainty in improving the overall results. Di et al. (2018) proposed a novel deterministic bi-level DNDP for maximising network flow accessibility and a two-stage stochastic programming model for DNDP to handle the uncertainty of demand considering the available budget resources.

2.2.3. The Multi-Objective Network Design Problem

The previously mentioned studies were focused on the application of the different solution approaches for solving CNDP and DNDP, where the main aim was to improve the overall network performances through the single objective function i.e. minimisation of the total travel time under various conditions (adding new lanes and links in the network, choosing the location of the highway corridors, etc.). However, in other cases of the bi-level network design problem, the optimisation could be the result of the multiple objective functions, considered in the upper level optimisation problem, such as travel time and environmental costs minimisation, equity maximisation, etc. In the literature, researchers proposed different approaches for the bi-level multi-objective NDP (Zhang & Gao (2009). Kolak et al. (2018) developed a bi-level multi-objective traffic optimisation model, where they considered the toll pricing and capacity enhancement as flow management strategies to obtain the vehicles' emission minimisation and equality accessibility in the upper level. Another study proposed by Kim et al. (2012) focused on the sustainable multi-objective road network design for minimizing the total travel time and emissions and maximising the social equity.

Several authors used the Karush-Kuhn-Tucker condition for reformulating the bi-level in a single-level optimisation problem (Rey, 2020; Ghomi-Avili et al.

2020; Farvaresh & Sepehri, 2011). Wang & Lo (2010) transformed the bi-level NDP in a single-level optimisation problem which resulted in finding the global optimum. Another study proposed by Xu et al. (2017) transformed a bi-level DNDP into the MILP formulation for finding optimal road toll pricing scheme, under the available budget and toll revenues. Erkut & Alp (2007) provided a case study in Italy for designing hazardous materials routes. The authors reformulated the bi-level hazmat NDP as a single-level optimisation problem. Fontaine et al. (2020) formulated a single-level MILP for the multimode hazmat transportation NDP, where objective functions aimed to evaluate risks and achieve better risk distribution among the population. Hammad (2019) reformulated the bi-level multi-objective as a single-level optimisation problem for solving the evacuation location assignment problem and obtaining the best locations for placing shelters. Another study proposed by Hammad et al. (2017) developed the single-level multi-objective facility location problem that minimised the total noise level and system's travel time.

2.2.4. The Mixed Network Design Problem (MNDP)

The MNDP aims to optimise the network performance through the addition of the new links and the capacity expansion of the existing links in the road network, which involves both discrete and continuous variables. Some authors proposed a global optimisation method for MNDP (Luathep et al. 2011; Liu & Chen, 2016). Mo et al. (2008) used a genetic algorithm for solving a bi-level MNDP for an urban road network. Chen et al. (2015) proposed a bi-level MNDP model, where the upper-level minimise the total average travel time considering the expansion of the existing road network, while the lower-level is a dynamic user-optimal condition. The model used a surrogate-based optimisation framework as a solution approach, which demonstrated a reduction of 17.73% of the average travel time considering the morning peak.

In other cases, the MNDP is formulated as a single level nonlinear mixed-integer bi-level programming model. For example, Liu & Chen, (2016) proposed the dimension-down iterative algorithm for solving MNDP. Another study proposed by Tolooie et al. (2020) developed a two-stage stochastic mixed-integer formulation for dealing with the demand uncertainty and facility failures in the supply chain network.

2.3. The studies related to the application of the eHighway system

To date, most of the studies estimated the impact of the eHighway system on required power demand and potential emission mitigation (Jelica et al. 2018; Akerman et al. 2016; Plötz et al. 2019). Extra energy demand is needed to satisfy the share of vehicles to be using the eHighway system; it will require new power generations and the usage of renewable energy sources. Plötz et al. (2019) investigated the market diffusion and energy generation for vehicles in ERS, referred to as “trolley trucks”, and their impact on the European electricity system. The expansion of trolley trucks should require additional electricity demand, but according to an optimistic scenario in the paper, their impact on total electricity demand should be less than 3%. However, the optimistic scenario showed that 30 Mt of CO_2 emissions in electricity production would lead to a reduction of 40-50 Mt of CO_2 emissions in road transport. The overall results could be significantly improved with the connexion of renewable energy sources capacities. Similar results were obtained by estimating emissions of the hourly electricity demand for light and heavy vehicles connected to ERS in three cities in Sweden (Jelica et al. 2018). The study assumed the usage of renewable energy sources, and therefore, zero-emissions from vehicles connected to ERS. The energy estimation for implementing ERS in Sweden, based on data sets of the highest hourly traffic volumes, would lead to the the electricity demand’s increase of around 4%, transportation efficiency’s increase in the range of 31-

71%, and to reduce of CO_2 emissions by 19%. Also, the case study in Norway and Sweden proposed by Taljegard et al. (2020) demonstrated the importance of infrastructure and environmental aspects for large-scale roads' electrification. The electrification of all roads in both countries and the usage of electric heavy traffic could cover more than 60% of CO_2 emissions, while the costs of electrification resulted in 0.03-0.15 € per vkm. Also, the authors stated the importance of infrastructure costs regarding light-duty vehicles traveling on the electrified roads.

To the best of the knowledge, the eHighway system has been scarcely investigated in the literature from a transportation point of view. Previous studies gave insights in technology assessment of eHighway system and questions related to the configuration of the required electrical system considering power demand, number, and the dimension of traction substations, the definition of a voltage level (Plougmann et al. 2017; Andersson et al. 2018; Sachse et al. 2014; Chen et al. 2015). Grunjes et al. (2014) reported the outcome of several successfully performed tests of the prototype of the eHighway system, which highlighted the efficiency of the eHighway system on a long-mile distance. Böttger et al. (2018) analysed different scenarios related to the availability of eHighway trucks and the share of controlled charging vehicles which showed that eHighway trucks were cost-efficient in all scenarios. Another study proposed by Jöhrens et al. (2020) investigated the opportunities for ERS using overhead HEV (O-HEV) in Germany. The authors introduced a model that examines the financial and ecological aspects of the system, the cost-benefit investment in O-HEV, the routes to be electrified in the network, and costs savings for truck operators. The objective function aimed to minimise the total cost of ownership where the first part was expressed through the fixed costs of ICE vehicles and the additional costs of O-HEV using the ERS system, while the second part was related to the electricity costs savings comparison of O-HEV compared to ICE trucks. Thus, they mainly focused on transportation company aspects without considering the environmental impact and infrastructure costs in the objective function.

3. THE eHIGHWAY SYSTEM

The eHighway system technology is designed to support the usage of OC hybrid trucks, as well as the renewable energy sources for the power supply (see Figure 1). The implementation of OC hybrid trucks in the eHighway system allows the usage of diverse alternative fuels, which makes it more suitable for the environment, since freight transportation is one of the highest contributors to the emission and pollution increment. Also, it gives the possibilities for various applications in freight transportation such as the shuttle transport for distances up to 50 km, i.e. in industrial areas and ports, electrified mine transport and long-haul traffic (Siemens, 2018).

Figure 1 - The eHighway system

Additionally, the efficiency of the eHighway system increases with the number of OC hybrid trucks operated on electrified road sections. In general, the installation of the eHighway system requires some aspects to be considered, such as the question of the energy demand, traffic volumes, technology assessment, infrastructure requirements, system management, definition of voltage level, etc.

3.1. The technology description

The main subsystems of the eHighways are the electric infrastructure and traction substations, the OC hybrid trucks, the power supply and distribution, etc. In the eHighway system, the energy is transmitted from the traction substations to the overhead wires and finally to the OC vehicles' active pantograph. Therefore, OC vehicles are receiving power in the eHighway system only when the active pantograph is connected to the overhead wires (Siemens, 2018). In the further, we briefly described the main elements of the eHighway system (active pantograph, overhead wires, and traction substations).

3.1.1. The overhead wires

The electric infrastructure of the eHighway system comprise the bi-polar catenary system (overhead wires) and traction substations. The overhead wires receive the energy directly from traction substations and are installed and placed between two poles, positioned alongside the road section, so that the eHighway system can operate without any failures (Grunjes, 2014). The height and the design of electric poles are constructed according to the highway network standards, while their position placement should avoid any contact with constructions e.g. bridges, tunnels, (Viktoria Swedish ICT, 2013). Each overhead wire consists of a still rope messenger and contact wire, tensioned with concrete weights, which are positioned at the start and end of the electrified section (Lehmann, 2018). Moreover, the vehicles' power equipment from overhead wires leads to an 80% efficiency level (Siemens AG, 2015). The catenary system is expected to have a longer life cycle, and to have no influence on the traffic flows. Besides, a different types of OC hybrid trucks running on various alternative fuels with the addition of active pantograph could be easily integrated in the catenary eHighway system, while the passengers' vehicles are still not the option. However, the catenary system has a limit related to the maximum number of vehicles to be served in the considered period due to the few constraints such as the length of the electrified section, the energy demand of traffic flow, the capacity of the station, the resistance of the overhead wires, etc.

3.1.2. The active pantograph

The OC hybrid trucks in the eHighway system slightly differ from general hybrid trucks in some technical characteristics such as the size and the battery charging range. Additionally, they require some modification to fit the technology of the catenary system, such as the equipment with an active pantograph (see Figure 2). The active pantograph ensures continuous electricity transfer and safe overtaking through safe retraction mechanism, at any speed range up to 90 km/h. Moreover, the application of active pantograph achieves the better well-to-wheel efficiency of about 80-85%, compared to ICE trucks, (Singh, 2016). The main feature of a pantograph is to ensure safe automatic connection/disconnection and power transmission from the overhead wires while driving or overtaking on the electrified section.

For achieving these characteristics, OC hybrid trucks must have a certain height size and the eHighway system cannot be applied for passengers' vehicles. In general, the serial hybrid configuration of vehicles has been demonstrated to give a better efficiency of the combustion engine and the recuperation of energy while braking.

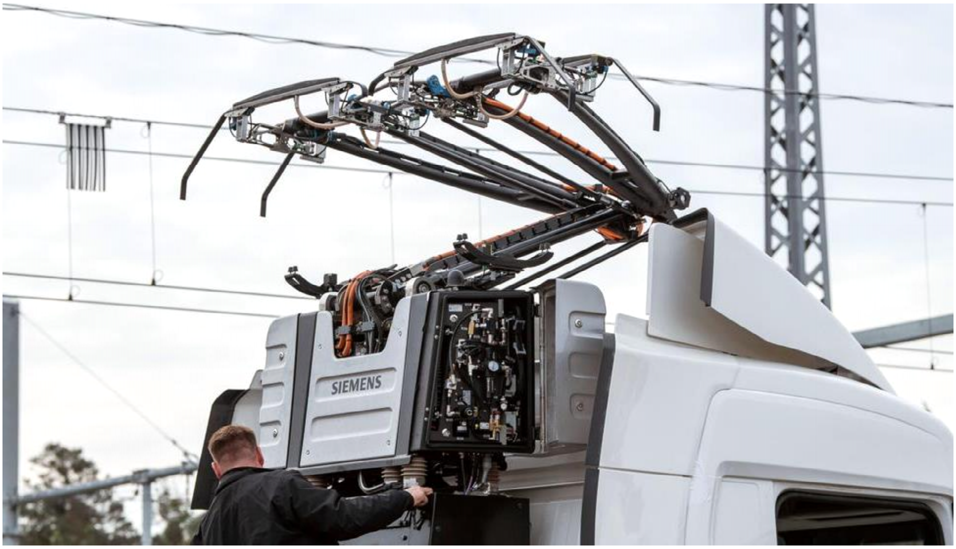


Figure 2 - The active pantograph of the eHighway system

3.1.3. The traction substation

In the eHighway system, traction substations receive the energy from the national or the regional grid power supply and are designed with enough capacity to satisfy vehicles' power demand on the electrified section. Certainly, one of the main issues in the eHighway system is related to the energy generation with the focus on the extra energy demand and continuous electricity supply. Also, it requires the transformation of the voltage level down to the acceptable eHighway system's voltage level, which could cause some extra costs and investments in the grid infrastructure. Accordingly, the basic purpose of the traction substations is to convert alternating current (AC) from a national or regional grid to direct current (DC) considering appropriate voltage levels (Sevcik & Prikryl, 2019). Furthermore, the usage of renewable energy sources e.g. wind energy along the highway road sections, could decrease the overall energy costs, considering that the electricity grid and the traction substations' capacity should be good enough to satisfy the traffic demand in the eHighway system.

In general, the traction substations are equipped with medium voltage switchgear, power transformers, rectifiers and controlled inverters which are feeding back the electric energy generated through the vehicles' regenerative braking (Conway, 2019). Generally, one traction substation could cover up to 2km of both lanes on the electrified road section in each direction, which leads to the necessity for another traction substation in approximately every second km of the road. Each segment of the electrified road section is controlled by a "power box" with a voltage range of 670-740 V DC (Suul & Guidi, 2018).

3.2. The costs of the eHighway system

One of the main concerns of the eHighway system technology are the initial infrastructure costs. According to Gmbh (2019), the total infrastructure costs considering substations, overhead wires, grid connection point, maintenance are around 2.2 Mio €/km. In general, costs of the catenary system are estimated as 400 000 €/km, while the costs of traction substation are around 1.8 Mio €/substation (Gmbh, 2019). Despite the high infrastructure costs of the eHighway system, the overhead wires are one of the less expensive solutions for hybrid trucks, considering that the high initial cost of the hybrid truck (Akerman, 2019). The report provided by Lehmann (2018) pointed out that the catenary system is more costly acceptable than the fast and overnight chargers for more than 10 000 hybrid trucks. According to the report provided by The Centre for Sustainable Road Freight, the electrification of 7,500 km of UK highway roads would cost around 19.3 billion £ and it would lead to a 5% emission decreasing. Therefore, the environmental and economic benefits of the eHighway system are expected in a long-term period. The savings were estimated around 20 000 € per 100 000 km for transportation companies considering fuel costs (Trans-info, 2020).

3.3. The advantages and disadvantages of the eHighway system

One of the benefits of the eHighway system is the regenerative braking and energy savings, which give the possibility for the OC hybrid trucks to return energy to the system in a first way, or in the second way to store extra energy in a battery. The vehicles' regenerative braking and energy saving are crucial for having a lower number of recharging while driving on smaller distances (Jelica, 2017). Moreover, the catenary system does not influence the road, which is beneficial from safety and operative point of view. In this case, any dysfunctionality of the eHighway system doesn't cause the collapse and interruption of traffic flows in the road network. Accordingly, in Table 1 are summarised the strengths and weaknesses of the eHighway system.

Table 1 - The advantages/opportunities and disadvantages of the eHighway system

The eHighway system characteristics	Advantages/ opportunities	Disadvantages
The possibility of receiving the energy from renewable energy sources.	+	/
The application of hybrid vehicles' technologies has been demonstrated as more efficient compared to diesel trucks.	+	/
The adaptation of active pantograph allows the flexibility of vehicles.	+	/
The energy recuperation and feeding back energy into the system when braking on the electrified section.	+	/
The zero-emissions of OC hybrid trucks while traveling on the electrified sections in the eHighway system	+	/

The reliability of the catenary system from safety and technological point of view.	+	/
Relatively easy installation of the catenary system with the possibility for overcoming physical obstacles (e.g. bridges, tunnels, etc.).	+	/
The electrified section is not reserved only for hybrid vehicle technologies since it has no installation on the road itself.	+	/
The integration of overhead wires alongside the road does not influence the driveway road.	+	/
The economic benefits in a long-term period and higher life cycle performance of the eHighway system.	+	/
The installation of traction stations could be more cost-efficient compared to the high number of fast-charging stations.	+	/
High initial infrastructure costs of overhead wires and overall eHighway system.	/	+
Necessitates for higher electricity demand.	/	+
The hybrid vehicles must be adopted to the eHighway system configuration which requires additional costs.	/	+
The limited range of one electrified section 1-3 km.	/	+
The efficiency of the eHighway system is correlated with the number of vehicles connected to the overhead wires.	/	+
The eHighway system is not used for passenger cars.	/	+
The eHighway system vehicles' demand uncertainty due to the higher investment costs.	/	+
Requires collaboration between all stakeholders.	/	+

4. THE PROBLEM DESCRIPTION

In this Chapter we introduce the problem description of the proposed single-level multi-objective network design problem (NDP) model and the bi-level multi-objective NDP model for the eHighway system which considers previously mentioned characteristics of the eHighway system technology. The problem description is followed by the mathematical formulations of the developed models which regard the adoption of the eHighway system technology on the road network, considering different criteria.

The common characteristics of the developed models, considering the previously mentioned features of the eHighway system technology, are presented as follows. Firstly, the energy is transmitted from the power plant generation that uses renewable sources of energy (wind, solar energy) to the bulk power supply and, then, to the traction substation (Grunjes et al. 2014). Traction substations are assumed to be connected to a 10 kV power grid, while the energy from a traction substation is converted from AC to DC and distributed to the OC hybrid trucks when approaching electrified arcs (Plougmann et al. 2017). Additionally, the capacity of each traction substation must satisfy the total demand of OC hybrid trucks, considering power losses during the energy transmission and minimum safe distance between trucks.

Secondly, an OC hybrid truck starts its trip from a depot running on fuel propulsion mode. After approaching the electrified section of its route, the truck's active pantograph automatically connects to overhead wires and switch to the electric propulsion mode. The OC hybrid truck can automatically connect and disconnect from the contact line at any speed from 0-90 km/h. During the overtaking, the OC hybrid truck can automatically switch to fuel propulsion mode without any loss of traction force or acceleration. In the proposed models, we assumed that OC hybrid trucks have an average speed of 80 km/h. In the further, several assumptions for developing the bi-level and single-level multi-objective NDP model were considered as follows:

- The proposed models consider a macroscopic point of view, and therefore, it is assumed that vehicles have average speed and energy demand, while traveling on the eHighway system's electrified sections;
- Since the proposed models consider a macroscopic point of view, the energy recovery during regenerative braking and battery's state of charge were not considered, neither that the energy consumption of trucks depends on acceleration/deceleration;
- In the proposed models, it is assumed that the eHighway system has a continuous electricity supply;
- The proposed models considered a homogenous fleet of OC hybrid trucks. Therefore, OC hybrid trucks have equal characteristics related to the power consumption per length and the minimum safe distance between trucks;
- Moreover, OC hybrid trucks have no GHG emissions while traveling on the electrified arcs since it is assumed that the energy is obtained from renewable sources;
- In the case of both models, we considered the multi-objective optimisation and different criteria in the objective functions, i.e. three in the single and four in the bi-level NDP.

For developing the single level and the bi-level multi-objective NDP model, the traction substation model developed by Plougmann et al. (2017) has been used. The applied model simulates the eHighway traction substations system and gives as an output the minimum number of traction substations needed for each arc, that serves as an input for the propose models. Accordingly, the models calculate not only the set of arcs to be electrified regarding defined criteria, but also the number of traction substations and the maximum number of vehicles operated by each traction substation according to the simulation model.

In the further, we described the traction substation model and the mathematical formulations of each model.

4.1. The traction substation model

The traction substation model developed by Plougmann et al. (2017) was applied for calculating the minimum required number of traction substations and the distance between two traction substations for each electrified section. The traction substations are one of the main points in the eHighway system since they are transmitting needed power to the trucks through the overhead wires. Thus, investigation of the optimal configuration, position, and the capacity of traction substations are crucial.

According to Plougmann et al. (2017), the capacity of 3 MW is set to be good enough to ensure the functionality of the system from operational and safety aspects, even considering the maximum traffic flow of trucks during the picking hours. The simulation model considers the single-feeder solution with the voltage of 660/600 V. The output voltage of traction substations is designed to transmit the required 600 V for trucks plus the additional 10% to ensure that the eHighway system can operate without any breakdown. Therefore, the 660 V is set to be the upper voltage level for trucks to work properly, while the bottom voltage level U_{min} is equal to 500 V. Additionally, OC hybrid trucks are not able to operate under the bottom voltage level,. However, the voltage level is not constant if we consider the resistance R in overhead wires. According to the voltage drops, each traction substation has a limit of the total number of OC hybrid trucks that could receive the power and operate without any failures.

The traction substation model aims to give the required number of traction substations $n_{min,a}$ needed for each electrified arc of the road, and the maximum number of vehicles $n_{vs,a}$ that could be served by each traction substation, while satisfying total traffic demand on the electrified arc in a given period. The $n_{vs,a}$ is established based on the speed V of trucks, minimum safe distance between two trucks l_{min}, the power consumption of trucks P_n, resistance in overhead wires, and needed voltage level U. Since OC hybrid trucks are driving with constant speed V and l_{min} when approaching the electrified arc, voltage drop depends on the resistance in overhead wires, the resistance of the truck R_t, the resistance between vehicles R_d, the resistance between vehicle and connection point R_v and the number of vehicles connected to the overhead wires for each traversed distance n_{vs}, during the fixed time. When approaching an electrified arc and connection point of traction substation, if no other trucks are connected to overhead wires, the resistance is fixed, and the truck can receive the maximal input voltage of 600 V (Plougmann et al. 2017). As moving further from the connection point of the traction substation, the resistance in overhead wires increases and, therefore, the next truck can receive lower input voltage. The model calculates the voltage drop until the traversed distance is equal to l_{min}, and another truck can approach the electrified arc in the eHighway system. When the voltage drop is lower than U_{min}, the system is not able to receive more trucks for a defined period. At the end, the model calculates the maximum distance L_{lim} for which the voltage level doesn't drop down to lower than U_{min} and gives the maximal number of trucks $n_{vs,a}$ that could be operated on L_{lim} of an electrified arc. The eHighway system configuration considering traction substations is presented in Figure 3.

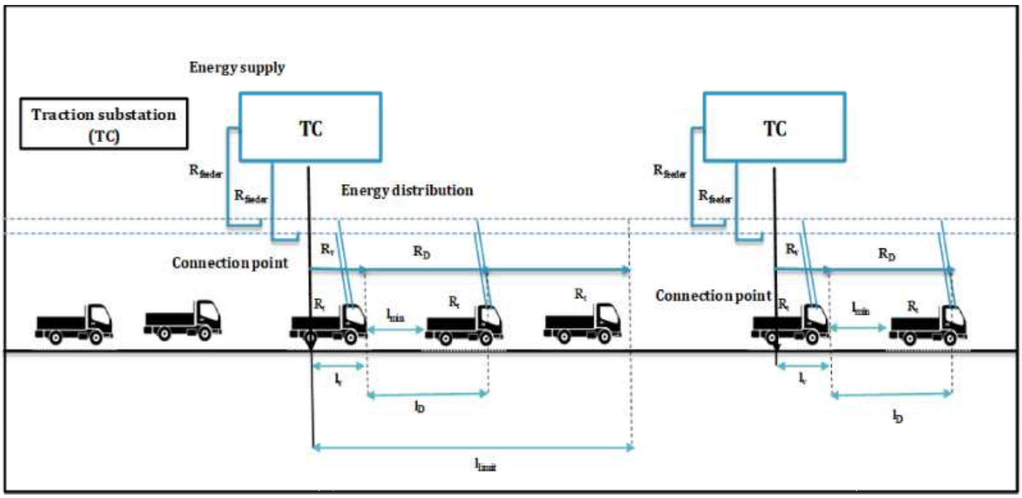


Figure 3 - The energy distribution in the eHighway system

4.2. The single-level multi-objective NDP model

The proposed single-level multi-objective NDP was modelled on the road network as a graph $G = (N, A)$, where N denotes the set of nodes $n \in N$ and A denotes the set of arcs a in the network, $a \in A$. Additionally, the O denotes the set of o origin nodes, $o \in O$, while D denotes the set of d destination nodes, $d \epsilon D$. Each arc a existing on graph G is associated with a traffic flow f_a during a given period t, length l_a and traffic density k_a. We assumed that all vehicles travel with a constant speed V when driving on each arc. However, the fixed assignment of traffic flows f_a was obtained applying the Stochastic User Equilibrium (SUE) traffic assignment model (Cascetta 2009). As already stated, the single-level multi-objective NDP model for the eHighway system aims to find the best set of the arcs to be electrified considering three criteria (infrastructure costs, environmental costs and maximisation of the average traffic flow of OC hybrid trucks on electrified arcs). In particular, the model also calculates the number of traction substations and the maximum number of vehicles operated by each traction substation according to the traction substation simulation model. The input parameter of the traction substation simulation model is the assignment of average hourly traffic flows obtained through the SUE traffic assignment model. The assignment model uses the Bureau of Public Roads (BPR) cost function and the Method of Successive Averages (MSA) for calculating equilibrium in the traffic network (Daganzo, 1977). However, it is important to note that we fixed the assignment of traffic flows and applied the simulation model. A detailed description of the assignment model is reported in Chapter 4.3.2.

Moreover, for evaluating the environmental improvement, i.e. emission reduction on electrified road segments, we applied the emission model based on the models proposed by Demir et al. (2011), Aksoy et al. (2014), and Andersson et al. (2018). The emission model calculates CO_2 emissions which were intended for the assigned fixed traffic flows on the non-electrified sections of the network, obtained from SUE traffic assignment. Additionally, the calculation of the CO_2 emissions, measured in t_{CO2}, is based on the fuel consumption and emission coefficient for diesel fuel depending on the aerodynamics, type of engine, road gradient, rolling resistance, load, and capacity of vehicles for a given period. For obtaining environmental impact C_e, expressed in [$€_{CO2}$/km], we considered the environmental costs c_m equal to 60 €/t_{CO2}, according to guidelines by the UK Dept. of Energy and Climate Change (2011). Additionally, we considered emissions for a lifetime period t of the eHighway infrastructure. Therefore, the emission model is described as follows.

The first part of the emission model (Eq. 1) is the aerodynamic resistance F_a [N], where c_d is the aerodynamic coefficient, A_f is the frontal surface area [m^2], ρ is the density of air [kg/m^3], and V is the average driving speed of vehicle [km/h].

$$F_a = \frac{c_d \cdot A_f \cdot V^2 \cdot \rho}{2 \cdot 3.6} \tag{1}$$

The second part of the emission model (Eq. 2) is the grade resistance F_g [N], where m is the load of a vehicle [t], g is the gravitational constant [m/s^2], and γ is is the road slope gradient.

$$F_g = \frac{m \cdot g \cdot \sin\gamma}{1000} \tag{2}$$

The third part of the emission model (Eq. 3) is the rolling resistance F_r [N], where c_r is the rolling resistance coefficient.

$$F_r = \frac{m \cdot c_r \cdot g \cdot \cos\gamma}{1000} \tag{3}$$

Accordingly, the total force T_f [N] is expressed as $T_f = F_a + F_g + F_r$. Thus, the total power P_t [kW] (Eq. 4), and diesel volume V_{fuel} [l] (Eq. 5) where f_e is the needed amount of fuel to produce one kWh of output energy [kg/kWh], f_d is the density of diesel [kg/l], are given as follows:

$$P_t = \frac{T_f \cdot v}{3.6 \cdot 1000} \tag{4}$$

$$V_{fuel} = P_t \cdot t \cdot \frac{f_e}{f_d} \tag{5}$$

Therefore, the environmental impact C_e, expressed as an external cost in [$€_{CO2}$/km], where e is the emission coefficient for diesel fuel [kg_{CO2}/l], c_m is the environmental cost [€/t_{CO2}], k_a is the traffic density [veh/km] is given as follows:

$$C_e = V_{fuel} \cdot \frac{e \cdot c_m \cdot k_a}{1000} \tag{6}$$

Therefore, the proposed emission model can be explicitly expressed as follows:

$$C_e = c_m \cdot \frac{e \cdot k_a \cdot t}{1000} \cdot \left[\frac{c_d \cdot A_f \cdot \rho \cdot V^3 \cdot f_e}{f_d \cdot 2 \cdot 3.6^2 \cdot 1000} + \frac{m \cdot (g \sin\gamma + c_r g \cos\gamma) \cdot f_e \cdot V}{1000 \cdot 3.6 \cdot f_d} \right] \tag{7}$$

Considering the above-mentioned formulation of the emission model, the proposed single-level multi-objective NDP model is given through the following three objective functions:

- z_1 – the minimization of the total infrastructure and maintenance costs;
- z_2 – the minimization of the total environmental costs;
- z_3 – the maximization of the average traffic flow of OC hybrid trucks on electrified arcs.

The nomenclature of the single-level multi-objective NDP model is reported in Table 2.

Table 2 – Nomenclature of the single-level multi-objective NDP model

Parameters	
r	Electrification costs of arc a [Mio €/km]
r_s	Electrification costs per substation on arc a [Mio €/sub]
r_v	Percentage of total costs, related to the cost of maintenance [%]
r_f	Fixed maintenance costs [€/year]
P_e	Needed power per vehicle [kWh/veh]
P_s	Power capacity of substation [kW]
k_a	Traffic density on arc a [veh/km]
$n_{min,a}$	Minimum number of traction substations for arc a obtained by traction substation simulation model
R_t	Total budget [Mio €]
l_a	Length of arc a [km]
f_a	Assigned traffic flow on arc a [veh/h]
Decision Variables	
$\mathbf{x}$	$\mathbf{x}$ is the vector of decision variables x_a, where x_a is equal to 1 if arc a is electrified, and 0 otherwise
$\mathbf{n_s}$	$\mathbf{n_s}$ is the vector od decision variables $n_{s,a}$, where $n_{s,a}$ is the number of traction substations on the electrified arc a

Accordingly, the mathematical formulation of the objective functions is given as follows:

$$min\ z_1(\mathbf{x},\mathbf{n_s}) = \sum_{a \in A} \left(r \cdot l_a \cdot x_a + r_s \cdot n_{s,a} \right) \cdot \left(1 + r_v \right) \tag{8}$$

$$min\ z_2(\mathbf{x}) = \sum_{a \in A} C_e \cdot l_a \cdot (1 - x_a) \tag{9}$$

$$max\ z_3(\mathbf{x}) = \sum_{a \in A} K_a \cdot x_a \tag{10}$$

The goal of the optimisation model is to find the best set of arcs to be electrified in the eHighway system, considering three objective functions expressed through the minimization of total eHighway infrastructure costs, including the electrification costs r, costs for installing traction substations r_s, and maintenance costs r_v on a segment a (Eq. 8); minimization of the total environmental costs (Eq. 9); maximization of average traffic density of OC hybrid trucks served on an electrified segment considering the percentage λ of the assigned traffic flows, related to the OC hybrid trucks on electrified arcs, so that $K_a = \lambda \cdot k_a \cdot l_a$ (Eq.10). Moreover, Eq. (10) points out that the total OC hybrid truck demand on the electrified arc must be satisfied.

Since the proposed single-level multi-objective NDP model includes different criteria in the objective function, the Pareto optimisation was applied for finding the solution of the multi-objective optimisation. The Pareto optimisation aims to find the optimal solution among the set of feasible solutions considering all objective functions, in such a way that there is no other solution that could guarantee the improvement of any of the considered objective functions $z_k(x) \leq z_k(x^*), k = 1, \dots i$, where $z_k(x^*)$, is the Pareto optimum of the k^{th}objective function. Therefore, instead of having a single solution, the multi-objective optimisation generates Pareto optimal solution and the corresponding Pareto front with the non-dominant solutions $z_k(x^*)$.

There are different techniques for finding Pareto optimum and solving a multi-objective optimisation problem like the weighted sum method (Marler et al., 2010), ε-constraint method (Mavrotas, 2009), evolutionary algorithms (Zhou et al., 2011), etc. However, in this thesis, we used the weighted sum approach in which different weight coefficients w_i are assigned to the objective functions so that the sum of these weights is equal to 1, i.e. $\sum_i w_i = 1$. To make objective functions comparable, each one of them was normalized by dividing it with its corresponding maximum values as follows:

$$z_1^*(\mathbf{x},\mathbf{n_s}) = \frac{\sum_{a\in A}\left(r\cdot l_a\cdot x_a + r_s\cdot n_{s,a}\right)\cdot\left(1+r_v\right)}{\sum_{a\in A}\left(r\cdot l_a + r_s\cdot n_{\min,a}\right)\cdot\left(1+r_v\right)} \tag{11}$$

$$z_2^*(\mathbf{x}) = \frac{\sum_{a\in A} C_e\cdot l_a\cdot(1-x_a)}{\sum_{a\in A} C_e\cdot l_a} \tag{12}$$

$$z_3^*(\mathbf{x}) = \frac{\sum_{a\in A} K_a\cdot x_a}{\sum_{a\in A} K_a} \tag{13}$$

Therefore, the objective function of the single-level multi-objective NDP model is given as follows:

$$Z(\mathbf{x},\mathbf{n_s}) = w_1\cdot z_1^*(\mathbf{x},\mathbf{n_s}) + w_2\cdot z_2^*(\mathbf{x}) - w_3\cdot z_3^*(\mathbf{x})$$

The resulting mathematical formulation of the programming model is given as follows:

$$\left[\mathbf{x}^\wedge,\mathbf{n_s}^\wedge\right] = Arg_{\mathbf{x},\mathbf{n_s}}\min Z(\mathbf{x},\mathbf{n_s}) \tag{14}$$

$$\sum_{a\in A}\left(r\cdot l_a\cdot x_a + r_s\cdot n_{s,a}\right)\cdot\left(1+r_v\right) + r_f\cdot t <= R_t \tag{15}$$

$$P_e\cdot k_a\cdot l_a\cdot x_a\cdot\lambda \le P_s\cdot n_{s,a} \quad \forall a\in A \tag{16}$$

$$x_a <= E_{dj} \quad \forall a\in A \tag{17}$$

$$n_{s,a} \geq n_{\min,a} \cdot x_a \qquad \forall a \in A \tag{18}$$

$$x_a \in \{0,1\} \tag{19}$$

$$n_{s,a} \geq 0 \tag{20}$$

where, **x** and **n_s** are vectors of the decision variables x_a and $n_{s,a}$, respectively; **x^** and **n_s ^** are the optimal solution for the vectors **x** and **n_s**;

The objective function of the single-level multi-objective NDP, obtained with the weighted sum method, in which different weight criteria w_i are given to the three objective functions (infrastructure costs, environmental costs, and the maximisation of average traffic density of OC hybrid trucks on electrified arcs), is reported in Eq. (14). Constraint (15) is related to the available budget considering total infrastructure costs per km and total installation costs of traction substations. Constraints (16) are the power capacity constraints, where the required power of OC hybrid trucks served by one traction substation must not be greater than the capacity of that traction substation. In constraints (17), arcs selection must be coherent with a compatibility matrix E, where E_{dj} is equal to 1 if the arc a is electrifiable, otherwise, E_{dj} is equal to 0. According to constraints (18), the number of traction substation on the electrified arc a must be greater or equal than the minimum number of traction substation $n_{min,a}$ obtained by the simulation model. Constraints (19) are related to the binary nature of variables x_a, where x_a is equal to 1 if the road arc a is electrified and 0 otherwise. The variables $n_{s,a}$ in constraints (20) take positive values related to the number of traction substation for each electrified arc, and 0 if the road arc is not electrified.

4.3. The bi-level multi-objective NDP model

The proposed bi-level multi-objective NDP model finds the set of arcs to be electrified in the eHighway system considering different criteria i.e. the minimisation of total travel time, minimization of the infrastructure and environmental costs, and the maximization of the average traffic flow of OC hybrid trucks on electrified arcs. Additionally, the bi-level NDP model deals with finding not only the set of the arcs to be electrified, but also, the capacity expansion of some electrified arcs, considering the available budget. On the one hand, the capacity expansion of the electrified arcs could increase the network's performance by reducing the needed traveling time, and on the other hand, it allows higher operativity and flexibility regarding the increment of OC hybrid trucks demand in the future. Also, through the capacity expansion, we could have lanes dedicated only for OC hybrid trucks.

The bi-level multi-objective NDP model aims to achieve the system optimisation regarding the technological aspect of the eHighway system, the capacity expansion, and the assigned traffic flows on the network. Also, the electrification of the road segment achieves the benefits for the public authorities expressed through the minimisation of the CO_2 emissions. The bi-level model is developed as an extension of the previously defined, the single-level multi-objective NDP model, in which decision of the lower level i.e. traffic flow assignment problem, influence the set of the arcs to be electrified and the capacity expansion in the upper level. The choice of the decision-makers in the bi-level multi-objective NDP model depends on the collaboration of both levels, where the solution of the lower level's fixed-point problem is passed to the upper level. The output of the proposed bi-level optimisation is the set of arcs to be electrified, considering the capacity expansion, the number of traction substations and the traffic flow assignment obtained from the lower level. In further, we described the mathematical formulations of the upper and lower level of the bi-level multi-objective NDP model.

4.3.1. The upper level of the bi-level multi-objective NDP model

Each arc $a \in A$ in the upper level of the bi-level multi-objective NDP, is associated with the traffic flow $f_a^*(y_a)$ and travel time $t_a(f_a, x_a, y_a)$ obtained as the result of the traffic flow assignment in the lower level. The number of vehicles using the eHighway system is assumed as a percentage λ of the traffic flow $f_a^*(y_a)$ and is considered that vehicles have no environmental impact while traveling on the electrified section of the eHighway network.

The outcome of the decision making, and the transportation planning process is obtained through the upper level, which aims to merge the interest of the public authorities and transportation companies. The upper level of the proposed bi-level model minimizes the total costs considering environmental and infrastructure point of view, maximisation of average traffic density of OC hybrid trucks on electrified arcs, the minimisation of the total travel time and the capacity expansion costs, while the lower level is related to the traffic assignment problem. The output of the upper level depends on the travel time function of the lower level and therefore, the perceived travel times of the users. In the upper level, the bi-level multi-objective NDP model considers the environmental impact of OC hybrid trucks not using the eHighway system, since OC hybrid trucks are running on ICE diesel mode when driving on non-electrified sections. It evaluates the adoption of the eHighway system in the network from the costs, the traffic, and the environmental point of view. At the same time, it tends to optimise the number of electrified arcs and to increase the capacity of the electrified arcs (adding more lanes on the electrified link), according to the available budget.

The nomenclature of the upper level of the proposed bi-level multi-objective NDP model is reported in Table 3.

Table 3 – Nomenclature of the bi-level multi-objective NDP model

Parameters	
P_n	Power consumption of vehicle [kWh/km]
λ	Percentage of the assigned traffic flow related to the number of OC hybrid trucks in the eHighway system

C_b	Battery capacity of the vehicle [kWh/veh]
B_1	Total available budget related to the capacity expansion [Mio €]
B_2	Total available budget of the eHighway system [Mio €]
ξ	Conversion factor
l_a	Length of arc a [km]
c_{lane}	Cost of lane [€/km]
u_a	Upper value of the capacity expansion on the electrified arcs a
Decision variables	
$\mathbf{x}$	$\mathbf{x}$ is the vector of decision variables x_a, where x_a is equal to 1, if arc $a \in A$ is electrified, 0 otherwise
$\mathbf{y}$	$\mathbf{y}$ is the vector of decision variables y_a, where y_a is the capacity expansion on the electrified arcs
$\mathbf{n_s}$	$\mathbf{n_s}$ is the vector of decision variables $n_{s,a}$, where $n_{s,a}$ is the number of traction substations on electrified arc $a \in A$

Accordingly, the mathematical formulation of the objective functions in the upper level is described as follows:

$$\min z_1(\mathbf{x},\mathbf{y}) = \sum_{a \in A} f_a^*(y_a) \cdot t_a\left(f_a^*(y_a), x_a, y_a\right) + \xi \sum_{a \in A} c_{lane} \cdot l_a \cdot y_a \tag{21}$$

$$\min z_2(\mathbf{x},\mathbf{n_s}) = \sum_{a \in A} \left(r \cdot l_a \cdot x_a + r_s \cdot n_{s,a}\right) \cdot (1 + r_v) \tag{22}$$

$$\min z_3(\mathbf{x}) = \sum_{a \in A} C_e\left(f_a^*\right) \cdot l_a \cdot (1 - x_a) \tag{23}$$

$$\max z_4(\mathbf{x}) = \sum_{a\in A} K_a \cdot x_a \tag{24}$$

The first objective function is related to minimisation of the total travel time and the costs of the capacity expansion on the electrified arcs, where ξ is the conversion factor (Eq. 21). The second objective function is related to the infrastructure, traction substations' and maintenance costs of the electrified arcs in the eHighway system (Eq. 22). The third objective function is related to the environmental costs of the non-electrified arcs (Eq. 23), and the fourth objective function is related to the maximisation of average traffic density of OC hybrid trucks on the electrified arcs (Eq. 24).

Since the proposed bi-level multi-objective NDP model is dealing with multi-objective optimisation, the weighted sum approach is used so that the normalization of the objective functions is obtained by dividing it with its corresponding maximum values, as follows:

$$z_1^*(\mathbf{x},\mathbf{y}) = \frac{\sum_{a\in A} f_a^*(y_a)\cdot t_a\left(f_a^*(y_a), x_a, y_a\right) + \xi \sum_{a\in A} c_{lane}\cdot l_a \cdot y_a}{\sum_{a\in A} f_a^*(y_a)\cdot t_a\left(f_a^*(y_a), y_a\right) + \xi \sum_{a\in A} c_{lane}\cdot l_a} \tag{25}$$

$$z_2^*(\mathbf{x},\mathbf{n_s}) = \frac{\sum_{a\in A}\left(r\cdot l_a\cdot x_a + r_s\cdot n_{s,a}\right)\cdot(1+r_v)}{\sum_{a\in A}\left(r\cdot l_a + r_s\cdot n_{\min,a}\right)\cdot(1+r_v)} \tag{26}$$

$$z_3^*(\mathbf{x}) = \frac{\sum_{a\in A} C_e\left(f_a^*\right)\cdot l_a\cdot(1-x_a)}{\sum_{a\in A} C_e\left(f_a^*\right)\cdot l_a} \tag{27}$$

$$z_4^*(\mathbf{x}) = \frac{\sum_{a\in A} K_a\cdot x_a}{\sum_{a\in A} K_a} \tag{28}$$

Accordingly, the objective function of the bi-level multi-objective NDP model is given as follows:

$$Z(\mathbf{x},\mathbf{n_s},\mathbf{y}) = w_1 \cdot z_1^*(\mathbf{x},\mathbf{y}) + w_2 \cdot z_2^*(\mathbf{x},\mathbf{n_s}) + w_3 \cdot z_3^*(\mathbf{x}) - w_4 \cdot z_4^*(\mathbf{x}) \tag{29}$$

$$\left[\mathbf{x}\hat{}, \mathbf{n_s}\hat{}, \mathbf{y}\hat{}\right] = Arg_{\mathbf{x},\mathbf{n_s},\mathbf{y}} \min Z(\mathbf{x},\mathbf{n_s},\mathbf{y}) \tag{30}$$

The constraints of the upper level of the optimization model are reported as follows:

$$f^*(y) = B \cdot P\left(B^T \cdot t\left(f^*, x, y\right)\right) \cdot D \tag{31}$$

$$y_a - M \cdot x_a \leq 0 \quad \forall a \in \mathrm{A} \tag{32}$$

$$\sum_{a \in A} c_{lane} \cdot l_a \cdot y_a \leq B_1 \tag{33}$$

$$P_e \cdot \frac{f_a^*(y_a)}{V} \cdot l_a \cdot x_a \cdot \lambda \leq P_s \cdot n_{s,a} \quad \forall a \in \mathrm{A} \tag{34}$$

$$\sum_{a \in A} \left(r \cdot l_a \cdot x_a + r_s \cdot n_{s,a}\right) \cdot (1 + r_v) + r_f \cdot t \leq B_2 \tag{35}$$

$$P_n \cdot l_a \cdot f_a^*(y_a) \cdot \lambda \cdot x_a \leq C_b \cdot \lambda \cdot f_a^*(y_a) \quad \forall a \in \mathrm{A} \tag{36}$$

$$n_{s,a} \geq n_{\min,a} \cdot x_a \quad \forall a \in \mathrm{A} \tag{37}$$

$$0 \leq y_a \leq u_a \quad \forall a \in \mathrm{A} \tag{38}$$

$$x_a \in \{0,1\} \quad \forall a \in \mathrm{A} \tag{39}$$

$$n_{s,a} \geq 0 \quad \forall a \in \mathrm{A} \tag{40}$$

$$y_a \in [0,..,u_a] \tag{41}$$

where, **x, y** and $\mathbf{n_s}$ are vectors of the decision variables x_a, y_a and $n_{s,a}$, respectively; **x^** , **y^** and $\mathbf{n_s}$**^** are the optimal solution for the vectors **x, y** and $\mathbf{n_s}$;

The objective function Z aims to minimise the total travel time, infrastructure and environmental costs and maximise the average traffic density of the OC hybrid trucks on the electrified arcs (Eq. 30). The constraint (31) is the traffic flow assignment, obtained as the fixed-point solution of the lower level problem. Constraints (32) are related to the capacity expansion of the electrified arcs, expressed in the number of lanes. The constraint (33) is related to the investment costs for the capacity expansions which must be in correspondence with the available budget B_1. Therefore, model choses the arcs, among the set of electrified arcs, for the capacity expansion, according to the budget limitation. The constraints (34) are related to the capacity constraint of the substations, where V is the average speed of vehicle and λ is the percentage of the assigned traffic flow $f_a^*(y_a)$ related to the number of OC hybrid trucks. The energy consumption of the number of OC hybrid trucks to be using the eHighway system should be lower than the capacity P_s of the traction substations $n_{s,a}$. The constraint (35) states that the fixed, infrastructure, traction substations and maintenance costs of the eHighway system considering the life-cycle t of 20 years, should be lower than the available budget B_2. Constraints (36) are related to the battery capacity of the OC hybrid trucks using the eHighway system. Constraints (37) determine the number of traction stations on electrified arcs, which should be greater or equal than the number of traction substations $n_{min,a}$ obtained as a result of the traction substation model. Constraints (38) are related to the lower and upper values of the decision variable related to the capacity expansion. Therefore, if there is a capacity expansion on the electrified arc, the decision variable y_a takes the values from 0 to the upper value u_a, and 0 otherwise. Constraints (39) are related to the binary nature of variables x_a, where x_a is equal to 1 if the road arc a is electrified and 0 otherwise. The decision variables in constraints (40) are related to the number of traction substations on the electrified arcs, which can take values greater than or equal to 0. Constraint (41) is related to the discrete nature of variable y_a.

4.3.2. The lower level of the bi-level multi-objective NDP model

The lower level of the proposed bi-level multi-objective NDP model is related to the traffic flow assignment problem. In the eHighway system, it is assumed that vehicles are travelling with average speed V Each link a on road section is associated with a traffic flow f_a, length l_a and capacity c_a. The assignment of traffic flows f_a^* was obtained applying the SUE traffic assignment model (Cascetta, 2009). In general, the SUE assignment model simulates the supply-demand interaction in the transportation system, where the input parameters are related to the network characteristics (length of arcs, origin-destination matrix, capacity, free-flow travel times, etc.), and the output is the traffic flow assignment.

Each arc $a \in A$ is associated with demand d_{od} between origin o and destination node d, so that $d_{od} \in D$, where D is the demand vector. The binary variable $b_{a,k}^{od}$ is equal to 1 if path $k \epsilon K_{od}$ between origin-destination pairs (o, d) traverses link $a \in A$, and 0 otherwise. The B denotes the link-path incidence matrix, so that $b_{a,k}^{od} \in B$. The set of all routes k connecting the origin and destination nodes (o, d) is denoted as as K_{od}, so that $k \epsilon K_{od}$.

In the SUE, users tend to choose the route paths according to their perception related to the minimum travel time for reaching the destination in the network. Therefore, the Logit model was used for obtaining drivers' route choices, and it is assumed that the users always try to maximise their perceived travel utility, of choosing route k from a set of routes K_{od}, based on the current travel information. Additionally, p denotes the vector of the probabilities $p_{od}^k \epsilon p$ that the user traveling from origin o to destination d will choose path k, $k \epsilon K_{od}$, while P is the path choice probability matrix, $p \epsilon P$.

For calculating links' traffic flows we used Dial's algorithm based on the implicit path enumeration. The algorithm uses the Logit path choice model and finds the set of efficient paths, i.e. the set of the shortest paths, based on the links' costs. The efficient links are links (i, j) in which the costs of the shortest path from an origin o to the initial node i of that link is less than the cost of the shortest path from origin to the final node j, (Cascetta, 2009). The links' costs are calculated with the modified BPR link travel time function $t_a(f_a, x_a, y_a)$ (Eq. 44). The pseudo code of Dial's algorithm (Cascetta, 1998) is reported in Algorithm 1. The input parameters of Dial's algorithm are:

- $d\ (o, d)$ is the demand between the origin $o$and destination d
- $t(a)$ is the cost of arc $a \in A$, expressed as the travel time function $t_a(f_a, x_a, y_a)$
- θ is the parameter od the Logit model
- $f_a(a)$ is the flow of arc a
- $ent(j)$ is the total flow entering at node j (according to the tree from origin o)
- $Wn(i)$ is the weight of node i, (considering origin o)
- $wa(a)$is the weight of arc a
- $lpr(j)$ is the arc added to the node j (according to the tree from origin o)
- $ord(k)$ is the node in k^{th} position of the node list ordered by ascending minimum cost (according to the tree of an origin o)
- $Z_c(i)$is the cost of the shortest path towards node a (according to the tree of an origin o)
- $shortestpath\ (c, o\ \rightarrow Z_c, ord)$ is a function that calculates the minimum path costs given the costs vector $t(a)$, the origin o and the ordered list ord.

Algorithm 1 – The pseudo code of Dial's algorithm

/Initialization/ Input parameters and data
$d(o,d), t(a), \theta, f(a), ent(j), Wn(i), wa(a), lpr(j), ord(k), Z_c(i),$
$shortestpath(c, o \to Z_c, ord)$
for each $a \epsilon I_a$
  $f(a) = 0$
for each o ϵI_o
  W$(o) = 1$
  run $shortestpath(c, o \to Z_c, ord)$
  $k = 1$
  repeat
    $k = k + 1; j = ord(k); W(j) = 0$
    for each $a \in BS(j)$ /converging arcs to node *j*/
      $i = in(a); w(a) = 0$
      if $Z_c(i) < Z_c(j)$ ***then***
        $wa(a) = Wn(i) * exp\left(-\frac{t(a)}{\theta}\right); Wn(j) = Wn(j) + wa(a)$
      else
        $wa(a) = 0$
  until $k = n$
  for each $i \epsilon Ind$
    $ent(i) = 0$
  for each $d \epsilon Id$
    $ent(d) = d(o,d)$
  $k = n$
  repeat
    $j = ord(k); k = k - 1$
     for each $a \epsilon BS(j)$ /converging arcs to node *j*/
        $i = in(a); e = ent(j) * \frac{wa(a)}{Wn(j)}$
        $f(a) = f(a) + e; i = in(a); ent(i) = ent(i) + e$
  until $k = a \quad \big(o = ord(k)\big)$

Accordingly, the nomenclature of SUE traffic assignment model is presented in Table 4.

Table 4 – The nomenclature of SUE model

Sets		
N	Set of nodes	$n \in N$
A	Set of arcs	$a \in A$
O	Set of origin nodes	$o \in O$
D	Set of destination nodes	$d \in D$
Parameters		
d_{od}	Travel demand for origin-destination pairs (o, d)	
P_{od}	Set of all paths connecting origin-destination pairs	
t_0	Free-flow time	
c_a	Capacity of link $a \in A$	
c_l	Additional capacity of lane	
α, β	Parameters of BPR cost function	
Variables		
f_a	Traffic flow of link $a \in A$	
y_a	Capacity expansion of the electrified arcs $a \in A$	

The lower level of the proposed bi-level multi-objective NDP model is presented as follows:

$$f^*(y) = B \cdot P\left(B^T \cdot t\left(f^*, x, y\right)\right) \cdot D \tag{42}$$

$$f^* \in S_f \tag{43}$$

where

$$t_a\left(f_a, x_a, y_a\right) = t_0 \cdot \left(1 + \alpha \cdot \left[\left(\frac{f_a}{c_a}\right) \cdot \left(1 - x_a\right) + \left(\frac{f_a}{c_a + c_l \cdot y_a}\right) \cdot x_a\right]^{\beta}\right) \tag{44}$$

The travel time function $t_a(f_a, x_a, y_a)$ is given as the modified BPR travel costs function (Eq. 44). In the travel time function, f_a is the traffic flow of link a, c_a is the capacity of link $a \in A$, t_0 is the free-flow traffic time, c_l is the capacity of the lane, y_a is the upper-level decision variable related to the capacity expansion seen as the number of lanes to be added on the electrified links $a \in A$, x_a is the upper-level decision variable that takes the value 1 if the arc is electrified and 0 otherwise, and the parameters of the travel costs functions are α and β.

The Method of Successive Averages (MSA-FA) is used to find the solution of the fixed-point problem using flow averaging through iterations k. The algorithm converges when the current solution of iteration k falls beyond the predefined threshold (Cascetta, 2009). The algorithm starts from a feasible solution $f^0 \epsilon S_f$, and, at each iteration k, it estimates the flows f^k considering the previous solution at iteration $k-1$. As already mentioned, flows f_d^k are calculated using Dial's algorithm. Therefore, the framework of the MSA-FA (45-48) where c_k is the vector costs obtained with travel costs function $t_a(f_a, x_a, y_a)$, at each iteration k, and α^k is the step size, is reported as follows:

$$c^k = c\left(f^{k-1}\right) \tag{45}$$

$$f_d^k = f\left(c^k\right) \tag{46}$$

$$f^k = f^{k-1} + \alpha^k \cdot \left(f_d^k - f^{k-1}\right) \tag{47}$$

$$k = k + 1 \tag{48}$$

5. THE SOLUTION APPROACH

In general, there are different methods for solving transportation network design problems depending on the complexity of the mathematical model, the size of the transportation network, etc. (e.g. exact, heuristics, metaheuristics approaches). While the optimality of the exact approaches is always guaranteed, the time needed for solving NP-hard problems could be exponential. However, this could be overcome with the application of heuristics and metaheuristics approaches, which give the feasible solution that is close to the optimal solution, the so-called, near-optimal solution. Sometimes the application of heuristic algorithms could be effective since they tend to be adjusted and formulated for the particular problem solving in acceptable computation time. However, in other cases, the complexity of the problem could be quite difficult to handle with heuristics algorithms, which could be solved with the application of metaheuristic algorithms (e.g. combinatorial optimisation problems, non-linear problems, multi-criteria problems, etc.). In general, the most spread metaheuristic algorithms for solving transportation network design problems are Genetic Algorithms, PSO, Simulated Annealing, etc., Iliopoulou et al. (2019). Thus, in this section are described the algorithms used for solving the proposed the single-level and the bi-level multi-objective NDP.

5.1. The solution approach for the single-level multi-objective NDP model

The proposed single-level multi-objective NDP model was developed in Matlab, where the exact solver that includes cut generation and the branch and bound method was used as a solution approach. The framework of the solution approach for the is presented in Figure 4. The process starts with loading the network data and is followed by the calculation of the traffic flow assignment. As previously mentioned, the obtained traffic flow assignment is fixed and is used for calculating the number of traction substations and, the objective function of the single-level multi-objective NDP model.

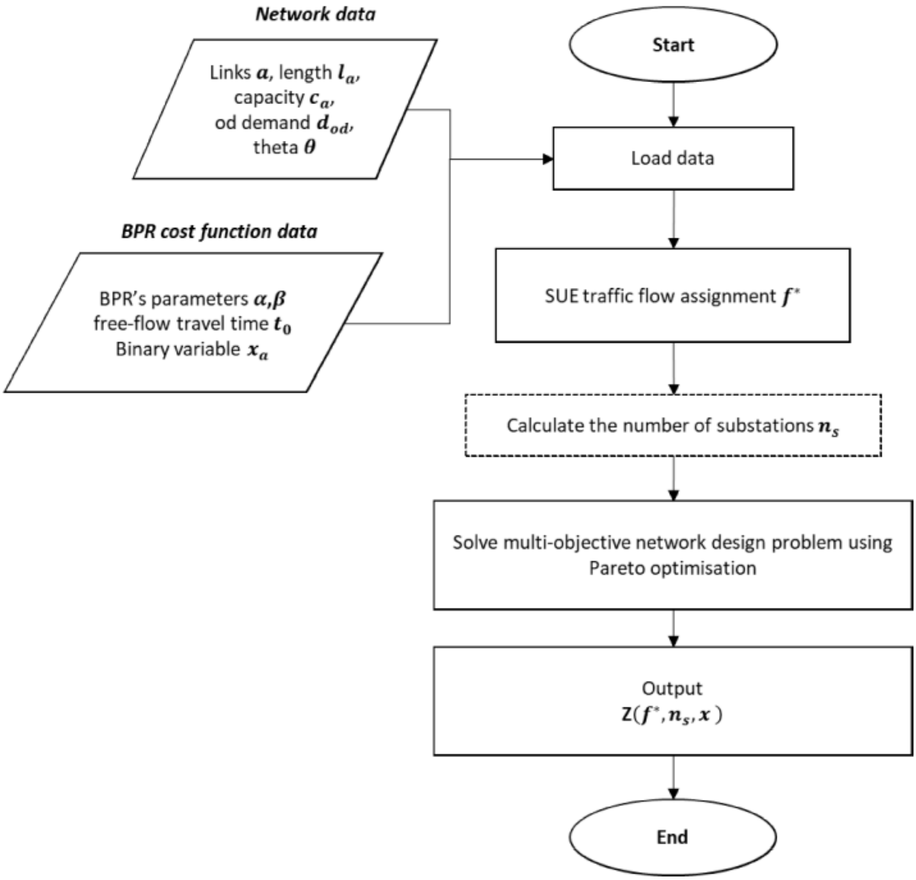


Figure 4. The framework of the single-level multi-objective NDP

5.2. The solution approach for the bi-level multi-objective NDP model

Generally, the bi-level NDPs are perceived as one of the most difficult problems since the optimisation of the upper level depends on the solution of the lower-level problem. Sometimes, the bi-level NDP model is formulated as a single level model in which the lower level could be alleged as a constraint of the main problem. Since the lower-level model consists of a non-linear constraint, the bi-level NDP is a non-convex minimisation problem that requires advanced approaches for obtaining the solution, such as genetic algorithms. The application of the genetic algorithm framework demonstrated the effectiveness in finding good-quality solutions for different sizes of the bi-level NDP, especially when the complexity of the formulation (e.g. big number of variables and constraints, complicated objective function, etc.) requires advanced solving techniques, which makes them suitable for network design problem solving.

Through the observation of the evolution processes in nature, scientists discovered some evolution properties which lead to the creation of the evolutionary algorithms that could be applied for solving a large number of problems in various fields, as well as in transportation. One of these algorithms, the genetic algorithm proposed by John H. Holland (1984), is based on Darwin's theory of evolution and the process of selection in the nature in which the strongest individuals in the population have the biggest chance of surviving and creating new offspring, (Holland, 1984) . The differences between the genetic material of the two consecutive generations are very small, but it has been noticed that these changes are becoming more significant through the evolutionary process, leading to the creation of new species. Thus, the individuals who inherit "better" genetic properties and genes from the previous generations, have a greater chance of survival.

The genes of each individual in the population are written in chromosomes, which they receive from their parents. The idea of the genetic algorithms is that each individual in the population represents one solution; each population consists of a set of individuals, represented by chromosomes and usually composed of zeros and ones which represent a solution of a problem. For finding result of the problem, it is necessary to determine the objective function, and are considered those solutions that have a better value of the objective function (lower values in the case of the minimisation problem) for the further selection process. In the case of the minimisation problem, genetic algorithms tend to find the local minimum in the area of feasible solutions, considering the entire population. The number of individuals in the population depends on the dimension of the problem. Usually, they are selected randomly, though roulette selection, tournament selection, etc. In nature, those solutions would have a greater chance of creating new offspring. On the selected individuals (solutions) could be performed genetic modifications, such as the selection of two individuals for exchanging genetic information through the different types of crossover operations, or through the mutations. This process is repeated until the stopping criteria are met, such as exceeded number of generations.

The flow chart of the solution approach of the proposed bi-level multi-objective NDP model is presented in Figure 5. Initially, we considered all data related to the network, and the parameters of the genetic algorithm. At the beginning, in the first generation (iteration), the initial solution $fitn_i^0$ is randomly generated and composed of the decision variables related to the electrification of the links a in the network. Then, the traffic flow assignment from the lower level's fixed-point problem solution is obtained through MSA and Algorithm 1. The travel time function is calculated according to the (Eq. 44), while the driver's route choice is obtained through the Logit model. According to the obtained assignment of the traffic flows $f_a^*(y_a)$, the number of the needed traction substations on each electrified arc it is calculated according to the percentage λ of the vehicles using the eHighway system, related to the OC hybrid trucks. In the next step, the solution of the upper level is obtained, considering objective function Z, and constraints (30-41). The process is repeated interactively, until the maximum number of generations, G_{max} is reached. The final output of the algorithm is the network design with the set of arcs to be electrified and the capacity expansion of the selected electrified arcs.

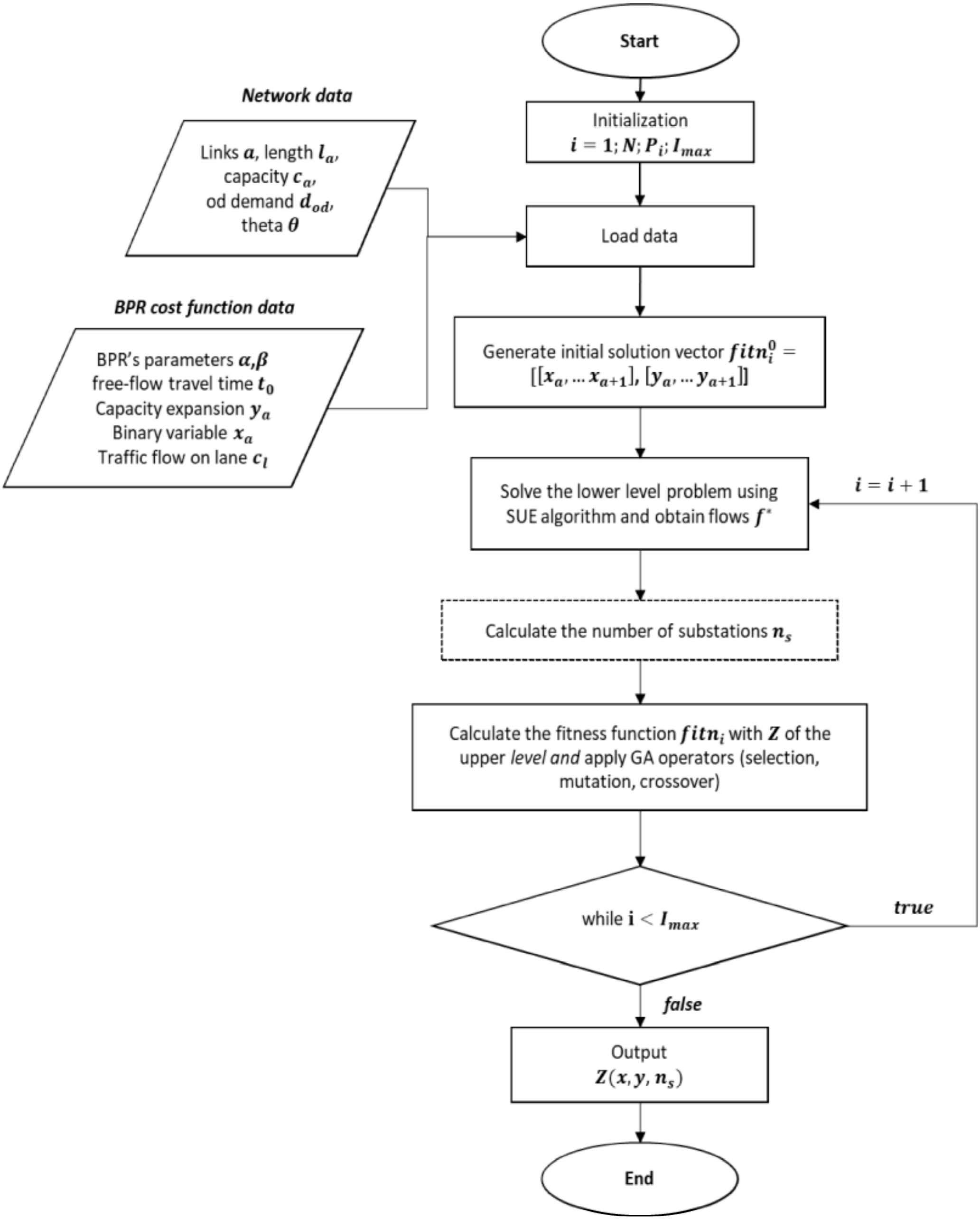


Figure 5. Flow chart of the bi-level NDP model

The pseudo code of the genetic algorithm for solving the proposed bi-level multi-objective NDP model is presented in Algorithm 2. In the initialization process, the parameters of the genetic algorithm were defined considering the size of the population P, the number of chromosomes N, the maximum number of generations G_{max}, mutation and crossover probabilities (m_{rate}, cr_{rate}). The number of individuals (chromosomes) N are randomly selected and compared with other individuals in the population through the fitness function value $fitn$. At the beginning, the number of generations k is equal to one, and for each individual in the population P_k the value of the fitness function $fitn_k$ is evaluated, which corresponds to the inverse of the objective function Z of the upper level problem. Hence, for improving the solution, the genetic operators such as mutation (with mutation probability m_{rate}) and crossover (with crossover probability cr_{rate}) are performed on random pairs of the individuals, and the value of the fitness function $fitn_k$ is updated. Then, for the next generation $k = k + 1$, the chromosomes are randomly selected, in such a way that the strongest individuals have the highest chance to be selected. Therefore, the process is repeated until the termination criteria are satisfied, i.e. the maximum number of generations G_{max} is reached.

Algorithm 2 – The pseudocode of the Genetic Algorithm

/Initialization/ Input parameters and data

$\boldsymbol{c_a, d_{od}, l_a, t_0}$→ Network data loading

$\boldsymbol{f^*}$ → Output of *SUE assignment model*

Genetic algorithm input parameters:

$\boldsymbol{k, N, P_k, cr_{rate}, G_{max}, m_{rate}}$

Begin

$k = 0$

for each $\boldsymbol{N}$ in $\boldsymbol{P_k}$

solve the *upper-level problem*

evaluate the fitness value $\boldsymbol{fitn}$ with problem (30)— (41)

end

while $(\boldsymbol{k} \leq \boldsymbol{G\_max})$

/*crossover operations*/

select a pair of $\boldsymbol{N}$ from $\boldsymbol{P_k}$ based on $\boldsymbol{fitn}$

perform crossover operation with $\boldsymbol{cr_{rate}}$

/*mutation operations*/

perform the mutation on some $\boldsymbol{N}$ with $\boldsymbol{m_{rate}}$

update $\boldsymbol{P_k, fitn}$

$$k = k + 1$$

repeat until the termination condition is satisfied

end while

Return the solution with best $\boldsymbol{fitn}$ from $\boldsymbol{P_{G\_max}}$

6. NUMERICAL APPLICATIONS AND RESULTS

We run the proposed models on a 64-bit Windows 10 operative system with an Intel(R) Core, CPU 1.80GHz and 16 GB of RAM. For evaluating the results, the developed models were tested on two networks: i) a medium-sized network consisting of 9 nodes and 28 links; ii) the Sioux-Falls network which consists of 24 nodes and 76 links. The arc capacity for the medium-sized network was set to be 4000 vehs/h, while the lengths of the arcs were randomly generated within integer values up to 6 km. The free-flow travel time is calculated as $t_0 = \frac{l}{V}$, where l is the length of the arc and V is the average speed. Moreover, the origin-destination matrix is generated randomly in the range from 300 to 2700.

For the Sioux-Falls network, we used the data existing in the literature, proposed by LeBlanc et al., (1975). The Sioux-Falls network is one of the most used networks in the literature for transportation studies, in particular network design, and it has characteristics of an extra-urban network since, for example, arcs' lengths are in the range of 2 to 10 km, that makes it useful for testing the eHighway network. For calculating traffic flows on the Sioux-Falls network, the data for each origin-destination pair, the length, and the capacity of each arc were considered. Since the original data consider the trips between nodes, expressed in thousands of vehicles per day, we assumed that hourly flows are 10% of initial data. When travelling on an electrified arc, the power consumption of vehicles is 1.45 [kWh/km], while the minimum safe distance between vehicles l_{min} depends on traffic density k_a.

Therefore, the parameters of the single-level and the bi-level multi-objective NDP model for the medium-sized and the Sioux-falls network are reported in Table 5 and Table 6, respectively.

Table 5 - Parameters' values of the medium-sized and Sioux-fall network for the single-level multi-objective NDP model

Parameter	Value	Parameter	Value
r	1	t	20
r_s	2.8	f_d	0.2
r_v	0.02	f_e	0.8
r_f	0.5	m	12000

P_e	150	c_r	0.006
P_s	3000	c_d	0.7
R_t	210/250	ρ	1.2
c_m	60	λ	0.2
e	2.64	A_f	2.1

Table 6 - Parameters' values of the medium-sized and Sioux-falls network for the bi-level multi-objective NDP

Parameter	Value	Parameter	Value
r	1	t	20
r_s	2.8	f_d	0.2
r_v	0.02	f_e	0.8
r_f	0.5	m	12000
P_e	150	c_r	0.006
P_s	3000	c_d	0.7
B_1	650/800	ρ	1.2
c_m	60	λ	0.2
e	2.64	C_b	120
A_f	2.1	B_2	210/250
c_{lane}	10	ξ	1
c_l	2000		

In the further, the results of the numerical applications and the analysis of the Pareto optimisation, and the corresponding Pareto front with non-dominant solutions, for the single level model will be discussed. Regarding the numerical application of the bi-level model, a sensitivity analysis was carried out in two parts. In the first part of the sensitivity analysis, the results were evaluated based on the different percentages λ related to the OC hybrid trucks using the eHighway system, while in the second part, a sensitivity analysis was carried out based on the different objective functions' weight criteria w_i. In particular, we defined three scenarios, which could be useful for decision-maker to understand the interaction between the previously defined objectives, the total costs and environmental impact of the overall system.

6.1. Results of the single-level multi-objective NDP model

As already mentioned, for finding the optimal solution of the single-level multi-objective NDP model was used the exact solution approach, and the considered parameters' values are reported in Table 5. We assumed the number of OC hybrid trucks as 1% of the obtained average flows. The stopping criterion of MSA was set up to be 0.01. According to the obtained traffic flows assignment f_a, traffic density k_a, and considering an average speed V of vehicles of 80 km/h, the minimum safe distance, l_{min} between OC hybrid trucks resulted to be 119 m for the medium-size network, while for the case of the Sioux-Falls network it resulted in 287 m.

After obtaining the fixed assignment of the traffic flows, the traction simulation model was used for calculating the minimum number of the substation $n_{min,a}$ on the network. Considering the assigned traffic flows, the results of the traction substation model regarding the number of substation $n_{min,a}$, the maximum number of OC hybrid trucks which could be equipped by substations $n_{vs,a}$, and the length of arcs l_a are presented in the Appendix (Table

A1) for the medium-sized network, and in the Appendix (Table A2) for the Sioux-falls network.

The results of Pareto optimisation were obtained considering weight coefficients w_i from 0.1 to 1. The Pareto front was constructed according to the obtained Pareto optimal solutions, as presented in Figure 6 for the medium-sized, and in Figure 7 for the Sioux-Falls network, respectively. As expected, an increase of electrified road segments and the number of OC hybrid trucks using the eHighway system resulted in higher environmental improvement. Moreover, it can be observed the Pareto front surface considering non-dominated solutions, from which a decision-maker can select the best one. Figure 6 shows the Pareto-optimal solutions for the medium-sized network, where solutions for the objective function z_1 are in the range of 5.92 to 194.20 Mio €, for the objective function z_2 are from 44.96 to 745.55 Mio €, for the objective function z_3 are from 1 to 28 vehicles. Figure 7 shows results for Sioux-Falls network where the Pareto-optimal solutions for the objective function z_1 are from 16.93 to 239.90 Mio €, for the objective function z_2 are from 503.29 to 1245.49 Mio €, for the objective function z_3 are from 2.52 to 28.76 vehicles. The percentage of electrification for the medium-sized network is up to 92.85%, while for Sioux-Falls network is up to 43.42%.

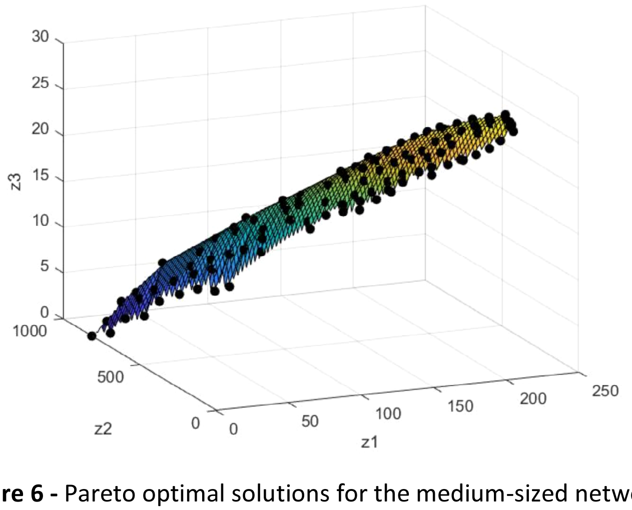


Figure 6 - Pareto optimal solutions for the medium-sized network

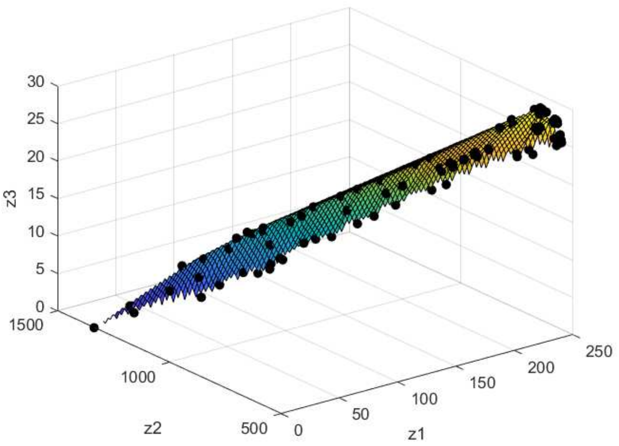


Figure 7 - Pareto optimal solutions for the Sioux-Falls network

- ***The results of the medium-sized network***

In Figure 8 is presented one of the optimal solutions for the medium-sized network with the obtained number of traction substations for each electrified arc, where electrified arcs are marked with red, and non-electrified arcs are marked with blue. The percentage of electrification is 43.15% considering the total length of the electrified arcs, where z_1 = 93.82 Mio €, z_2 = 347.55 Mio €, z_3 =18 vehicles/h. The weight coefficients w_i for the three objective functions are w_1 = 0.5, w_2= 0.17, $w_2 =$ = 0.33, and the value of the objective function is Z= 0.0885. The total length of the electrified road network is 57.58 km, while the percentage of environmental improvement is 57.13%.

In Figure 9 is presented the relation between environmental improvement and the electrification percentage for the medium-sized network. The figure shows that the correlation between these variables is almost linear, imposing that increment of the number of electrified arcs on the medium-sized network causes higher environmental improvement.

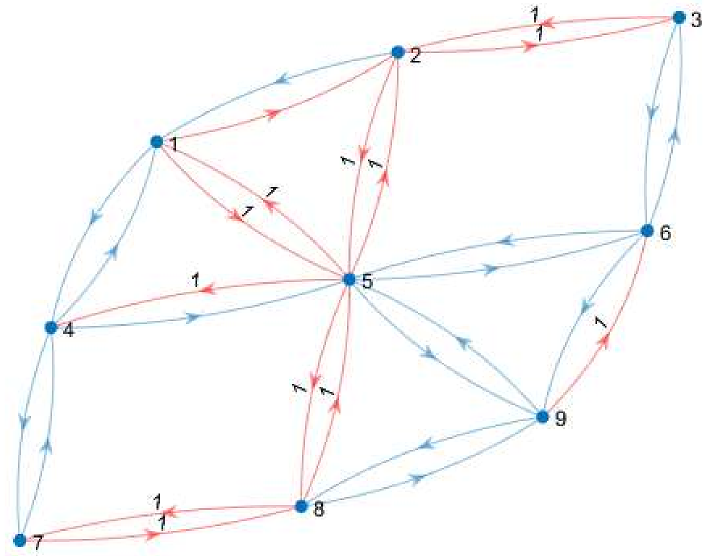


Figure 8 - Pareto optimal solution for the medium-sized network

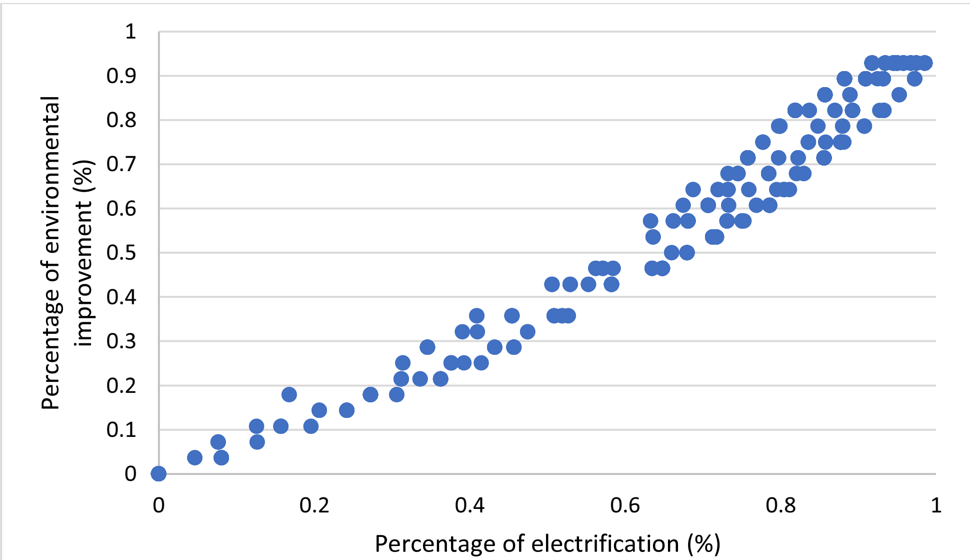


Figure 9 - Environmental improvement (%) of a medium-sized network depending on the number of electrified arcs (%)

- ***The results of the Sioux-falls network***

Figure 10 shows one of the obtained Pareto optimal solutions for the Sioux-Falls network, for weight coefficients w_1= 0.2, w_2 = 0.2, w_3 = 0.6. The values of objective functions are z_1 = 239.90 Mio €, z_2 = 521.21 Mio €, z_3 = 28.75 vehicles/h. The percentage of electrification is 44.59% considering the length of total electrified arcs, while the percentage of emission reduction is 60.99%. The total length of electrification is 140 km. The results of one of the Pareto optimal solutions are reported in Table 7 in terms of: $n_{s,a}$– the number of substations per electrified arc ;l – the length of an electrified arc; $n_{vs,a}$ - the number of vehicles served by one substation.

Table 7 - Pareto optimal solution values for the Sioux-Falls network

Electrified arc	$n_{s,a}$	l[km]	$n_{vs,a}$ [veh/sub]
(11,4)	1	6	10
(16,8)	1	5	15
(10,9)	1	3	19
(9,10)	1	3	18
(11,10)	1	5	22
(15,10)	1	6	17
(16,10)	1	4	17
(17,10)	2	8	28
(10,11)	1	5	24
(12,11)	1	6	14
(14,11)	1	4	12
(11,12)	1	6	14
(24,13)	1	4	15

(15,14)	1	5	12
(10,15)	1	6	24
(14,15)	1	5	12
(19,15)	1	3	15
(22,15)	1	3	17
(8,16),	1	5	21
(10,16)	1	4	26
(17,16)	1	2	21
(10,17)	2	8	8
(16,17)	1	2	32
(19,17)	1	2	32
(15,19)	1	3	18
(17,19)	1	2	22
(20,19)	1	4	18
(19,20)	1	4	12
(22,20)	1	5	12
(15,22)	1	3	22
(20,22)	1	5	14
(13,24)	1	4	15

The solutions of the objective function z_1 and z_2 for Sioux-Falls network depending on weights w_1 are presented in Figure 11. We can observe that increment of the weight w_1 leads to a decrease in total electrification costs z_1 and the increase in total environmental costs z_2. The lower environmental impact could be obtained by increasing the percentage of electrified arcs, as presented in Figure 12.

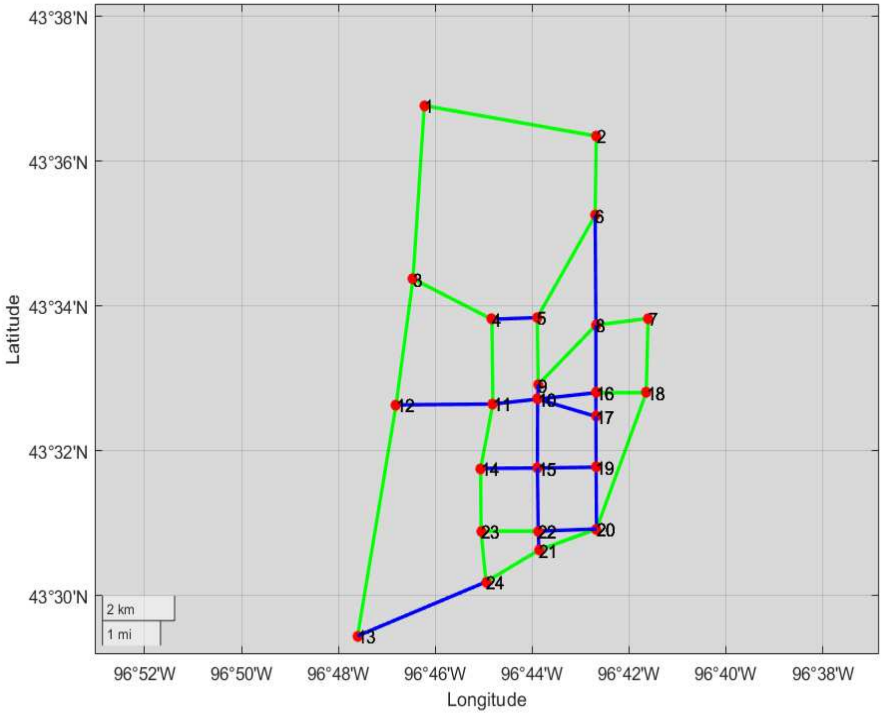
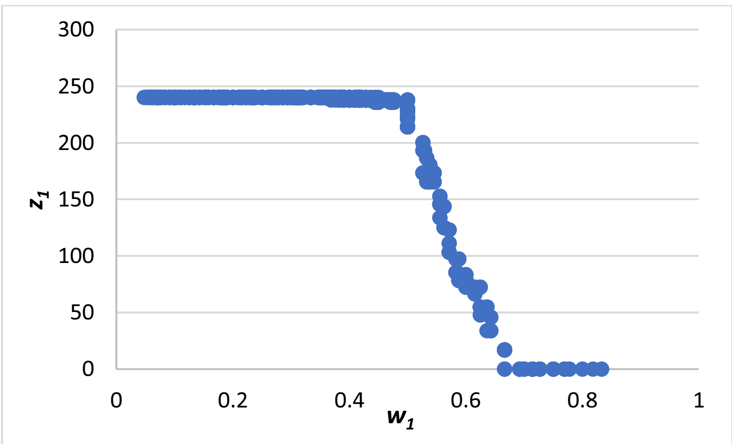


Figure 10 - Pareto optimal solution graph for the Sioux-Falls network

a)



b)

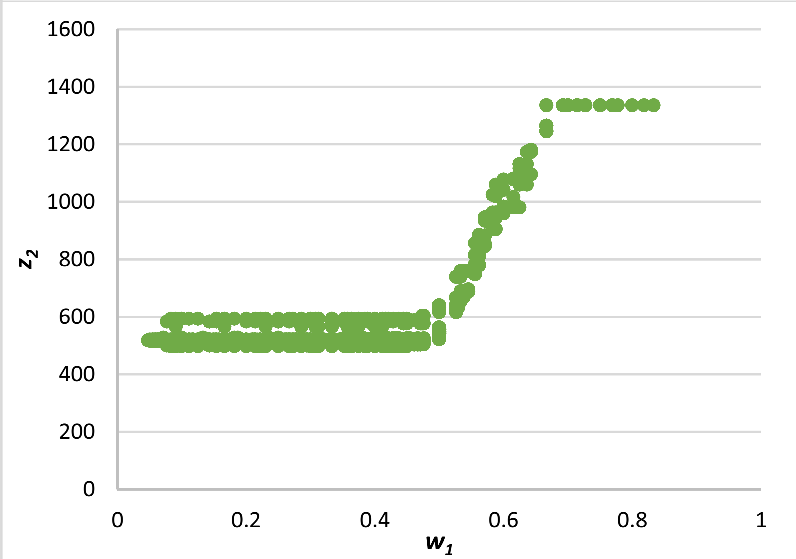


Figure 11 - Pareto solutions for the Sioux-Falls network: a) z_1 depending on weight w_1; b) z_2 depending on weight w_1

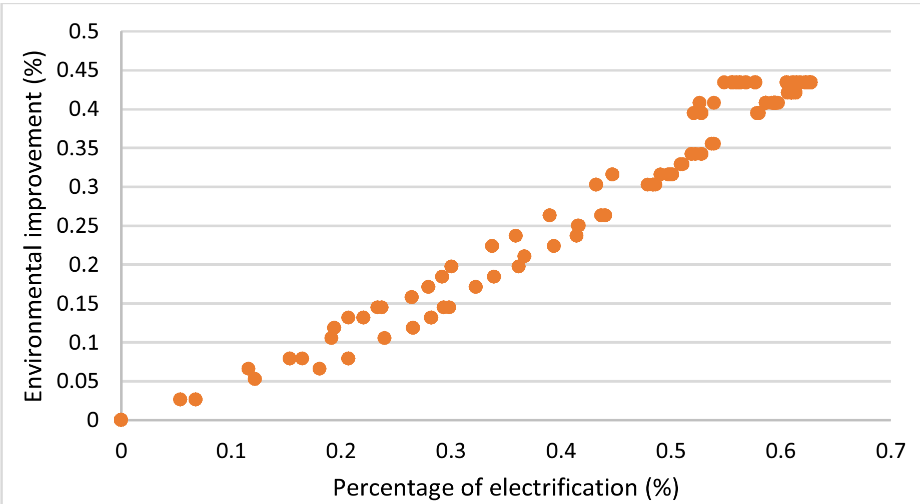


Figure 12 - Environmental improvement (%) depending on the percentage of electrified arcs for the Sioux-Falls network

6.2. Results of the bi-level multi-objective NDP model

The bi-level multi-objective NDP model was developed in Matlab and it was tested on the medium-sized and the Sioux-falls network. For obtaining the results of the numerical applications, the parameters of the upper and lower level related to the length, capacity, free-flow travel time, speed, and the origin-destination matrix were set up according to the data presented in the literature. In the lower-level model, the parameters of the travel costs function α and β, take the common values as, $\alpha = 0.15$ and $\beta = 4$, while the parameter of the Logit route path choice model θ is set up as 0.9. We assumed the number of OC hybrid trucks to be using the eHighway system as a percentage λ of the assigned traffic flow f^*, which is set up as 1%. The stopping criterion of the MSA-FA algorithm is set up as 0.01, while the maximum number of the iterations k_{max} for reaching the convergence in MSA-FA is 200. Additionally, the parameters of the Genetic algorithm were defined as follows. The number of maximum number of generations G_{max} is set as 20, the crossover fraction is 0.8, while the size of the population P is 10.

6.2.1. Results of the medium-sized network

For obtaining the solution of the medium-sized network numerical application, we considered the equal criteria weight w_i = 0.25. The best solution of 10 runs for the medium-sized network (Table 8) obtained by applying the genetic algorithm is Z^* = 0.177, while the percentage of electrification, calculated as the percentage of total electrified length, is 61.08%, which resulted in an environmental improvement of 59.31%. Additionally, the results of the objective functions are z_1 = 366.62, z_2 = 205.92 Mio €, z_3= 336 Mio €, z_4= 502. It is observed in almost all runs that the increment of the percentage of electrification causes decrease of the total costs.

Table 8 – The solutions of 10 runs for the medium-sized network

Number of run	$Z^\wedge$	Percentage of electrified network (%)	Percentage of environmental improvement (%)
1	0.222	44.64%	49.63%
2	0.191	66.11%	66.65%
3	0.206	56.65%	54.88%
4	0.210	51.99%	53.91%
5	0.184	59.54%	59.95%
6	0.223	48.91%	50.29%
7	0.198	59.43%	57.08%
8	0.212	52.86%	51.54%
9	0.207	51.56%	53.25%
10	**0.177**	**61.08%**	**59.31%**

In Figure 13, is presented one of the obtained solutions according to defined maximum number of generations G_{max}, while in Figure 14 is shown the best found solution for the medium-sized network, obtained after 10 runs. The set of electrified arcs in Figure 14 is marked with the green colour, while the set of non-electrified arcs is marked with blue. Moreover, in Figure 14 are reported the traffic flows for electrified and non-electrified arcs.

However, the number of traction substations for most of the found solutions in the medium-sized network is equal to one or two, due to the size of the network and lower traffic flows. The results of the capacity expansion and traffic flows of electrified arcs considering the best-found solution of the genetic algorithm are reported in Table 9. Therefore, the capacity expansion, which resulted in one lane, was obtained for some of the electrified arcs, considering the total investment costs of 650 Mio €. As observed from Table 9, the electrified arcs with the higher flows were considered for the capacity expansion. The addition of lanes on these arcs contributes to the system optimisation, resulting in the decrease of the total travel time and total costs.

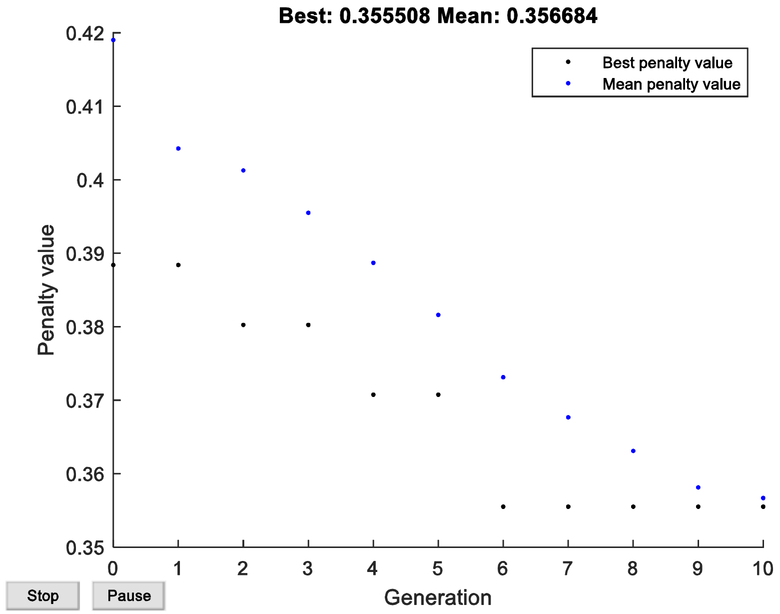


Figure 13 – One of the obtained solutions of the bi-level multi-objective NDP for the medium-sized network

Table 9 – The capacity expansion y_a of the best solution for medium-size network

Electrified arcs	y_a	Traffic flow f^*
(1,2)	1	662
(1,4)	1	203
(2,1)	1	352
(2,5)	0	885
(4,1)	0	349
(4,5)	0	203
(4,7)	1	117

(5,2)	0	450
(5,6)	0	190
(5,8)	0	721
(6,9)	0	528
(7,4)	0	302
(8,5)	1	350
(8,9)	0	238
(9,5)	1	472
(9,6)	1	31
(9,8)	0	168

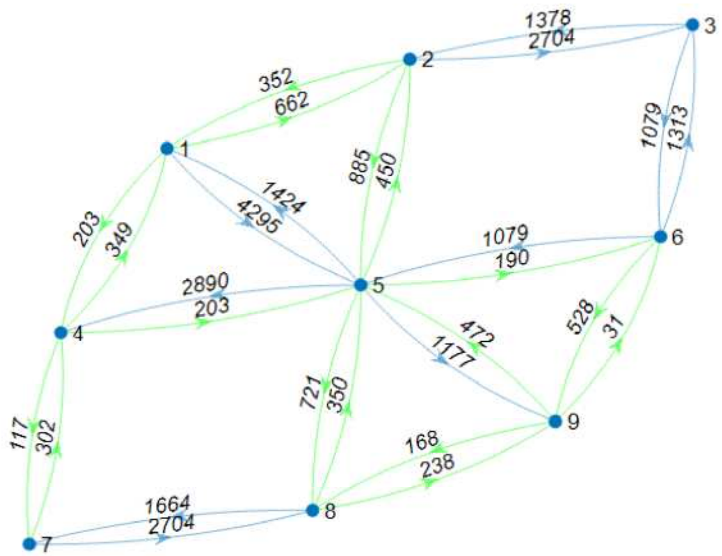


Figure 14 – The result of the bi-level multi-objective NDP for the medium-sized network

6.2.2. Results of the Sioux-falls network

After several runs, the best results of the numerical application for percentage λ = 1% related to the Sioux-falls network regarding bi-level multi-objective NDP, are presented in Table 10, where we considered the criteria weight equal for all objective functions, w_i = 0.25. In the further will be discussed the sensitivity analysis related to different criteria weight. It is observed that the differences between the values Z^ slightly variate, and according to the reported solutions, the highest gap is around 0.015. The column related to the percentage of electrification indicates that the overall costs slightly increase with the increment of the number of the electrified arc. However, since the relationship between total costs, traffic flow, and the percentage of electrification is not linear, few indicators determine the total costs, such as the obtained traffic flow assignment, and how much OC hybrid trucks have been served on the electrified arc. According to Table 10, after 10 runs, the best value of the objective function regarding the minimum costs Z^ = 0.330, resulted in the electrification's percentage up to 28.95% and the percentage of environmental improvement up to 35.18%.

Table 10 – The best solutions for Sioux-falls network

Number of run	Z^	Percentage of electrified network (%)	Percentage of environmental improvement (%)
1	0.345	23.68	28.25
2	0.337	39.47	36.96
3	0.331	32.89	36.78
4	0.333	31.58	33.58
5	**0.330**	**28.95**	**35.18**

6	0.336	23.68	29.17
7	0.334	35.53	34.25
8	0.339	30.26	32.67
9	0.339	34.21	32.19
10	0.341	27.63	32.06

In Figure 15 is graphicly represented one of the solutions obtained for the Sioux-falls network, where the electrified arcs are marked with red, while non-electrified arcs are marked with blue. Additionally, the results of the capacity expansion and traffic flow on the electrified arcs of the Sioux-falls network regarding the best-found solutions are reported in Table 11. According to the results and available budget B_1, the capacity expansion was considered for five electrified arcs. Also, for most of the electrified arcs, the increase of the capacity was one lane, while just a one of them had the expansion of two lanes. The bi-level model tends to increase the capacity on the electrified arcs with relatively high flows and small-sized length, due to the costs of expansion per lane in objective function z_1.

For all the runs, the number of traction substations $n_{s,a}$ for each electrified arc was in the range from 1 to 3 traction substations per electrified arc, which is in correspondence with the technical characteristics of the eHighway system. In particular, since the most arcs' lengths in the Sioux-falls network are up to 6 km and considering that traction substations are usually placed at each 2 km, the obtained results of the number of traction substations are justifiable. However, the percentage of the electrification resulted higher for the medium-sized network, due to the size of the medium-sized network.

Table 11 – The capacity expansion y_a of the electrified arcs of the best solution in the Sioux-falls network

Electrified arcs	y_a	Traffic flow f^*
(1,2)	0	359
(4,3)	0	895
(4,11)	0	706
(6,5)	0	1019
(8,6)	0	1591
(8,16)	0	1367
(10,11)	0	2157
(11,4)	0	717
(11,10)	1	2148
(14,15)	0	883
(15,10)	0	1501
(15,19)	2	1721
(16,10)	0	2654
(18,16)	0	1332
(19,15)	0	1754
(20,19)	0	731
(21,24)	0	1127
(22,15)	0	2287
(23,14)	1	881
(23,22)	1	1072
(24,21)	1	1085

(24,23)	0	840

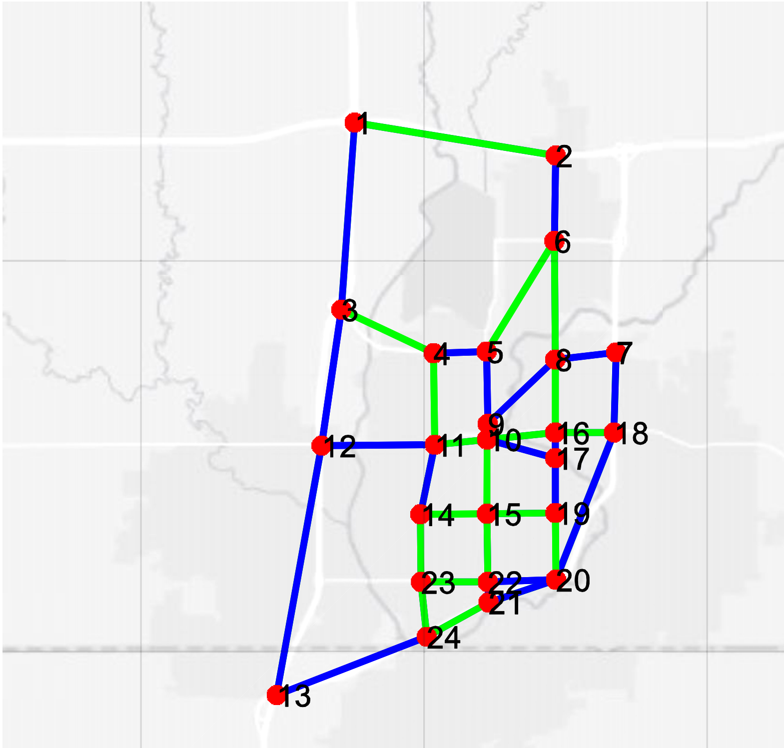


Figure 15 – The result of the Sioux falls network for the bi-level multi-objective NDP model

6.2.3. Sensitivity analysis

Considering the previously described results of the medium-sized and Sioux-falls network, we carried out sensitivity analysis, where the first part of the sensitivity analysis regards the percentage λ, while the second part of the sensitivity analysis considered different scenarios regarding criteria weight w_i. The results of the objective function Z^ regarding different percentage λ for the medium-sized network and the Sioux-falls network are reported as follows.

- ***The medium-sized network***

In the case of the medium-sized network, we considered the percentage λ in the range from 1 to 20 % and in Table 12 are reported the best results, obtained after three runs. The percentage of electrification and the environmental improvement are calculated considering total electrified length and the total environmental improvement per electrified length. In almost all runs, the percentage of electrification was more than 50%. The values of the objective function Z^ slightly differ and the highest gap is around 0.07. According to the obtained results, the number of substations and the capacity expansion have the highest influence on the total costs, as presented in Appendix (Table A3). Considering all three runs, the best value of the objective function is obtained for the λ = 0.14. The value of objective function Z^ = 0.168, while the percentage of electrification is 58.03%, which resulted in an environmental improvement of 66.25%. Additionally, the obtained results of the objective functions z_1= 3516.64, z_2 = 187.64 Mio €, z_3= 22312 Mio €, z_4= 349.

Table 12 – The best solutions of the medium-sized network regarding different percentage $\boldsymbol{\lambda}$ (%)

λ = 1			
Number of run	Z^	The percentage of electrified network	The percentage of environmental improvement
1	0.230	50.09%	51.18%
2	**0.199**	**58.25%**	**51.94%**
3	0.202	52.14%	48.67%
λ = 2			

Number of run	$Z^{\wedge}$	The percentage of electrified network	The percentage of environmental improvement
1	0.196	52.65%	56.32%
2	0.202	61.24%	54.42%
3	**0.185**	**64.91%**	**70.51%**
$\lambda = 3$			
Number of run	$Z^{\wedge}$	The percentage of electrified network	The percentage of environmental improvement
1	0.201	57.76%	59.01%
2	**0.176**	**57.05%**	**63.37%**
3	0.189	65.05%	62.85%
$\lambda = 4$			
Number of run	$Z^{\wedge}$	The percentage of electrified network	The percentage of environmental improvement
1	**0.174**	**58.19%**	**60.31%**
2	0.182	60.27%	63.73%
3	0.176	57.46%	61.62%
$\lambda = 5$			
Number of run	$Z^{\wedge}$	The percentage of electrified network	The percentage of environmental improvement
1	0.199	52.78%	56.60%

2	**0.172**	**62.52%**	**69.10%**
3	0.194	49.00%	60.52%
$\lambda = 6$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	**0.183**	**50.95%**	**61.77%**
2	0.205	54.66%	59.28%
3	0.193	59.25%	65.08%
$\lambda = 7$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	**0.172**	**67.36%**	**70.96%**
2	0.183	50.95%	73.06%
3	0.190	67.06%	67.93%
$\lambda = 8$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.216	47.05%	52.13%
2	**0.186**	**46.93%**	**60.67%**
3	0.201	48.88%	51.93%
$\lambda = 9$			

Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.235	36.46%	46.42%
2	**0.186**	**56.44%**	**61.90%**
3	0.207	51.20%	48.41%
$\lambda = 10$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.206	46.27%	50.29%
2	**0.195**	**59.33%**	**61.59%**
3	0.198	45.70%	55.25%
$\lambda = 11$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement (%)
1	**0.179**	**64.70%**	**70.91%**
2	0.183	58.34%	55.93%
3	0.206	53.71%	55.54%
$\lambda = 12$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	**0.183**	**52.81%**	**57.16%**

2	0.240	46.66%	43.03%
3	0.224	52.92%	49.35%
$\lambda = 13$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	**0.194**	**59.02%**	**59.43%**
2	0.210	58.06%	57.82%
3	0.222	58.67%	53.10%
$\lambda = 14$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	**0.168**	**58.03%**	**66.25%**
2	0.242	46.36%	47.78%
3	0.186	56.67%	61.90%
$\lambda = 15$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.193	59.98%	63.12%
2	0.215	54.03%	56.81%
3	**0.180**	**60.53%**	**65.64%**
$\lambda = 16$			

Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.208	47.57%	50.17%
2	0.234	44.04%	48.57%
3	**0.185**	**58.76%**	**59.28%**
$\lambda = 17$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.216	62.53%	51.67%
2	**0.198**	**55.96%**	**60.60%**
3	0.211	58.23%	57.01%
$\lambda = 18$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	**0.178**	**65.40%**	**72.06%**
2	0.228	46.19%	53.95%
3	0.213	45.78%	46.34%
$\lambda = 19$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	**0.186**	**63.67%**	**66.92%**

2	0.202	57.98%	62.87%
3	0.194	59.65%	56.27%
λ = 20			
Number of run	Z^	The percentage of electrified network	The percentage of environmental improvement
1	0.222	44.64%	49.63%
2	**0.191**	**66.11%**	**66.65%**
3	0.206	56.65%	54.88%

- ***The Sioux falls network***

The sensitivity analysis regarding different percentage λ for the Sioux falls network application is presented in Table 13. According to the results, it is observed that the percentage of electrification is around 30%. The lowest value of objective value Z^ = 0.312 was obtained for the percentage λ=0.15, which resulted in 34.08%. Also, in the case of the Sioux-falls network, the percentage of electrification and the total costs are correlated with the number of substations and the capacity expansion on the electrified arcs as presented in Appendix (Table A4). The bi-level model tends to increase the capacity on the electrified arcs with the higher flows and the lower number of substations which leads to decrease of the total costs in the network.

Table 13 – The best solutions of Sioux-falls network regarding different percentage $\boldsymbol{\lambda}$ (%)

$\lambda = 1$			
Number of run	Z^	The percentage of electrified network	The percentage of environmental improvement
1	0.334	30.57%	35.79%
2	0.330	42.04%	42.53%
3	**0.329**	**30.25%**	**35.96%**
$\lambda = 2$			
Number of run	Z^	The percentage of electrified network	The percentage of environmental improvement
1	0.339	24.52%	29.72%
2	**0.333**	**25.48%**	**32.90%**
3	0.338	18.79%	24.33%
$\lambda = 3$			
Number of run	Z^	The percentage of electrified network	The percentage of environmental improvement
1	0.338	26.43%	29.57%
2	**0.330**	**22.93%**	**33.03%**
3	0.331	22.93%	30.88%
$\lambda = 4$			

Number of run	Z^	The percentage of electrified network	The percentage of environmental improvement
1	0.359	13.38%	14.04%
2	**0.333**	**27.71%**	**33.77%**
3	0.340	28.66%	33.04%
		$\lambda = 5$	
Number of run	Z^	The percentage of electrified network	The percentage of environmental improvement
1	0.346	29.30%	30.87%
2	0.339	28.66%	33.97%
3	**0.335**	**28.66%**	**31.61%**
		$\lambda = 6$	
Number of run	Z^	The percentage of electrified network	The percentage of environmental improvement
1	**0.330**	**32.17%**	**36.46%**
2	0.340	24.52%	29.80%
3	0.334	27.71%	33.97%
		$\lambda = 7$	
Number of run	Z^	The percentage of electrified network	The percentage of environmental improvement
1	0.346	21.97%	26.18%

2	**0.333**	**28.34%**	**31.81%**
3	0.346	20.38%	22.67%
$\lambda = 8$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	**0.332**	**32.80%**	**37.75%**
2	0.345	27.71%	27.71%
3	0.354	16.24%	16.57%
$\lambda = 9$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement (%)
1	**0.331**	**33.76%**	**37.54%**
2	0.346	27.39%	27.29%
3	0.336	22.93%	28.40%
$\lambda = 10$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement (%)
1	0.343	33.44%	35.00%
2	0.332	21.02%	28.26%
3	**0.326**	**28.66%**	**36.54%**
$\lambda = 11$			

Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement (%)
1	**0.325**	**28.03%**	**35.19%**
2	0.333	31.85%	39.03%
3	0.337	31.85%	33.92%
$\lambda = 12$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement (%)
1	0.354	21.34%	21.29%
2	**0.329**	**30.57%**	**41.28%**
3	0.350	24.20%	28.17%
$\lambda = 13$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.357	19.75%	19.79%
2	**0.335**	**32.17%**	**35.33%**
3	0.336	26.11%	34.23%
$\lambda = 14$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.346	22.61%	25.48%

2	**0.345**	**29.62%**	**32.30%**
3	0.354	28.03%	25.14%
$\lambda = 15$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	**0.312**	**34.08%**	**46.38%**
2	0.348	17.83%	21.96%
3	0.344	21.02%	25.28%
$\lambda = 16$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.339	24.52%	29.61%
2	0.337	30.25%	34.89%
3	**0.331**	**29.62%**	**35.81%**
$\lambda = 17$			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.348	34.39%	29.99%
2	0.352	22.29%	23.19%
3	**0.343**	**23.25%**	**28.82%**
$\lambda = 18$			

Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.351	14.97%	17.50%
2	0.330	34.08%	39.86%
3	**0.328**	**32.48%**	**39.01%**
λ = 19			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.343	25.48%	28.65%
2	0.347	27.71%	27.90%
3	**0.344**	**26.75%**	**30.62%**
λ = 20			
Number of run	$Z^\wedge$	The percentage of electrified network	The percentage of environmental improvement
1	0.334	40.76%	39.30%
2	0.333	28.03%	36.17%
3	**0.331**	**28.98%**	**36.51%**

The second part of the sensitivity analysis is related to the different objective functions' criteria weight w_i obtained with the fixed percentage λ = 1%. We considered three scenarios, defined as follows:

- The criteria weights w_i of Scenario I: w_1= 0.7, w_2= 0.1, w_3= 0.1, w_4= 0.1
- The criteria weights w_i of Scenario II: w_1= 0.1, w_2= 0.1, w_3= 0.7, w_4= 0.1

- The criteria weights w_i of the Scenario III: w_1= 0.1, w_2= 0.1, w_3= 0.1, w_4= 0.7

In Scenario I the highest criteria weight is given to the objective function z_1 related to the minimisation of total travel time and the capacity expansion costs; In the Scenario II, the highest criteria weight is given to the objective function z_3, related to the environmental costs; in Scenario III the highest criteria weight is given to the objective function z_4 related to the maximisation of the average traffic density of OC hybrid trucks on the electrified arcs. The results of the three scenarios regarding different criteria weight w_i for the medium-sized and the Sioux-falls network are reported as follows.

- ***The medium-sized network***

The results of the bi-level model regarding previously mentioned scenarios are reported in Table 14 and Table 15, respectively. In Scenario I, the highest criteria weight is given to the z_1, and the best-found solution resulted in the lower percentage of the electrification equal to 30.74% and the environmental improvement equal to 38.02%.

In Scenario II, the highest value of the criteria weight is related to the environmental costs z_3. The best-found solution of Scenario II, compared to Scenario I, resulted in higher percentage of electrification and environmental improvement of 54.96% and 65.63%, respectively. Since in the minimisation problem, the importance is given to the lower criteria weight, the Scenario II resulted in the lower value of the objective value, $Z^\wedge$ = 0.332. In this case, the priority is given to the electrification, which resulted in the lower overall costs and the significantly highest percentage of electrification and environmental improvement.

In Scenario III, the highest criteria weight w_4 is given to the objective function z_4 related to the maximisation of the average traffic density of OC hybrid trucks on the electrified arcs. Since the optimisation problem tends to minimise total costs, the increment of the traffic density on electrified arcs could lead to the decrease of the overall costs, as we can observe from the results. Similar like in Scenario II, the lower criteria weight of objective function z_1, z_2, z_3 give the precedence to the electrification, which resulted in 70.86% and the environmental improvement is 63.06%. In Table 16 are reported the best-found solutions of each scenario, and the corresponding percentage of network electrification and the environmental improvement.

Table 14 – The best solutions of the medium-sized network regarding different weight $\boldsymbol{w_i}$

Best solution	w_1=0.7	w_2=0.1	w_3=0.1	w_4=0.1
$Z^{\wedge}$	z_1	z_2	z_3	z_4
0.787	50.6	20.77	752.49	4
0.752	**78.9**	**66.10**	**501.42**	**5**
0.775	50.6	44.57	668.81	8
0.761	50.6	52.22	564.95	9
0.757	50.6	64.99	553.33	12
Best solution	w_1=0.1	w_2=0.1	w_3=0.7	w_4=0.1
$Z^{\wedge}$	z_1	z_2	z_3	z_4
0.337	273.6	131.568	305.09	27
0.332	**281.0**	**117.91**	**283.14**	**21**
0.393	513.8	129.31	344.20	23
0.364	342.7	126.01	319.40	23

0.341	160.9	126.03	301.83	22
Best solution	w_1=0.1	w_2=0.1	w_3=0.1	w_4=0.7
$Z^\wedge$	z_1	z_2	z_3	z_4
-0.431	**533.7**	**147.38**	**304.98**	**27**
-0.303	266.0	120.17	384.79	21
-0.343	400.5	121.84	320.64	23
-0.428	424.5	139.18	261.11	26
-0.201	211.4	99.13	532.24	17

Table 15 – The percentage of electrification and environmental improvement of the middle-sized network regarding different weight $\boldsymbol{w_i}$

w_1=0.7, w_2=0.1, w_3=0.1, w_4=0.1		
$Z^\wedge$	Percentage of electrified network	Percentage of the environmental improvement
0.787	9.29%	8.65%
0.752	**30.74%**	**38.02%**
0.775	20.88%	18.81%
0.761	24.53%	31.41%
0.757	29.90%	32.82%
w_1=0.1, w_2=0.1, w_3=0.7, w_4=0.1		
$Z^\wedge$	Percentage of electrified network	Percentage of the environmental improvement
0.337	61.00%	63.09%
0.332	**54.96%**	**65.63%**
0.393	61.46%	58.21%

0.364	58.96%	61.22%
0.341	58.96%	63.35%
w_1=0.1, w_2=0.1, w_3=0.1, w_4=0.7		
Z^	Percentage of electrified network	Percentage of the environmental improvement
-0.431	**70.86%**	**63.06%**
-0.303	56.68%	53.29%
-0.343	57.95%	61.16%
-0.428	66.80%	68.41%
-0.201	47.19%	35.39%

Table 16 – The best solution of the medium-sized network for every scenario

Scenario	Z^	Percentage of electrified network	Percentage of the environmental improvement
Scenario I	0.752	30.74%	38.02%
Scenario II	0.332	54.96%	65.63%
Scenario III	-0.431	70.86%	63.06%

- ***The Sioux-falls network***

The best solutions regarding different weight w_i of the Sioux-falls network and fixed percentage λ, obtained after 5 runs, are reported in Table 17 while in Table 18 are reported the values of the best solutions and the corresponding percentage of the electrification and environmental improvement. In all the scenarios, the percentage λ of the assigned traffic flows is 0.01. Since we are dealing with the minimisation problem, the lower value of the objective function's criteria weight w_i will tend to maximise the importance of the corresponding objective function z_i.

In Scenario I, the highest criteria weight w_1 is related to the minimisation of the total travel time and the capacity expansion costs. Therefore, the obtained results of Scenario I give the lowest acceptable percentage of electrification in the eHighway system, which will also result in the lowest capacity expansion costs. The results obtained after 5 runs showed that Scenario, I doesn't consider capacity expansion due to the high criteria weight w_1. At the same time, it tends to minimise the number of electrified arcs in the eHighway system, which resulted in the higher environmental costs. The best value of Scenario I is $Z^\wedge$ =0.792, with the percentage of the electrification equal to 7.96%, and environmental improvement equal to 11.37%. According to the obtained results of Scenario I and the low criteria weight for environmental costs in objective function z_3, the non-electrification in the Sioux-falls network leads to the highest total costs.

In Scenario II, the highest criteria weight is given to the environmental costs in the objective function z_3 and the highest importance is given to the electrification in the eHighway system. Therefore, this resulted in the highest percentage of electrification equal to 35.67%, and the highest environmental improvement equal to 42.97%. However, the low criteria weight related to the objective function z_1, z_2 resulted in higher capacity expansion due to the priority of electrification and the minimisation of infrastructure costs. Therefore, it is observed that the capacity expansion costs have higher influence on the overall costs than the infrastructure costs, which resulted in the higher value of objective function $Z^\wedge$ = 0.528. Moreover, according to the best obtained solutions, the Scenario II results in the highest percentage of network electrification of 35.67% and the environmental improvement of 42.97%.

The Scenario III gives the highest weight criteria to the objective function z_4. The maximisation of the traffic density of OC hybrid trucks on the electrified arcs is strictly correlated with the number of electrified arcs in the eHighway system i.e. the more arcs are electrified, the higher number of OC hybrid trucks will be served in the eHighway system. Thus, according to the results of the Scenario III, the best solution of the objective function $Z^\wedge$ = 0.079 resulted in the percentage of the electrification equal to 33.12%, and the environmental improvement equal to 37.00%, due to the lower criteria weight for the z_1 and z_2. According to the comparison of Scenario II and Scenario III it is observed that the environmental criteria has the highest influence on the electrification.

In Table 19 are reported the best-found solutions of each scenario, and the corresponding percentage of network electrification and the environmental improvement. The capacity expansion of the best solutions for each Scenario of the medium-sized network and the Sioux-falls are reported in the Appendix (Table A5 and Table A6, respectively).

Table 17 – The best solutions of the Sioux-falls network regarding different weight $\boldsymbol{w_i}$

Best solution	w_1=0.7	w_2=0.1	w_3=0.1	w_4=0.1
$Z^\wedge$	z_1	z_2	z_3	z_4
0.800	5420.63	7.96	1145.48	1
0.798	5420.63	10.81	1131.07	1
0.792	**5420.63**	**45.49**	**1025.22**	**2**
0.798	5420.63	29.78	1097.82	1
0.795	5420.63	53.45	1053.39	2
Best solution	w_1=0.1	w_2=0.1	w_3=0.7	w_4=0.1
$Z^\wedge$	z_1	z_2	z_3	z_4
0.620	5800.03	155.45	827.13	6
0.587	5979.71	179.32	764.07	7
0.585	5790.58	169.52	766.33	6
0.573	5820.55	205.02	740.45	8
0.528	**6199.52**	**194.21**	**659.57**	**8**
Best solution	w_1=0.1	w_2=0.1	w_3=0.1	w_4=0.7
$Z^\wedge$	z_1	z_2	z_3	z_4
0.105	6170.28	170.54	800.43	6

0.079	**5929.94**	**183.19**	**728.67**	**7**
0.081	5770.56	173.20	749.10	7
0.119	5680.41	119.75	892.78	5
0.087	5500.63	169.32	771.31	6

Table 18 – The percentage of electrification and environmental improvement of the Sioux-falls network regarding different weight $\boldsymbol{w_i}$

w_1=0.7, w_2=0.1, w_3=0.1, w_4=0.1		
$Z^\wedge$	Percentage of electrified network	Percentage of the environmental improvement
0.800	1.59%	0.97%
0.798	1.59%	2.22%
0.792	**7.96%**	**11.37%**
0.798	5.73%	5.09%
0.795	9.55%	8.93%
w_1=0.1, w_2=0.1, w_3=0.7, w_4=0.1		
$Z^\wedge$	Percentage of electrified network	Percentage of the environmental improvement
0.620	28.03%	28.49%
0.587	32.80%	33.93%
0.585	31.53%	33.75%
0.573	37.26%	35.99%
0.528	**35.67%**	**42.97%**
w_1=0.1, w_2=0.1, w_3=0.1, w_4=0.7		
$Z^\wedge$	Percentage of electrified network	Percentage of the environmental improvement
0.105	31.85%	30.80%
0.079	**33.12%**	**37.00%**
0.081	30.89%	35.24%

0.119	21.34%	22.82%
0.087	30.57%	33.32%

Table 19 – The best solution of the Sioux-falls network for every scenario

Scenario	$Z^\wedge$	Percentage of electrified network	Percentage of the environmental improvement
Scenario I	0.792	7.96%	11.37%
Scenario II	0.528	35.67%	42.97%
Scenario III	0.079	33.12%	37.00%

7. CONCLUSIONS

In this thesis, we introduced two network design models for green transportation by adopting a novel technology, the eHighway system. This technology is enhancing the long-term decision-making questions regarding the mitigation of environmental pollutions and emissions. Since the expansion of light-duty trucks and heavy-duty trucks causes major emissions in the city, the eHighway system highlights the environmental advantage of OC hybrid trucks. Through the electrification of highway road segments, the eHighway system allows the OC hybrid trucks to use electric mode while driving on these road arcs, without any interruptions. We developed the novel models for assessing the impact of the eHighway system, formulated as a single-level network design and a bi-level multi-objective NDP model.

For the single-level multi-objective NDP model, we considered three objective functions: minimization of the total infrastructure and maintenance costs, minimization of total environmental costs and maximization of average traffic density related to the OC hybrid trucks on electrified arcs. In particular, we introduced the third objective to: i) give much more priority to arcs with high OC hybrid trucks traffic volume; ii) maximise the utility of the eHighway system; iii) to help decision- makers in estimating benefits of using the eHighway system. The constraints of the single-level multi-objective NDP model are related to the power capacity of each traction substation and the total available budget resources. We used a simulation model that applied the energy system behaviour of eHighway technology to obtain the optimal number of traction substations on each electrified arc according to OC hybrid trucks traffic flow. An emission model was introduced in the single-level multi-objective network design formulation for calculating environmental improvement. We considered emissions for a lifetime period of the eHighway infrastructure of 20 years. The model was tested on a medium-sized and the Sioux-Falls network. After testing it on the proposed networks, the model showed the effectiveness in mitigating emissions as soon as we introduce electrified arcs. The optimization model obtained feasible and good-quality solutions, resulting in environmental improvement up to 62.73% for the Sioux-Falls network and up to 98.52% for the medium-sized network.

For the bi-level multi-objective NDP model, developed as an extension of the single-level model, we considered four objectives in the upper level related to the minimisation of the total travel time, infrastructure and environmental costs and maximisation of average traffic density of OC hybrid trucks on electrified arcs. The decision of the upper level depends on the output of the lower level which is formulated as a fixed-point SUE traffic assignment problem. Moreover, the proposed bi-level model deals not only with finding the set of the arcs to be electrified but also with the capacity expansion of the electrified arcs for improving the performance of the overall system. The model uses the traction substation model for determining the minimum number of the traction substations on the electrified arcs and the emission model for calculating the environmental costs of the overall network. Moreover, the model helps the decision-makers in achieving the transportation system optimisation by maximising the number of OC hybrid trucks and minimising the total travel time on the electrified, according to the available budget. Therefore, the capacity expansion was introduced to minimise the travel time on the electrified arcs on the one side, but on the other side the increase of links' capacity allows the demand flexibility due to the future increase of the OC hybrid trucks demand. The constraints of the proposed bi-level NDP model are related to the capacity of substations, the number of traction substations on the electrified arcs, the budget limitations regarding the eHighway system costs and available budget for the capacity expansion, perceived as the number on lanes to be added on the electrified arcs, etc. Moreover, the proposed model used a genetic algorithm as a solution approach. The model was tested on a numerical application on the Sioux-falls and medium-sized network, while the sensitivity analysis was carried out based on the percentage of the OC hybrid trucks to be using the eHighway system and the different criteria weight related to the objective function in the upper level. The results of the model showed good performances regarding the environmental improvement and the number of the electrified arcs i.e. almost 30% for the Sioux falls network and 60% for the medium-sized network, according to the available budget resources and the assumed percentage of the total assigned traffic flows related to the OC hybrid trucks.

The performance and results of the developed models could help decision-makers to decide whether to adopt this technology or not, according to the limited budget resources. Also, the developed models could benefit authorities who are making long-term decisions since the advantages could be achieved for a long period (e.g. we investigated 20 years). However, as future developments we intend to: i) consider energy recovery during regenerative braking and energy consumption of vehicles depending on acceleration/deceleration; ii) consider traffic assignment based on a traffic demand forecasting model; iii) provide an application to a real case study.

ACKNOWLEDGMENT

It is my pleasure to mention several persons which contribution was of the significant importance for my personal and professional growth during my Ph.D study. Firstly, I would like to express gratitude to my supervisors prof. Mauro Dell'Orco and prof. Mario Marinelli for their support, knowledge, and motivation during these years, as well as for giving me the opportunity to be the part of their research group. In particular, I'm thankful for the guidance and help of prof. Mario Marinelli in the process of writing the Ph.D thesis.

Secondly, I'm sincerely thankful to the prof. Michele Ottomanelli for the support and the opportunity for carrying out my contribution in transportation research field, as well as prof. Leonardo Caggiani, for the ideas and knowledge in implementing models in various transportation research topics during my studies. Also, my special thanks to my friend and college Luigi Pio Prencipe for the patience and remarkable collaboration that we accomplished together in these years. Furthermore, I'm grateful for being a member of the Poliba transportation research group, which provide me a great opportunity to obtain scientific experience. Also, I'm grateful to prof. Jorge Freire de Sousa for his support during my research period abroad in the University of Porto in Portugal.

Last but not the least, I would like to thank to the people that I met and friends that I made throughout this period, and my flatmates for making that my staying in Italy feels "like home".

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APPENDIX

Table A1 - Results of simulation model for the medium-sized network

Arc a	$n_{min,a}$	$n_{vs,a}$	l_a
(1,2)	1	30	3.563
(1,4)	1	50	5.892
(1,5)	1	25	3.005
(2,1)	1	47	5.612
(2,3)	1	40	4.740
(2,5)	1	38	4.546
(3,2)	1	44	5.215
(3,6)	1	35	4.197
(4,1)	1	48	5.756
(4,5)	1	50	5.957
(4,7)	1	41	4.895
(5,1)	1	38	4.465
(5,2)	1	29	3.475
(5,4)	1	30	3.614
(5,6)	1	39	4.639
(5,8)	1	26	3.107
(5,9)	1	41	4.91
(6,3)	1	32	3.76
(6,5)	1	45	5.40
(6,9)	1	38	4.48
(7,4)	1	45	5.33
(7,8)	1	45	5.38
(8,5)	1	48	5.76
(8,7)	1	46	5.44
(8,9)	1	49	5.82
(9,5)	1	25	3.01

(9,6)	1	27	3.26
(9,8)	1	30	3.56

Table A2 - Results of simulation model for the Sioux-Falls network

Arc a	$n_{min,a}$	$n_{vs,a}$	l_a
(1,2)	1	21	6
(1,3)	1	14	4
(2,1)	1	21	6
(2,6)	1	17	5
(3,1)	1	14	4
(3,4)	1	14	4
(3,12)	1	14	4
(4,3)	1	14	4
(4,5)	1	7	2
(4,11)	1	21	6
(5,4)	1	7	2
(5,6)	1	14	4
(5,9)	1	17	5
(6,2)	1	17	5
(6,5)	1	14	4
(6,8)	1	7	2
(7,8)	1	10	3
(7,18)	1	7	2
(8,6)	1	7	2
(8,7)	1	10	3
(8,9)	2	35	10
(8,16)	1	17	5
(9,5)	1	17	5
(9,8)	2	35	10
(9,10)	1	10	3

(10,9)	1	10	3
(10,11)	1	17	5
(10,15)	1	21	6
(10,16)	1	14	4
(10,17)	2	28	8
(11,4)	1	21	6
(11,10)	1	17	5
(11,12)	1	21	6
(11,14)	1	14	4
(12,3)	1	14	4
(12,11)	1	21	6
(12,13)	1	10	3
(13,12)	1	10	3
(13,24)	1	14	4
(14,11)	1	14	4
(14,15)	1	17	5
(14,23)	1	14	4
(15,10)	1	21	6
(15,14)	1	17	5
(15,19)	1	10	3
(15,22)	1	10	3
(16,8)	1	17	5
(16,10)	1	14	4
(16,17)	1	7	2
(16,18)	1	10	3
(17,10)	2	28	8
(17,16)	1	7	2
(17,19)	1	7	2
(18,7)	1	7	2

(18,16)	1	10	3
(18,20)	1	14	4
(19,15)	1	10	3
(19,17)	1	7	2
(19,20)	1	14	4
(20,18)	1	14	4
(20,19)	1	14	4
(20,21)	1	21	6
(20,22)	1	17	5
(21,20)	1	21	6
(21,22)	1	7	2
(21,24)	1	10	3
(22,15)	1	10	3
(22,20)	1	17	5
(22,21)	1	7	2
(22,23)	1	14	4
(23,14)	1	14	4
(23,22)	1	14	4
(23,24)	1	7	2
(24,13)	1	14	4
(24, 21)	3	18	3
(24, 23)	2	20	2

Table A3 - The best-found solutions related to the $\boldsymbol{n_{s,a}}$ and $\boldsymbol{y_a}$ per electrified arc for the medium-sized network regarding percentage $\boldsymbol{\lambda}$

Links	Percentage λ											
	1%		2%		3%		4%		5%		6%	
	y_a		y_a	n_s^a	n_s^a	y_a	n_s^a	n_s^a	y_a	n_s^a	n_s^a	y_a
(1,2)	1	2	0	0	1	1	2	1	2	1	2	1
(1,4)	1	0	0	0	0	0	0	0	2	0	0	0

(1,5)	1	0	1	0	0	0	1	0	0	0	2	0
(2,1)	1	0	0	0	0	0	0	0	2	0	0	0
(2,3)	0	0	1	0	2	0	0	0	2	1	2	1
(2,5)	0	0	2	1	2	0	2	1	2	1	2	1
(3,2)	0	0	1	0	1	1	2	0	0	0	2	1
(3,6)	1	1	1	1	1	0	1	0	0	0	1	0
(4,1)	0	0	0	0	2	1	2	0	2	1	0	0
(4,5)	1	1	0	0	1	1	0	0	2	1	0	0
(4,7)	1	1	1	0	0	0	1	0	1	0	0	0
(5,1)	1	0	1	1	1	1	0	0	0	0	0	0
(5,2)	1	2	0	0	1	1	1	0	0	0	2	1
(5,4)	0	0	1	1	1	1	2	2	2	1	2	1
(5,6)	1	0	1	0	0	0	0	0	1	0	0	0
(5,8)	1	1	1	0	1	0	0	0	2	2	2	1
(5,9)	1	0	0	0	1	1	1	1	0	0	2	1
(6,3)	1	0	0	0	1	1	0	0	1	1	1	1
(6,5)	0	0	1	2	0	0	2	1	0	0	2	2
(6,9)	0	0	1	0	2	0	0	0	2	1	2	1
(7,4)	1	1	1	0	0	0	2	0	0	0	2	0
(7,8)	1	2	2	1	0	0	2	0	2	0	0	0
(8,5)	0	0	2	2	0	0	0	0	2	1	0	0
(8,7)	0	0	1	1	2	1	0	0	0	0	0	0
(8,9)	0	0	1	2	0	0	2	0	2	1	0	0
(9,5)	0	0	0	0	1	0	1	2	1	0	1	0
(9,6)	1	0	0	0	1	1	1	0	0	0	1	1
(9,8)	1	0	1	0	0	0	1	0	0	0	0	0

Links	Percentage λ											
	7%		8%		9%		10%		11%		12%	
	y_a		y_a	n_s^a	n_s^a	y_a	n_s^a	n_s^a	y_a	n_s^a	n_s^a	y_a
(1,2)	2	0	2	2	2	1	2	2	2	0	2	2
(1,4)	2	1	0	0	2	1	0	0	0	0	0	0
(1,5)	2	0	2	0	2	0	0	0	2	0	0	0
(2,1)	0	0	0	0	0	0	0	0	2	0	0	0
(2,3)	2	1	0	0	0	0	0	0	0	0	3	2
(2,5)	2	0	3	1	3	1	3	0	3	1	3	0

(3,2)	2	0	0	0	2	2	0	0	0	0	2	1
(3,6)	1	0	0	0	2	0	2	2	2	1	0	0
(4,1)	2	0	2	0	0	0	2	2	3	1	0	0
(4,5)	0	0	0	0	2	2	2	1	2	0	2	0
(4,7)	1	0	1	0	0	0	2	1	0	0	2	1
(5,1)	2	1	2	0	0	0	2	0	2	2	0	0
(5,2)	0	0	2	0	2	2	0	0	2	0	2	2
(5,4)	2	0	2	2	2	1	0	0	2	0	2	1
(5,6)	2	2	0	0	0	0	2	0	2	1	0	0
(5,8)	2	1	2	2	2	1	2	0	0	0	2	0
(5,9)	2	0	0	0	0	0	0	0	0	0	0	0
(6,3)	0	0	0	0	2	0	0	0	2	0	2	0
(6,5)	2	0	0	0	0	0	2	1	0	0	2	1
(6,9)	2	0	2	1	0	0	2	0	0	0	2	1
(7,4)	2	1	2	0	2	1	0	0	2	0	0	0
(7,8)	0	0	0	0	3	1	3	1	3	0	0	0
(8,5)	0	0	2	0	0	0	2	1	3	1	0	0
(8,7)	2	1	2	2	0	0	2	0	2	2	2	0
(8,9)	0	0	0	0	2	0	2	0	2	0	0	0
(9,5)	0	0	2	0	2	0	2	1	2	0	2	0
(9,6)	0	0	0	0	1	1	0	0	0	0	1	0
(9,8)	1	2	0	0	1	0	0	0	0	0	1	0

Links	Percentage λ											
	13%		14%		15%		16%		17%		18%	
	y_a		y_a	n_s^a	n_s^a	y_a	n_s^a	y_a	y_a	n_s^a	n_s^a	y_a
(1,2)	2	1	2	2	2	1	2	1	3	2	2	4
(1,4)	0	0	2	0	2	0	0	0	0	0	0	0
(1,5)	0	0	2	0	0	0	0	0	0	0	0	0
(2,1)	0	0	0	0	3	1	0	0	0	0	0	0
(2,3)	3	0	0	0	3	1	0	0	3	0	0	0
(2,5)	0	0	3	1	3	2	3	2	3	0	2	3
(3,2)	0	0	0	0	2	0	2	0	2	2	0	0
(3,6)	2	1	0	0	0	0	2	2	0	0	0	0
(4,1)	3	0	3	0	0	0	3	0	0	0	0	0
(4,5)	2	0	0	0	0	0	2	0	2	2	0	0

(4,7)	0	0	0	0	0	0	0	0	0	0	0	0
(5,1)	2	0	2	1	2	0	2	0	2	0	0	2
(5,2)	2	2	2	1	2	2	2	0	0	0	0	2
(5,4)	2	2	0	0	2	1	0	0	2	0	0	0
(5,6)	0	0	2	1	0	0	2	0	0	0	0	0
(5,8)	2	2	2	0	2	1	2	0	0	0	0	0
(5,9)	2	1	0	0	2	1	0	0	2	0	0	0
(6,3)	0	0	0	0	0	0	0	0	0	0	0	0
(6,5)	0	0	2	1	2	1	2	0	2	0	0	2
(6,9)	0	0	3	2	0	0	0	0	3	0	0	0
(7,4)	0	0	0	0	0	0	3	0	3	0	0	0
(7,8)	3	0	3	0	3	0	0	0	3	0	0	0
(8,5)	3	2	3	0	3	0	3	0	3	1	0	0
(8,7)	2	0	3	1	3	1	3	0	3	2	0	3
(8,9)	2	1	0	0	0	0	3	0	0	0	0	0
(9,5)	2	1	2	1	0	0	2	1	0	0	1	0
(9,6)	1	1	1	1	1	1	0	0	1	2	0	1
(9,8)	1	1	2	1	2	1	0	0	0	0	0	2

Links	Percentage λ			
	19%		20%	
	y_a	n_s^a	y_a	n_s^a
(1,2)	2	0	0	0
(1,4)	0	0	3	1
(1,5)	0	0	0	0
(2,1)	3	0	3	0
(2,3)	3	1	3	0
(2,5)	4	1	4	1
(3,2)	3	0	3	0
(3,6)	2	0	2	2
(4,1)	3	0	0	0
(4,5)	3	0	0	0
(4,7)	0	0	2	0
(5,1)	2	0	2	2
(5,2)	2	1	2	0
(5,4)	2	1	0	0

(5,6)	0	0	0	0
(5,8)	2	0	2	0
(5,9)	0	0	2	1
(6,3)	0	0	2	0
(6,5)	2	2	2	1
(6,9)	3	0	0	0
(7,4)	3	1	3	0
(7,8)	3	1	4	1
(8,5)	0	0	3	2
(8,7)	0	0	3	0
(8,9)	3	1	0	0
(9,5)	0	0	2	0
(9,6)	0	0	0	0
(9,8)	2	1	0	0

Table A4 - The best-found solutions related to the $\boldsymbol{n_{s,a}}$ and $\boldsymbol{y_a}$ per electrified arc for the Sioux-falls network regarding percentage $\boldsymbol{\lambda}$

Links	Percentage λ											
	1%		2%		3%		4%		5%		6%	
	y_a		y_a	n_s^a	n_s^a	y_a	n_s^a	n_s^a	y_a	n_s^a	n_s^a	y_a
(1,2)	0	0	0	1	0	0	0	0	0	0	0	1
(1,3)	0	0	2	1	0	0	0	0	0	0	0	1
(2,1)	0	1	0	0	0	0	0	0	1	1	0	0
(2,6)	0	0	0	0	2	1	2	1	0	0	0	1
(3,1)	0	1	0	0	0	1	0	1	0	1	0	0
(3,4)	0	0	0	0	0	0	0	0	0	0	0	1
(3,12)	0	0	0	0	0	0	0	0	0	0	0	0
(4,3)	0	0	0	0	1	1	1	1	0	1	0	1
(4,5)	1	1	0	0	2	1	2	1	0	1	1	1
(4,11)	0	0	0	0	0	0	0	0	0	0	0	0
(5,4)	0	0	0	1	0	0	0	0	0	0	0	0
(5,6)	0	0	1	1	0	1	0	1	0	1	2	1
(5,9)	0	0	2	1	1	1	1	1	0	0	0	1
(6,2)	0	0	0	0	0	0	0	0	0	0	0	0

(6,5)	0	1	0	0	0	0	0	0	0	0	0	0
(6,8)	1	1	0	0	0	0	0	0	0	0	1	1
(7,8)	0	0	0	0	0	0	0	0	0	1	0	0
(7,18)	0	0	0	0	1	1	1	1	0	1	0	0
(8,6)	0	1	0	0	0	0	0	0	0	0	0	0
(8,7)	0	0	0	0	0	0	0	0	0	0	0	0
(8,9)	0	0	0	0	0	0	0	0	0	0	0	0
(8,16)	1	1	0	1	0	2	0	2	0	2	0	0
(9,5)	0	1	0	0	0	1	0	1	0	0	0	0
(9,8)	0	0	0	0	0	0	0	0	0	0	0	0
(9,10)	0	1	0	0	1	1	1	1	2	1	0	0
(10,9)	0	0	0	0	0	0	0	0	0	0	0	1
(10,11)	0	0	0	0	0	0	0	0	0	0	0	0
(10,15)	0	0	0	0	0	0	0	0	0	2	0	0
(10,16)	1	1	0	0	0	0	0	0	0	0	0	0
(10,17)	0	0	0	0	0	0	0	0	0	0	0	0
(11,4)	0	0	0	0	0	0	0	0	0	0	0	2
(11,10)	0	1	0	1	0	2	0	2	0	0	1	2
(11,12)	0	1	0	0	0	0	0	0	0	2	0	0
(11,14)	0	0	0	1	0	0	0	0	0	0	0	0
(12,3)	0	0	0	0	0	1	0	1	0	1	0	0
(12,11)	0	0	0	0	0	2	0	2	0	2	0	0
(12,13)	2	1	2	1	0	0	0	0	0	0	0	1
(13,12)	0	1	0	0	0	0	0	0	0	1	0	0
(13,24)	2	1	0	0	1	1	1	1	1	1	0	0
(14,11)	0	1	0	0	0	0	0	0	0	1	1	2
(14,15)	0	0	0	0	0	0	0	0	0	0	0	0
(14,23)	0	0	0	0	0	0	0	0	0	1	0	1
(15,10)	0	0	0	0	0	0	0	0	0	0	0	2
(15,14)	0	1	0	0	0	0	0	0	0	0	0	0
(15,19)	0	0	0	0	0	1	0	1	0	0	1	1
(15,22)	0	0	1	1	1	1	1	1	0	0	0	0
(16,8)	0	0	2	1	0	0	0	0	0	0	0	2
(16,10)	0	0	1	1	1	2	1	2	0	0	1	2
(16,17)	0	0	0	0	0	0	0	0	2	1	1	1

(16,18)	0	0	0	0	0	0	0	0	0	0	0	0
(17,10)	0	0	0	0	0	0	0	0	0	0	0	0
(17,16)	1	1	1	1	1	1	1	1	0	0	0	1
(17,19)	0	0	0	1	0	0	0	0	0	0	0	0
(18,7)	0	0	0	0	0	0	0	0	2	1	2	1
(18,16)	1	1	0	1	0	0	0	0	0	0	0	0
(18,20)	0	0	0	1	0	0	0	0	0	0	0	1
(19,15)	0	0	0	1	0	0	0	0	0	1	0	0
(19,17)	0	1	2	1	0	0	0	0	0	0	0	0
(19,20)	2	1	0	1	0	0	0	0	0	1	0	0
(20,18)	0	1	0	0	0	0	0	0	0	0	0	0
(20,19)	0	0	0	0	0	0	0	0	0	0	0	0
(20,21)	0	0	0	0	0	0	0	0	0	0	1	1
(20,22)	0	0	0	0	0	0	0	0	0	0	0	0
(21,20)	0	0	0	0	0	0	0	0	0	0	0	0
(21,22)	0	0	1	1	0	1	0	1	0	1	0	0
(21,24)	0	0	0	1	1	1	1	1	0	0	0	0
(22,15)	0	0	0	0	0	0	0	0	0	0	0	0
(22,20)	1	1	0	1	0	0	0	0	0	0	0	0
(22,21)	0	1	0	0	0	0	0	0	0	0	0	0
(22,23)	0	0	0	0	0	1	0	1	0	0	0	0
(23,14)	0	1	0	0	0	0	0	0	0	0	0	1
(23,22)	0	0	0	0	0	1	0	1	0	0	0	0
(23,24)	1	1	0	0	1	1	1	1	0	0	1	1
(24,13)	0	0	0	0	0	0	0	0	1	1	0	0
(24,21)	0	0	0	0	0	0	0	0	0	1	0	0
(24,23)	0	0	0	0	1	1	1	1	0	0	0	0

Links	Percentage λ											
	7%		8%		9%		10%		11%		12%	
	y_a		y_a	n_s^a	n_s^a	y_a	n_s^a	n_s^a	y_a	n_s^a	n_s^a	y_a
(1,2)	0	0	0	0	0	0	0	0	0	0	0	0
(1,3)	0	1	0	0	0	0	2	1	0	0	0	0
(2,1)	0	0	0	1	0	0	1	2	0	2	0	0
(2,6)	0	0	0	0	0	0	0	0	0	0	0	0
(3,1)	0	0	0	0	1	1	0	0	0	0	0	0

(3,4)	0	0	0	0	1	1	0	0	0	0	0	0
(3,12)	0	1	0	0	0	0	0	0	0	0	2	2
(4,3)	0	1	0	0	0	1	0	0	0	0	2	2
(4,5)	0	0	0	0	0	0	0	0	0	0	0	0
(4,11)	0	0	2	2	0	0	0	0	0	0	0	0
(5,4)	0	0	0	1	0	0	0	1	0	1	0	0
(5,6)	0	0	0	0	0	2	0	0	0	0	2	2
(5,9)	0	0	0	0	0	0	0	0	0	0	0	0
(6,2)	0	0	0	0	0	0	0	2	0	0	0	0
(6,5)	0	0	0	1	0	0	0	2	0	0	0	0
(6,8)	2	1	0	1	0	0	0	0	2	1	0	0
(7,8)	0	0	0	0	1	1	0	0	0	1	0	0
(7,18)	0	0	0	0	0	0	0	1	1	1	0	0
(8,6)	0	1	0	1	0	1	0	0	0	1	0	0
(8,7)	0	0	1	1	2	1	2	1	0	0	0	0
(8,9)	0	0	0	0	0	2	0	0	0	0	0	0
(8,16)	0	2	0	0	0	0	0	2	0	0	0	0
(9,5)	0	0	0	0	0	0	0	2	0	0	0	0
(9,8)	0	0	0	0	0	0	0	0	0	0	0	0
(9,10)	0	0	2	1	1	1	2	1	1	2	0	0
(10,9)	0	0	0	1	0	0	0	0	0	2	0	0
(10,11)	0	0	0	2	0	0	0	2	0	0	2	2
(10,15)	0	0	0	2	0	0	0	0	0	2	0	3
(10,16)	0	0	0	2	1	2	0	0	0	0	1	2
(10,17)	0	0	0	0	0	0	0	0	0	0	0	0
(11,4)	0	2	0	0	0	0	0	0	0	0	0	0
(11,10)	0	0	0	0	0	0	0	2	0	0	0	2
(11,12)	0	2	0	2	0	2	0	0	0	2	1	2
(11,14)	0	0	0	2	1	2	0	0	2	2	0	0
(12,3)	0	0	0	0	0	0	0	0	0	0	0	0
(12,11)	0	0	0	0	1	2	0	0	0	0	0	0
(12,13)	0	0	0	0	0	1	0	0	0	0	0	1
(13,12)	0	0	0	0	0	0	0	0	0	0	0	0
(13,24)	0	1	0	0	0	2	0	0	0	0	0	2
(14,11)	0	0	0	0	0	0	0	2	0	0	1	2

(14,15)	0	0	0	0	0	0	0	0	0	2	0	0
(14,23)	0	1	0	0	0	1	0	0	0	2	0	0
(15,10)	0	2	2	2	0	0	0	0	0	0	1	3
(15,14)	0	0	0	0	0	2	0	0	0	0	0	0
(15,19)	0	0	0	0	0	0	2	1	0	0	1	2
(15,22)	0	1	0	0	0	0	0	0	2	2	1	2
(16,8)	0	0	0	0	0	0	0	0	0	2	0	0
(16,10)	0	0	0	0	2	2	0	2	0	2	0	0
(16,17)	1	1	0	0	2	1	0	1	0	1	0	0
(16,18)	2	1	0	0	0	0	0	0	0	1	0	0
(17,10)	0	2	0	0	0	0	0	0	0	0	0	0
(17,16)	0	1	0	0	0	0	0	0	0	0	0	1
(17,19)	0	1	0	0	0	1	2	1	0	0	0	1
(18,7)	0	0	0	0	0	0	0	0	0	1	0	0
(18,16)	0	0	0	0	0	0	0	1	0	0	2	1
(18,20)	0	1	0	1	1	2	0	0	0	2	0	0
(19,15)	0	0	0	0	0	0	0	0	0	0	0	0
(19,17)	0	0	0	0	0	1	0	1	0	0	0	0
(19,20)	0	0	0	0	0	0	2	1	0	0	0	0
(20,18)	0	1	1	1	0	0	0	0	0	0	0	0
(20,19)	0	0	0	0	1	1	0	0	0	0	0	2
(20,21)	0	0	0	2	0	0	0	2	0	0	0	0
(20,22)	0	2	0	2	0	0	0	0	0	0	0	2
(21,20)	0	0	0	0	0	0	0	0	0	0	0	0
(21,22)	0	0	0	0	1	1	2	1	0	1	0	0
(21,24)	0	0	0	1	0	0	0	0	0	0	0	0
(22,15)	0	1	0	0	0	0	0	2	0	0	0	0
(22,20)	0	0	0	2	0	0	0	0	0	0	0	2
(22,21)	0	0	2	1	0	0	0	1	0	1	0	0
(22,23)	1	1	0	1	1	2	0	0	0	2	2	2
(23,14)	0	0	0	0	0	1	0	0	2	2	0	0
(23,22)	0	0	2	1	0	0	0	0	0	0	0	2
(23,24)	2	1	0	0	0	1	0	0	0	1	0	1
(24,13)	0	0	0	2	0	0	0	2	0	0	0	2
(24,21)	0	0	0	0	1	1	0	0	0	1	0	0

(24,23)	0	0	0	0	0	0	0	0	0	0	0	0

Links	Percentage λ											
	13%		14%		15%		16%		17%		18%	
	y_a		y_a	n_s^a	n_s^a	y_a	n_s^a	y_a	y_a	n_s^a	n_s^a	y_a
(1,2)	1	2	0	0	0	0	0	0	0	0	0	0
(1,3)	0	0	0	0	0	0	0	2	0	0	0	0
(2,1)	0	0	0	0	2	2	0	2	0	0	0	0
(2,6)	0	0	0	2	0	0	0	2	0	0	0	0
(3,1)	2	1	0	2	0	0	0	0	1	2	0	2
(3,4)	0	0	0	0	0	2	0	2	0	0	1	2
(3,12)	1	2	0	0	0	0	0	2	0	0	1	2
(4,3)	0	0	0	0	0	0	0	0	0	0	0	0
(4,5)	0	1	0	0	0	0	0	0	0	0	0	1
(4,11)	2	2	0	0	0	0	0	0	0	0	0	0
(5,4)	0	1	0	0	0	0	0	1	0	0	0	0
(5,6)	1	2	0	0	0	0	0	2	1	2	0	0
(5,9)	0	0	0	0	0	0	0	0	0	0	0	0
(6,2)	0	0	0	0	0	0	0	0	0	2	0	2
(6,5)	0	0	0	0	0	0	0	0	0	0	0	0
(6,8)	0	1	0	0	1	1	0	0	0	0	0	0
(7,8)	2	1	0	0	0	0	0	0	2	1	0	1
(7,18)	0	1	0	0	0	1	1	1	0	0	1	1
(8,6)	2	1	0	0	0	0	1	1	0	0	0	0
(8,7)	0	1	0	1	2	1	0	0	0	0	0	0
(8,9)	0	0	0	0	0	0	0	0	0	0	0	0
(8,16)	0	0	0	0	0	0	0	0	0	0	0	2
(9,5)	0	0	0	0	0	0	0	0	0	0	0	0
(9,8)	1	2	1	2	0	0	0	0	0	0	0	2
(9,10)	0	0	1	2	0	0	0	0	0	0	0	2
(10,9)	0	0	0	0	0	2	2	2	0	2	0	0
(10,11)	0	3	0	0	0	3	0	0	0	0	1	3
(10,15)	0	0	0	0	0	3	0	3	1	3	0	0
(10,16)	0	0	0	0	0	2	0	0	0	0	1	3
(10,17)	0	0	0	0	0	0	0	0	0	0	0	0
(11,4)	0	0	2	2	0	2	0	2	0	0	0	0

(11,10)	0	3	0	3	0	3	1	3	0	0	0	0
(11,12)	0	2	1	2	0	2	0	0	0	0	0	3
(11,14)	0	0	0	0	0	0	2	2	1	2	0	0
(12,3)	0	0	0	0	0	0	0	0	0	2	0	0
(12,11)	0	0	0	0	0	2	0	0	1	3	0	3
(12,13)	0	1	0	0	0	0	0	0	0	0	0	0
(13,12)	0	0	0	2	0	0	2	2	1	2	0	0
(13,24)	0	0	0	0	2	2	0	0	0	0	0	0
(14,11)	1	2	0	0	0	0	0	0	2	2	0	0
(14,15)	0	0	0	0	0	2	0	2	0	0	0	2
(14,23)	0	0	0	0	0	0	0	0	0	0	0	0
(15,10)	0	0	1	3	0	0	0	3	0	0	0	0
(15,14)	0	2	0	0	0	2	0	2	0	0	0	0
(15,19)	0	2	0	0	0	0	2	2	2	2	2	2
(15,22)	0	2	0	2	1	2	0	2	0	0	0	0
(16,8)	0	0	0	0	0	0	0	0	0	2	0	0
(16,10)	0	0	1	2	0	2	0	0	0	0	2	3
(16,17)	2	1	2	1	2	1	0	1	0	1	0	0
(16,18)	0	0	0	0	0	0	0	0	0	0	0	0
(17,10)	0	0	1	2	0	0	0	0	0	0	0	0
(17,16)	0	1	0	0	0	0	2	1	0	0	0	2
(17,19)	0	0	0	0	2	1	0	0	0	0	0	1
(18,7)	0	0	0	1	0	0	1	1	0	0	0	0
(18,16)	0	1	0	0	0	2	0	0	0	0	0	0
(18,20)	0	2	1	2	0	0	0	0	0	0	0	0
(19,15)	0	0	0	0	1	2	0	0	0	0	1	2
(19,17)	0	0	2	1	0	0	0	1	0	1	0	1
(19,20)	0	0	0	0	0	0	0	0	0	0	0	0
(20,18)	0	0	0	0	0	0	0	0	0	0	0	0
(20,19)	0	0	0	0	0	0	0	0	0	0	0	0
(20,21)	0	0	0	0	0	0	0	0	0	0	0	0
(20,22)	0	0	0	2	0	0	0	0	0	0	0	0
(21,20)	0	0	0	0	0	0	0	0	0	0	0	0
(21,22)	0	0	0	0	1	1	0	0	0	1	0	0
(21,24)	0	0	0	0	0	1	1	2	0	2	1	2

(22,15)	0	0	2	2	2	2	0	0	1	2	0	0
(22,20)	0	0	0	0	0	0	0	0	0	0	0	0
(22,21)	0	0	1	1	0	1	0	0	0	0	0	0
(22,23)	0	0	0	0	0	0	0	0	1	2	0	2
(23,14)	0	2	0	0	2	2	0	0	0	0	0	2
(23,22)	0	0	0	2	0	0	0	0	0	0	0	0
(23,24)	0	0	0	0	0	1	0	0	0	0	0	0
(24,13)	0	0	0	0	0	0	0	0	0	0	1	2
(24,21)	0	0	0	1	0	0	0	0	0	2	0	2
(24,23)	0	1	0	0	1	1	0	0	0	0	0	0

Links	Percentage λ			
	19%		20%	
	y_a	n_s^a	y_a	n_s^a
(1,2)	1	2	1	2
(1,3)	0	0	0	0
(2,1)	0	0	0	0
(2,6)	0	2	0	2
(3,1)	0	2	0	2
(3,4)	0	0	0	0
(3,12)	0	0	0	0
(4,3)	0	0	0	0
(4,5)	0	0	0	0
(4,11)	0	0	0	0
(5,4)	0	1	0	1
(5,6)	0	0	0	0
(5,9)	0	0	0	0
(6,2)	0	0	0	0
(6,5)	0	0	0	0
(6,8)	0	0	0	0
(7,8)	0	0	0	0
(7,18)	0	0	0	0
(8,6)	0	0	0	0
(8,7)	1	1	1	1
(8,9)	0	0	0	0

(8,16)	0	0	0	0
(9,5)	0	0	0	0
(9,8)	0	0	0	0
(9,10)	0	0	0	0
(10,9)	0	0	0	0
(10,11)	0	0	0	0
(10,15)	0	3	0	3
(10,16)	1	3	1	3
(10,17)	0	0	0	0
(11,4)	0	0	0	0
(11,10)	0	0	0	0
(11,12)	0	0	0	0
(11,14)	0	0	0	0
(12,3)	0	0	0	0
(12,11)	0	0	0	0
(12,13)	0	2	0	2
(13,12)	1	2	1	2
(13,24)	0	0	0	0
(14,11)	0	0	0	0
(14,15)	0	0	0	0
(14,23)	1	2	1	2
(15,10)	0	3	0	3
(15,14)	0	2	0	2
(15,19)	0	0	0	0
(15,22)	1	2	1	2
(16,8)	0	0	0	0
(16,10)	1	3	1	3
(16,17)	1	2	1	2
(16,18)	0	0	0	0
(17,10)	0	0	0	0
(17,16)	1	2	1	2
(17,19)	1	2	1	2
(18,7)	0	1	0	1
(18,16)	0	0	0	0
(18,20)	0	0	0	0

(19,15)	0	0	0	0
(19,17)	0	0	0	0
(19,20)	0	0	0	0
(20,18)	0	2	0	2
(20,19)	1	2	1	2
(20,21)	1	2	1	2
(20,22)	0	0	0	0
(21,20)	0	0	0	0
(21,22)	0	1	0	1
(21,24)	0	0	0	0
(22,15)	2	2	2	2
(22,20)	0	0	0	0
(22,21)	2	1	2	1
(22,23)	0	0	0	0
(23,14)	0	0	0	0
(23,22)	0	0	0	0
(23,24)	0	0	0	0
(24,13)	1	2	1	2
(24,21)	0	0	0	0
(24,23)	0	0	0	0

Table A5 – The capacity expansion of the best solution of the medium-sized network regarding different weight's scenarios

Scenario I		
Electrified arcs	y_a	$n_{s,a}$
(1,4)	2	1
(3,6)	1	1
(4,1)	2	1
(4,5)	1	1
(4,7)	0	1
(5,2)	1	1

(5,4)	1	1
(8,7)	0	1
(9,5)	0	1
Scenario II		
Electrified arcs	y_a	$n_{s,a}$
(2,5)	0	1
(3,2)	0	1
(3,6)	2	1
(4,1)	0	1
(4,5)	0	1
(5,1)	0	1
(5,4)	0	1
(5,6)	0	1
(5,9)	2	1
(6,3)	0	1
(6,5)	0	1
(6,9)	1	1
(7,4)	0	1
(7,8)	0	1
(8,9)	0	1
(9,5)	0	1
Scenario III		
Electrified arcs	y_a	$n_{s,a}$
(1,2)	1	1
(1,4)	0	1
(2,1)	0	1
(2,5)	1	1
(3,2)	1	1
(3,6)	0	1

(4,1)	1	1
(4,5)	1	1
(4,7)	1	1
(5,1)	0	1
(5,2)	0	1
(5,4)	0	1
(5,9)	0	1
(7,4)	0	1
(8,5)	0	1
(8,7)	0	1
(8,9)	2	1
(9,6)	1	1
(9,8)	1	1

Table A6 – The capacity expansion of the best solutions of the Sioux-falls network regarding different weight's scenarios

Scenario I		
Electrified arcs	y_a	$n_{s,a}$
(11,14)	0	1
(13,24)	0	1
(14,11)	0	1
(15,22)	0	1
(17,16)	0	1
(23,14)	0	1
(24,13)	0	1
Scenario II		
Electrified arcs	y_a	$n_{s,a}$
(2,1)	1	1

(2,6)	1	1
(3,1)	0	1
(3,12)	0	1
(4,3)	0	1
(6,8)	0	1
(7,18)	0	1
(9,5)	0	1
(10,11)	2	1
(10,16)	0	1
(11,10)	0	1
(12,3)	1	1
(13,24)	2	1
(14,11)	1	1
(14,15)	2	1
(14,23)	0	1
(15,10)	0	1
(15,14)	2	1
(15,22)	0	1
(16,10)	0	1
(17,19)	0	1
(18,7)	1	1
(18,20)	0	1
(20,22)	1	1
(22,23)	1	1
(23,14)	0	1
(23,24)	1	1
(24,13)	2	1
Scenario III		
Electrified arcs	y_a	$n_{s,a}$
(2,1)	2	1

(3,4)	2	1
(3,12)	0	1
(4,5)	2	1
(5,6)	2	1
(5,9)	1	1
(6,5)	0	1
(8,7)	0	1
(8,16)	0	1
(10,15)	0	1
(11,10)	1	1
(13,12)	1	1
(14,15)	0	1
(14,23)	0	1
(15,19)	0	1
(16,10)	0	1
(16,17)	2	1
(18,7)	0	1
(19,15)	0	1
(20,18)	0	1
(20,21)	0	1
(21,20)	0	1
(21,22)	0	1
(22,15)	0	1
(22,20)	0	1
(22,21)	0	1
(23,24)	1	1

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PUBLICATIONS	
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