

JAKOV TOPIĆ, M.Sc.

E-mail: jakov.topic@fsb.hr

FILIP MALETIĆ, M.Sc.

E-mail: filip.maletic@fsb.hr

BRANIMIR ŠKUGOR, Ph.D.

E-mail: branimir.skugor@fsb.hr

PROF. JOŠKO DEUR, Ph.D.

E-mail: josko.deur@fsb.hr

University of Zagreb, Faculty of Mechanical Engineering and Naval Architecture

Ivana Lučića 5, 10000 Zagreb

SOFTWARE TOOL FOR PLANNING OF CITY BUS TRANSPORT ELECTRIFICATION

ABSTRACT

This paper presents a software tool that is intended as a support in simulation, optimization and decision making in the process of planning of city bus transport electrification. It provides techno-economic comparison between fleets of conventional buses and different types of electrified buses. The tool consists of four software modules that are responsible for key steps in providing the final result: (i) module for processing of recorded driving cycle data, (ii) module for simulation of city bus fleets, (iii) module for e-bus fleet charging management optimisation; and (iv) module for conducting the techno-economic analysis itself.

KEY WORDS

ICT tool; transport electrification; driving cycles processing; city bus simulation; charging management; techno-economic analysis.

1. INTRODUCTION

Due to environmental concerns, there is a strong tendency of electrifying the existing road transport system, which mainly relies on internal combustion engine (ICE)-based propulsion technology. Electric vehicles (EV) are meant to be most viable solution for the replacement of the ICE-propelled vehicles. Apart from reducing pollutant and CO₂ emissions, EVs are characterised by substantially reduced noise pollution, lower operating costs (including energy and maintenance cost) and generally better driving characteristics; while on the other hand, higher investment cost, slow battery charging and limited driving range inhibit their faster proliferation. This is why the transition to fully electric vehicles (FEV or BEV) is characterized by the presence of hybrid electric vehicles (HEV) and plug-in hybrid electric vehicles (PHEV).

A natural candidate for electrification relates to city bus fleets, aiming at improvement in city air quality and reduction of noise. Since the city bus operation is highly determined (i.e. known in advance) and intermittent, the range- and charging-related issues may be overcome to a significant extent by combining fast charging at end stations and slow charging in depot centre. In order to encourage and accelerate replacement of conventional vehicle fleets with electric ones, detailed techno-economic analyses comparing the conventional and EV fleets should be conducted.

First, all routes on which a conventional bus fleet operates should be analysed, and the most relevant ones to be covered by EV buses (e.g. routes in city centres) should be identified. Then, driving cycle data (e.g. vehicle velocities, GPS positions, elevation, etc.) and powertrain data (e.g. engine speed and torque, gear ratio, etc.) should be recorded and collected in real time for the buses that operate on the selected routes, based on installation of a GPS/GPRS tracking. In order to cover

all typical operations of the considered bus fleet, the driving data should be continuously recorded over the full year period. Then, the recorded driving data should be post-processed and analysed in order to reveal the main characteristics of the considered fleet. Afterwards, a hypothetical fleet of e-buses should be simulated over the given bus routes in order to obtain the information about the total amount of fuel and electricity consumed. This information is fed into an EV charging management optimisation algorithm to determine the charging schedules for both fast (daily) charging located at the end stations and slow (overnight) charging conducted at depot. Finally, a detailed techno-economic analysis of conventional and e-bus fleets should be conducted by using the obtained data.

To facilitate this process, a software tool for planning the city bus transport electrification has been developed and it is described in this paper. The overall tool is organised into four modules: (i) post-processing and analysis of recorded driving cycles, (ii) simulation of conventional and e-bus fleets, (iii) e-bus fleet charging management optimisation, and (iv) techno-economic analysis.

Similar efforts in calculating cost-effectiveness of city buses exist in literature. Software tool presented in [1] uses defined bus schedules and routes along with assumed fuel and energy consumption, whereas tool presented in this paper uses real driving data recorded on actual vehicles as well as detailed simulation models of e-buses which allows more precise fuel and energy consumption calculation.

The paper is organised as follows. Section 2 describes the architecture of the developed software application. Sections 3 describes the individual software tool modules. Section 4 describes the obtained simulation results of a techno-economic analysis for an illustrative example of conventional and electric vehicles. Concluding remarks are given in Section 5.

2. ORGANIZATIONAL STRUCTURE OF SOFTWARE APPLICATION

The developed software tool for planning of city bus transport electrification is implemented in the object-oriented programming language Python by using built-in modules and packages like *numpy* and *scipy*, whose main advantage is that they are implemented in C++ programming language, thus significantly increasing the program execution speed. The overall application consists of the following tools (see Figure 1): (i) Data Post-processing Module (DPPM) – tool for post-processing and analysis of recorded driving cycles, (ii) E-bus Simulation Module (EBSM) – tool for simulation of various bus models (i.e. conventional, hybrid electric, plug-in hybrid electric and fully electric ones), (iii) Charging Optimisation Module (COM) – tool for EV fleet charging optimisation, and (iv) Techno-Economic Analysis Module (TEAM) – tool for techno-economic analysis related to the replacement of conventional vehicle fleet with an electric one. The aforementioned tools are organized within the application as independent modules.

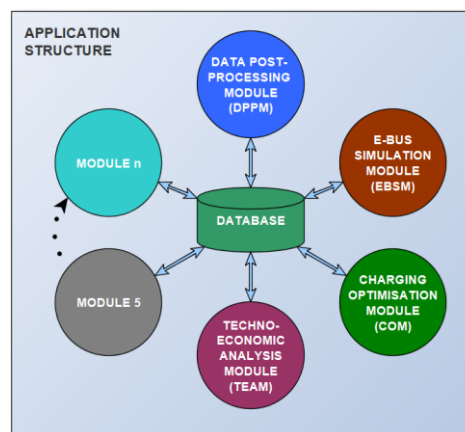


Figure 1 – Modular structure of the developed software application

Connections between the developed ICT modules (DPPM, EBSM, COM and TEAM) are defined as shown in Figure 2. The application takes recorded driving cycles data as main input, which represent the basis for further calculations. Each of the developed modules has its own output dataset, along with the dataset which it shares or passes to the other modules (data streams are defined by the colourful arrow lines). The data exchange between the software modules is realised through a shared database and specific files (i.e. CSV, JSON, TXT file formats). The overall operation of the ICT tool is designed as follows, and it results in calculation of the *total cost of ownership* (TCO) of a vehicle fleet, as its final output:

- The recorded driving cycle data is processed and stored into database by DPPM, thus preparing it for using in other modules. Data processing includes various filtering and interpolation methods, along with calculation of basic statistics of the city bus transport system.
- Various types of buses (conventional, HEV, PHEV, and BEV) are meant to be simulated within EBSM over recorded driving cycles in order to calculate their fuel and electricity consumption. Apart from providing the operational cost of bus fleet, the EBSM is also designed to be the platform for optimisation, development and verification of realistic powertrain control strategies, whose description is beyond the scope of this paper.
- A hypothetical fleet of e-buses is simulated within COM over the given driving schedules and using the driving cycles processed in DPPM. This simulation includes both daily charging of e-buses via fast chargers and overnight charging in depot. As a result, the information related to a total distance travelled, required amount of electric energy needed for charging, and the required number of e-buses and charging stations, necessary to fulfil the daily driving schedule, is obtained.
- The TCO is calculated within TEAM for both conventional and electric vehicles by using the aforementioned resulting datasets, and data regarding the loan payments, registration renewal, insurance, maintenance, and irregular costs as inputs to TEAM.

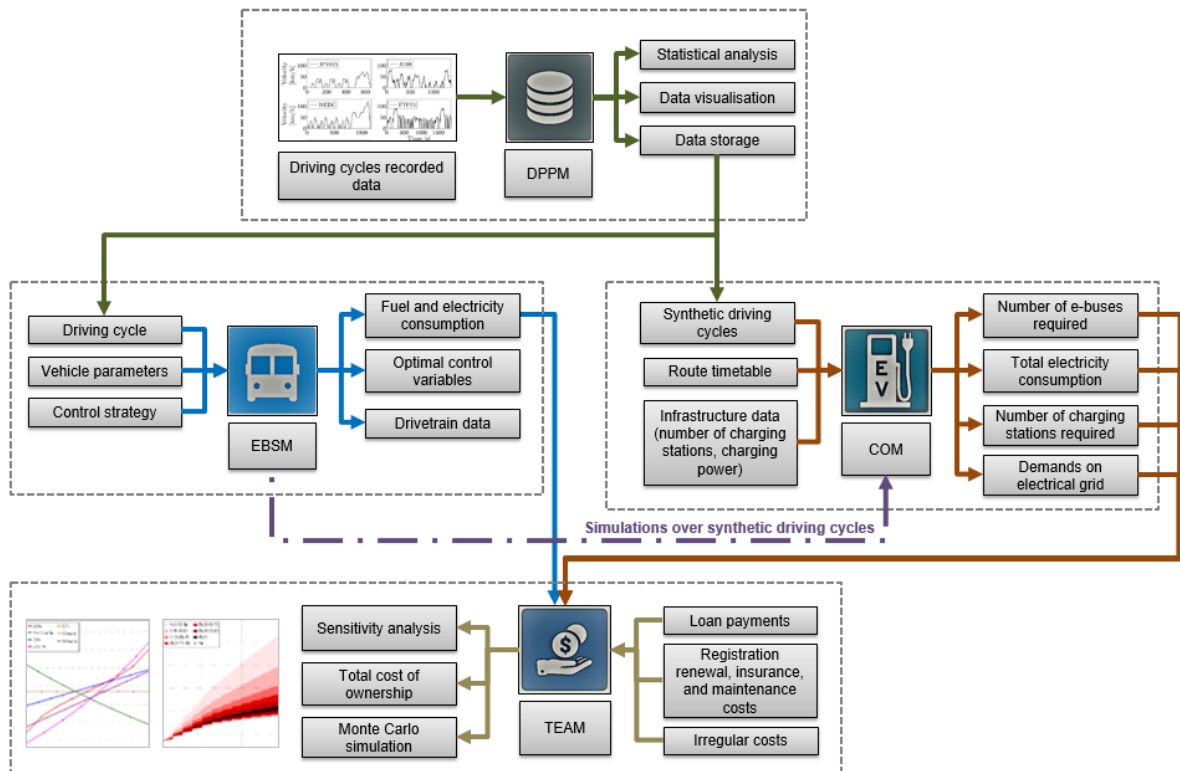


Figure 2 – Scheme of connections between developed ICT modules (DPPM, EBSM, COM and TEAM)

3. DESCRIPTION OF ICT TOOLS

This section gives brief description of the developed ICT tools (DPPM, EBSM, COM and TEAM), including their main functionalities and the role in calculation of the TCO as the final output.

3.1. Data Post-processing Module (DPPM)

Methodology of recording the driving routes and taking measurements of relevant driving parameters/variables for public-bus fleet is based on utilizing the telemetry electronic tracking module (e.g. STM-Eagle unit, manufactured by Artronic, Croatia), which is equipped with GPS receiver, GPRS communication line and CAN communication with vehicle powertrain. These recorded (raw) driving cycles (velocity vs. time and road slope and vehicle mass vs. travelled distance profiles) are then post-processed inside DPPM software module, thus representing key inputs to be used in computer simulations of conventional and e-bus fleets, aimed at calculation of related operational costs and defining proper charging system structure and management. The module is divided into three main categories:

1. **Data insertion** - operations related to insertion of recorded driving data into the database. These operations include various methods for adapting the input data format along with the validity checks (e.g. existence of duplicate data within files).
2. **Data processing** - operations related to organisation of stored driving data as driving cycles (an unique driving cycle number is assigned to each data record), along with the data filtering and interpolation. Fig. 5 in Subsection 3.2 shows an example of driving cycle data postprocessed by the DPPM.
3. **Calculations** – operations related to calculation of: (i) vehicle parking time, (ii) basic statistics and (iii) limit powertrain curves. The process of vehicle parking detection calculates when, where and for how long the vehicle has been parked. The basic statistics is calculated for entire vehicle fleet, individual vehicles and their respective driving cycles and includes a total of 43 features (e.g. vehicle total distance travelled, idle and cruise time share, number of stops per kilometre, mean, maximum, and minimum values of velocity, acceleration and elevation height, corresponding values of standard deviations, etc.; see Fig. 3 for an example). The limit curves calculation process includes vehicle maximum acceleration in dependence on velocity, and maximum acceleration and maximum velocity in dependence on road slope.

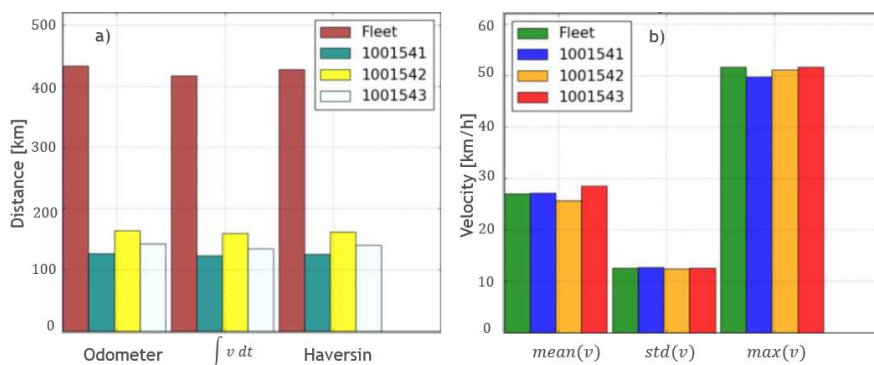


Figure 3 – An example of basic statistic plot: a) total distance travelled, and b) velocity characteristics for individual vehicles and entire fleet.

3.2. E-bus Simulation Module (EBSM)

This module provides a simulation environment for different types of buses (i.e. conventional, HEV, PHEV and BEV), where the considered bus model is meant to be simulated over realistic driving

cycles (obtained and prepared by DPPM module), thus providing a basis for a comparative analysis of different types of buses in terms of fuel and electric energy consumption. The e-bus simulation also provides an insight into vehicle operation characteristics such as demanded power on wheels, torque and rotational speed values of an electric motor and internal combustion engine, amount of energy recuperated by regenerative braking, etc. Simulation models of the selected bus configurations (conventional, HEV, and PHEV and BEV) are built up along with the corresponding realistic powertrain control strategy. Also, the off-line control variable optimisations are conducted for HEV and PHEV powertrains by using dynamic programming (DP) optimisation method, in order to gain insight into the optimal powertrain operation for different driving conditions and the optimal/minimal fuel consumption. The globally optimal DP results are used as a benchmark for the design and verification of a realistic energy management control strategy. The proposed online control strategy combines the rules (rule-based strategy, RB) and the instantaneous optimisation of equivalent consumption (Equivalent Consumption Minimisation Strategy, ECMS) for which is verified that even with the lack of road grade and driving cycle preview, it can still approach the globally optimal results by the margin of up to 2% in terms of fuel consumption for both HEV- and PHEV-type.

Currently at the market, Volvo 7900 city bus platform all three EV variants (HEV / PHEV / BEV [2], [3]). Therefore, this bus platform has been taken as a basis for this research, without losing generality of the research, because powertrain simulation model can easily be modified, either by changing powertrain parameters (e.g. battery capacity), consumption and efficiency maps, or by changing the powertrain structure (e.g. from parallel to series), thus representing another bus type. Volvo 7900 HEV and PHEV are parallel hybrid powertrains, which at the current state-of-the-art may be considered as a good trade-off choice between operational and investment cost of the bus. For the purpose of simulation, all Volvo e-buses were modeled as backward models based on point mass representation of the vehicle given in configurations showed in Fig. 4.

By using the developed ICT tool (EBSM), a simulation of Volvo 7900 HEV over the selected driving cycle (see Fig. 5) has been conducted for demonstration purposes. The driving cycle was recorded on the circular bus route, by using a precise GPS receiver [4]. The bus station Babin kuk is considered to be the starting and the end point of each driving cycle, which is terminated on the eastern part of cycle by the bus station Pile. The total length of the given route (Babin kuk – Pile – Babin kuk) is around 11.8 kilometers. The initial vehicle battery state-of-charge (SoC) value is set to 0.5 (50% of battery capacity), while the previously developed realistic control strategy RB+ECMS is used for powertrain control [5]. The internal combustion engine (ICE) fuel consumption map and the electric motor/generator (M/G) efficiency map are represented by Willans approximation maps [6], while each of the battery types are represented by the exact numerical maps (i.e. battery open circuit voltage $OCV(SoC)$ and internal resistance $R(SoC)$ profiles). The corresponding ICE and M/G operating points, along with the fuel consumptions and SoC responses are shown in Fig. 6. As it can be seen from these results, operating points of both ICE and M/G largely lie in efficient map regions. The operating points distributed outside of the maximum torque curve in the generator quadrant (electromotor torque is negative, $\tau_{MG} < 0$; braking phase), represent the points where the bus powertrain could not recuperate all the braking energy by the means of regenerative braking (most of the energy is regenerated, while the rest is covered by mechanical brakes).

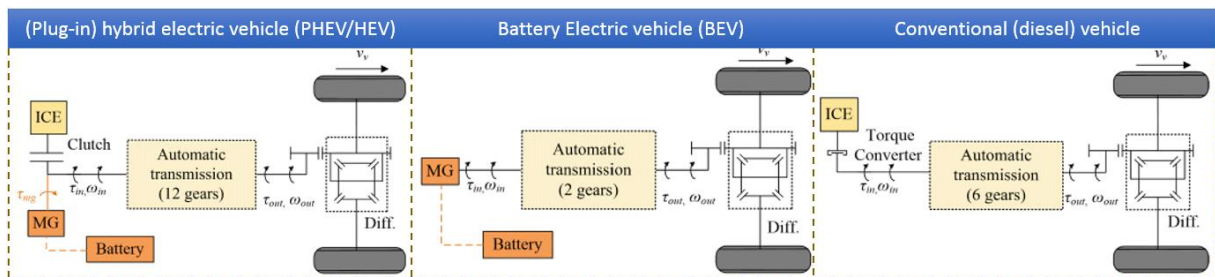


Figure 4 – Driveline configurations of Volvo 7900 PHEV/HEV, BEV, and conventional buses [2].

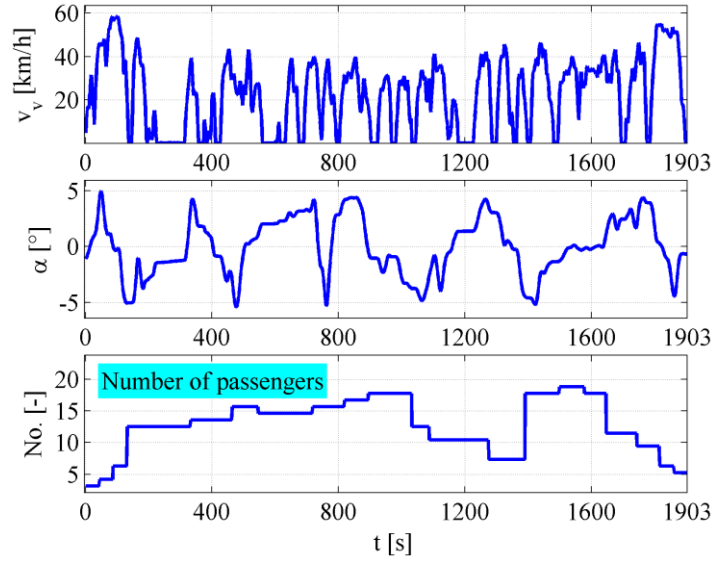


Figure 5 – City bus driving cycle used in HEV/PHEV simulation, including vehicle velocity v_v , road grade α , and number of passengers over time profiles.

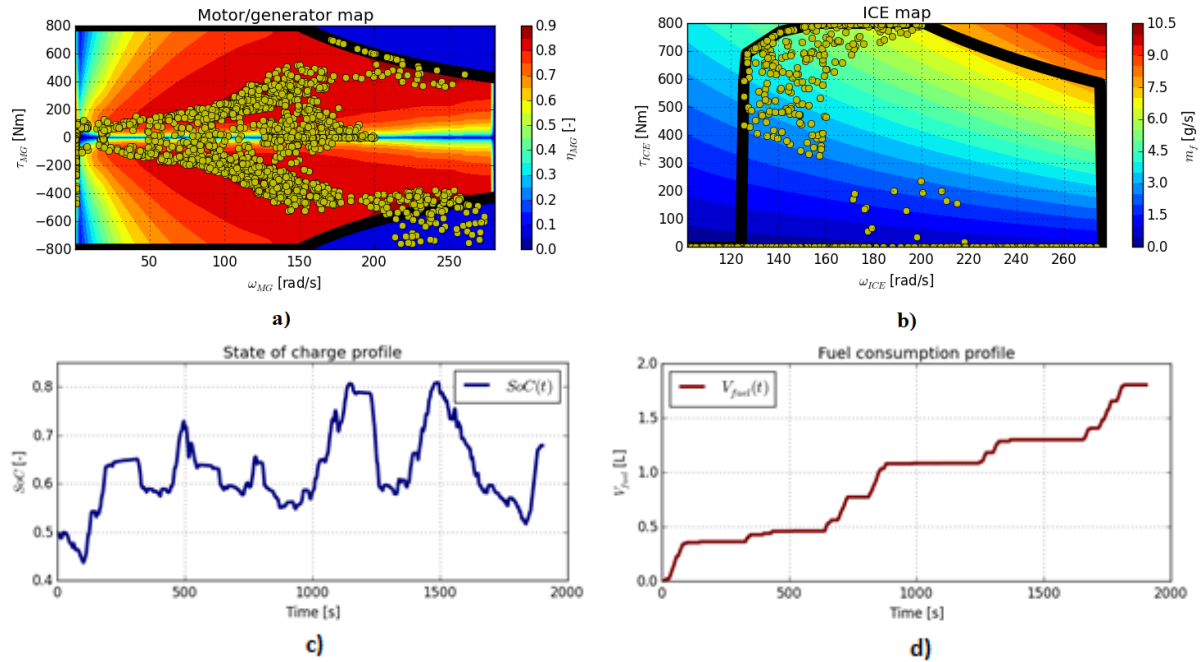


Figure 6 – Simulation results for a Volvo 7900 HEV bus: a) M/G operating points distribution, b) ICE operating points distribution, c) battery SoC vs time profile, and d) cumulative fuel consumption vs time profile.

3.3. Charging Optimisation Module (COM)

A generic framework of e-bus fleet operation is established through this software module, which serves as a basis for conducting an e-bus fleet simulation and charging power optimisation. The generic e-bus fleet operation is divided into two parts: (i) e-buses serving daily city driving missions according to prescribed timetables over given routes, and (ii) e-buses being parked in a depot and being optimally charged according to prescribed criteria. Since e-buses have limited range, a daily fast charging of e-buses is allowed between driving missions in order to ensure that minimal number of e-buses can serve prescribed timetables. In order to provide a realistic e-bus fleet charging

conditions, the daily fast charging is separated from the overnight charging in a depot, and is conducted through simple heuristic rules. Functionality of the developed framework was demonstrated through the case study assuming bus time schedules on the aforementioned circular bus route Babin kuk – Pile – Babin kuk in the City of Dubrovnik. In order to provide realistic scenario, different synthetic driving cycles over the route were generated by using Markov chain statistical methodology and the corresponding transition probability matrix (TPM), which is parameterised by using the previously recorded and processed GPS data on the considered bus route (see Subsection 3.1). The framework involves five different subjects (see Fig. 7):

- **Depot** - a place where e-buses are sheltered, maintained and charged when they are out of service;
- **E-bus fleet** - a hypothetical city bus fleet consisting of all-electric buses (propelled only by electric power from a battery);
- **Home station** - represents the starting point of a given bus route (only one home station is shown in Fig. 7 for the sake of illustration, although the number of home stations in the framework is not limited);
- **EV charging station** - an element of an infrastructure that supplies electrical energy for an e-bus fleet charging (can be placed in depot or on specific location in the city such as end stations, with the maximum charging power allowed to be specified by the user);
- **Route timetable** - a time schedule of bus departures from the corresponding home station that needs to be fulfilled.

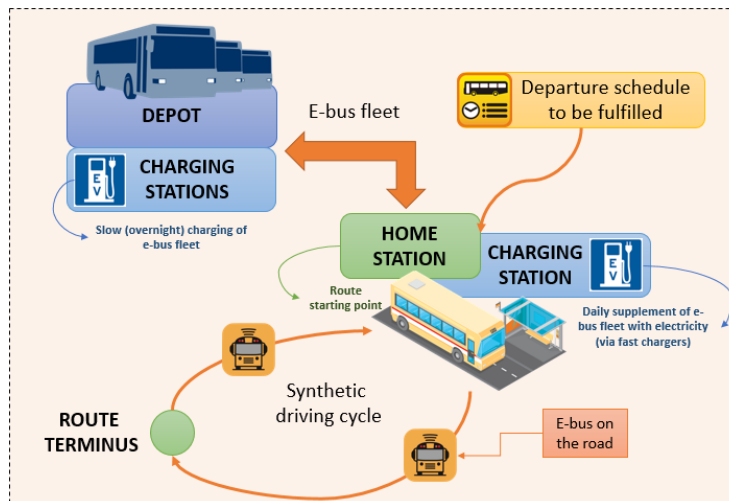


Figure 7 – A generic framework of an e-bus fleet operation.

An e-bus fleet modelled within EBSM (see Subsection 3.2) is simulated over the synthetic driving cycles that are generated based on DPPM outputs. The purpose of the e-bus fleet simulation is twofold: **(a)** to obtain the data required as inputs for the charging optimisation algorithm, and **(b)** to provide specific operating and investment costs for TCO analysis (see Fig. 8). The former data, referring to the charging optimisation, consists of the following distributions: **(i)** departure times of e-buses from the depot along with their SoC-at-departure values, **(ii)** arrival times of e-buses to depot along with their SoC-at-arrival values, **(iii)** time intervals in which the e-buses were available for charging, and **(iv)** time instants in which the e-buses were disconnected from the grid. The latter group of data, referring to TCO analysis, includes the following parameters: **(v)** number of e-buses required for fulfilling the imposed driving schedule for a given route on a daily basis, **(vi)** total amount of electrical energy consumed by charging stations located at home stations (for a daily fast charging of active e-bus), and **(vii)** the number of corresponding fast charging stations required along with the demands on the electrical grid and charging power supply.

The EV fleet slow charging in depot is managed based on optimisation which includes both charging cost minimisation and penalisation of aggregate charging power peaks. The problem can conveniently be formulated to be solved by using available linear programming (LP) and particularly quadratic programming (QP) solvers [7]. Illustration of the e-bus fleet charging optimisation results, for the case of three e-buses within fleet, are shown in Fig. 9; for the case of only minimising the charging cost (Fig. 9a), and for the case of only minimising the electrical grid power peaks (i.e. peak shaving effect; Fig. 9b). In both cases the upper constraint on the maximum power which can be drawn from the grid is satisfied (i.e. $P_{max,grid} = 30$ kW). Also, it is worth noting that the aggregate charging power profiles obtained as the LP solution lies within the low-tariff electricity intervals, unlike with QP where these profiles are expanded into the high-tariff intervals to minimise the grid power fluctuations.

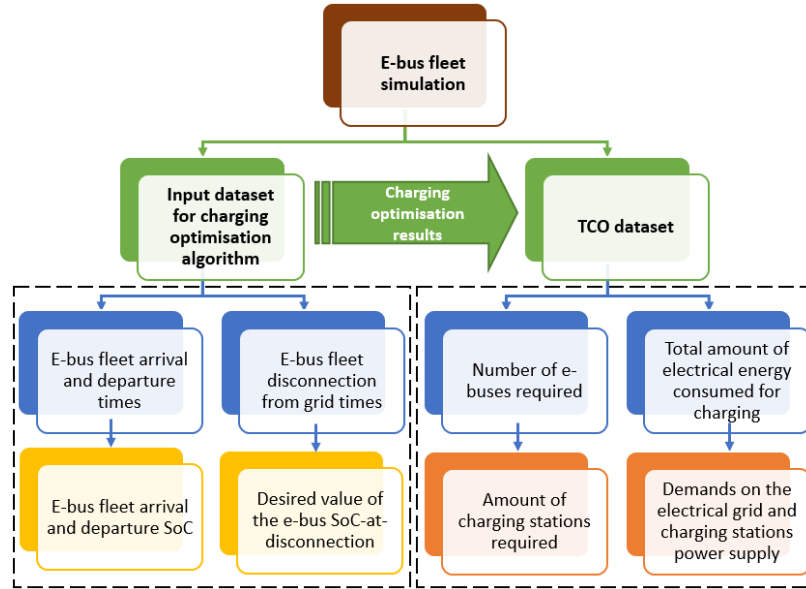


Figure 8 – Interface of e-bus fleet simulation toward the charging optimisation and TCO modules.

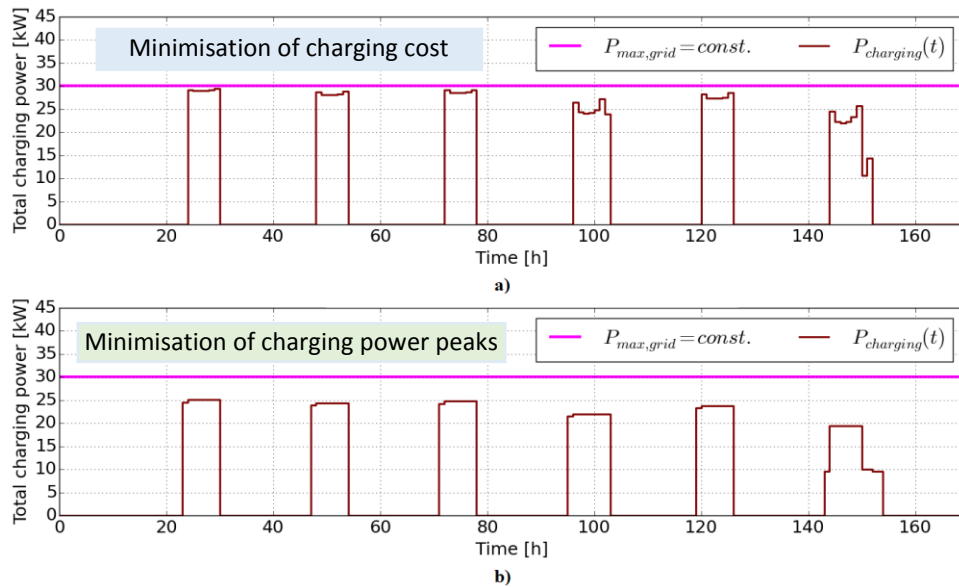


Figure 9 – Illustration of optimal aggregate charging power vs time profile for the case of overnight (slow) charging of three e-buses at depot: (a) LP solution, and (b) QP solution.

3.4. Techno-economic analysis module (TEAM)

The main purpose of TEAM module is to provide a simulation environment for calculation of Total Cost of Ownership (TCO) regarding the conventional and electric city bus fleet. Techno-economic dataset, which is input to this module, contains various cost-related indicators that can be crucial when deciding about electrification of a considered conventional vehicle fleet. The key cost-related indicators can be categorised as:

- **Operational costs** which include daily driving costs manifesting themselves in vehicle fuel and/or energy costs
- **Financing costs** that include one-time purchase costs and/or loan payments costs, as well as corresponding sale taxes (which can also indirectly include state or other incentives for EVs and/or penalties for higher-polluting conventional vehicles)
- **Registration renewal and insurance costs**
- **Maintenance costs**
- **Infrastructure costs** that valorises investment that would likely be needed to accommodate for introduction of an electrified vehicle fleet (e.g. charging stations and related infrastructure).

The dataset also contains data about projected or expected money inflows that a vehicle fleet could provide. That can either be a:

- **Real revenue** that vehicle could provide (in the particular case of a city bus fleet that would consist mainly of passenger tickets), or
- **Salvage value** which is a market value of used vehicle (or its costly components such as batteries), that can be turned into the real revenue at the moment of vehicle sale.

Different costs have different frequencies of occurrence, which are categorised as follows:

- **Daily** – operational costs,
- **Monthly** - loan payments,
- **Yearly** - maintenance, registration, and insurance costs, and
- **Extra** - irregular costs (e.g. tire replacement, repairs, etc.) and/or infrastructure costs (e.g. power infrastructure upgrade to accommodate introduction of an electrified fleet).

TCO is then the Net Present Value (NPV) of all those costs and revenues summed all together with respect to their value over time [8], i.e. taking into account time value of money with inflation and discount rates, respectively. General idea for TCO calculation is illustrated in Fig. 10 [9].

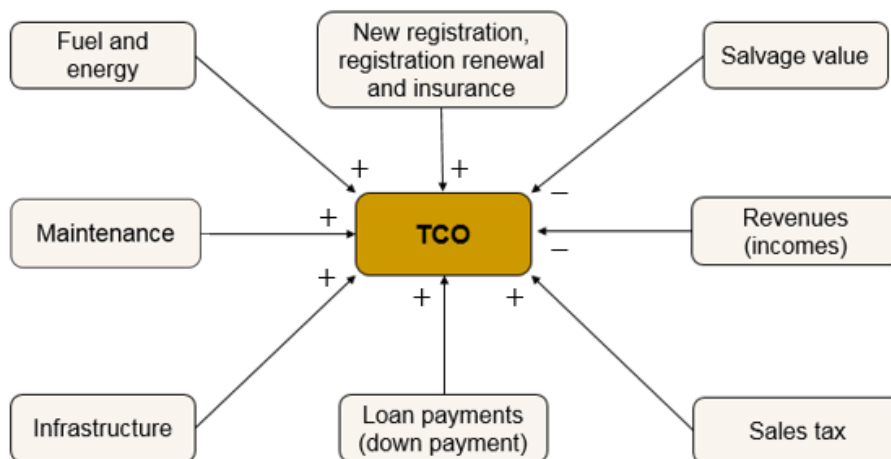


Figure 10 – General representation of calculation of total cost of ownership (TCO).

There are two types of TCO calculation: (i) deterministic calculation where all input parameters are given as single values, and therefore, calculation returns a single-value TCO; and (ii) stochastic simulation, where some of inputs can be given as stochastic variables (i.e. statistical distributions),

rather than single values. The latter approach is useful for taking into account expected volatility of some of the input parameters (e.g. fuel and energy prices, daily distance driven, etc.). The stochastic TCO calculation is carried out using the Monte Carlo approach where significant amount of calculations are conducted with different combination of input samples. Another useful indicator implemented within the techno-economic analysis module is sensitivity analysis, which allows for investigating to what extent variations of a particular input parameter affect the final result, i.e. the TCO value.

Presented TCO calculation model was firstly developed using GoldSim, a simulation software solution for dynamic modelling of complex systems in engineering and business. It supports decision-making and risk analyses by simulating future performance, while quantitatively representing the uncertainty and risks inherent to all complex systems [10]. It supports Monte Carlo simulations, and provides interface for sensitivity analysis of model parameters. As such, it is convenient tool for development of a preliminary TCO calculation model [11], which has then been implemented as TEAM module of the presented software tool. The input and output components of TEAM module are illustrated as a part of Fig. 2.

4. SIMULATION RESULTS

This section presents simulation results of TCO calculation in general case, i.e. for a generic compact size passenger car. This kind of vehicle was chosen in the initial stage of software tool development, because of amount available information which is used to parametrize the TCO model. Parameters for TCO calculation model were mostly taken from [9], and calculation has not taken into account the salvage value of the vehicle.

Simulation was carried out for expected vehicle usage of twelve years, and for two types of personal vehicles: (i) conventional vehicle (CV), and (ii) electrified PHEV-type vehicle (marked as EV in simulation results) with 60 kWh battery (when battery capacity is not sufficient for a given daily driving cycle, rest of distance is covered with the same expenses as those calculated for the CV). Financing of vehicles is modelled with down payment of \$10,000 and rest of price being paid through loan with equal monthly payments over 5 years. Prices of new vehicles are \$35,000 and \$25,000 for EV and CV, respectively.

Results of a deterministic simulation are shown in Figures 11 and 12. The cumulative time propagation of costs, along with a simple model [9] of salvage value (SV), is shown in Figs. 11a and 11b for CV and EV, respectively. Sum of all expenses from Fig. 11 (except salvage value), named total expenses, for both types of vehicles, is shown in Fig. 12a. Finally, Fig. 12b shows TCO time propagation, i.e. NPV value of total expenses values from Fig. 12a. EV is more expensive vehicle than CV, so that monthly costs (loan payments) showed with a blue line are significantly higher in this case. On the other hand, EV consumes less energy (in terms of energy price) and has lower maintenance costs. This is the reason why total expenses for EV has lower raise rate after year 5, i.e. after loan is finished.

Figure 13 shows results of a stochastic simulation for the two vehicles, where stochastic inputs were daily driving cycles, fuel and electric energy prices. Areas with different colour represent percentiles of all simulations. Namely, the brightest red colour represent area in which only 1% of all simulations have fallen, while darker the colour, greater percentage of simulations can be found in that area of the plot. Dashed line represents simulation results corresponding to mean values of the stochastic inputs, i.e. these results are the same as the results of a deterministic simulations. It is obvious that the TCO for CV has larger uncertainty, mainly due to high variations in the fuel price that cause high variations in the operational cost.

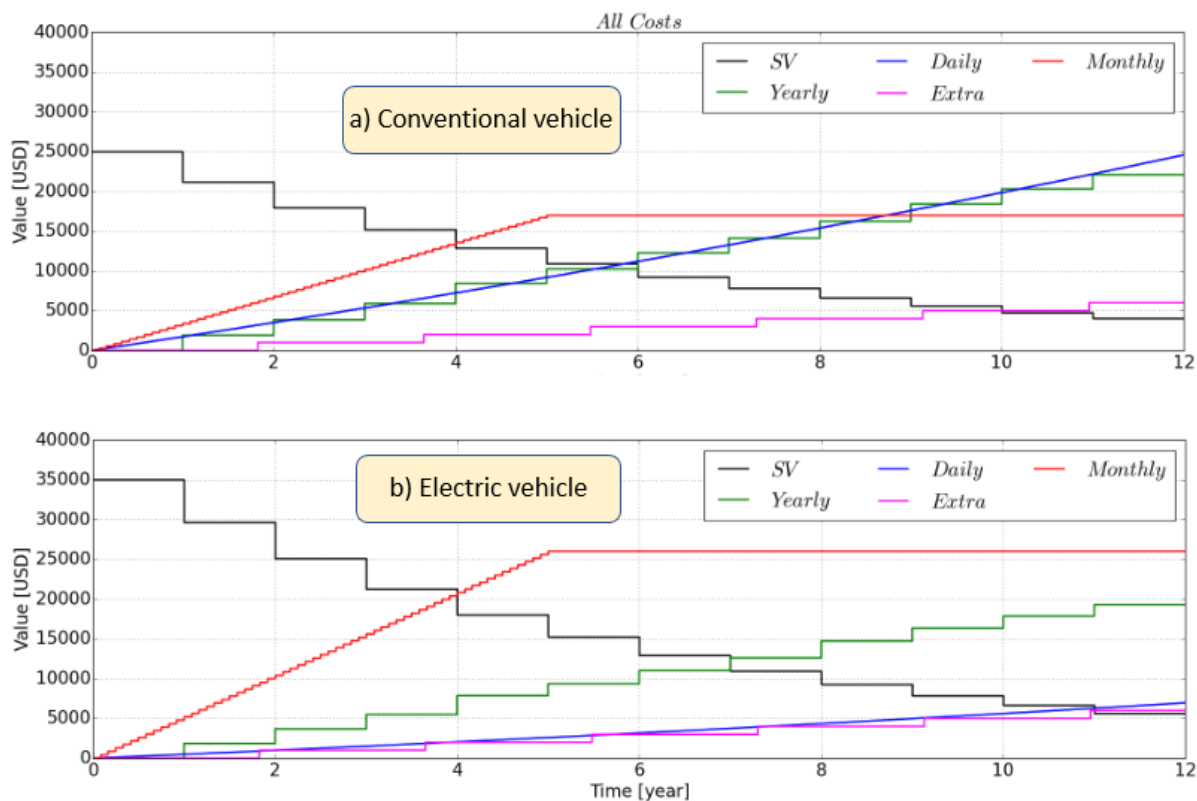


Figure 11 – Expenses by the category for: a) CV and b) EV.

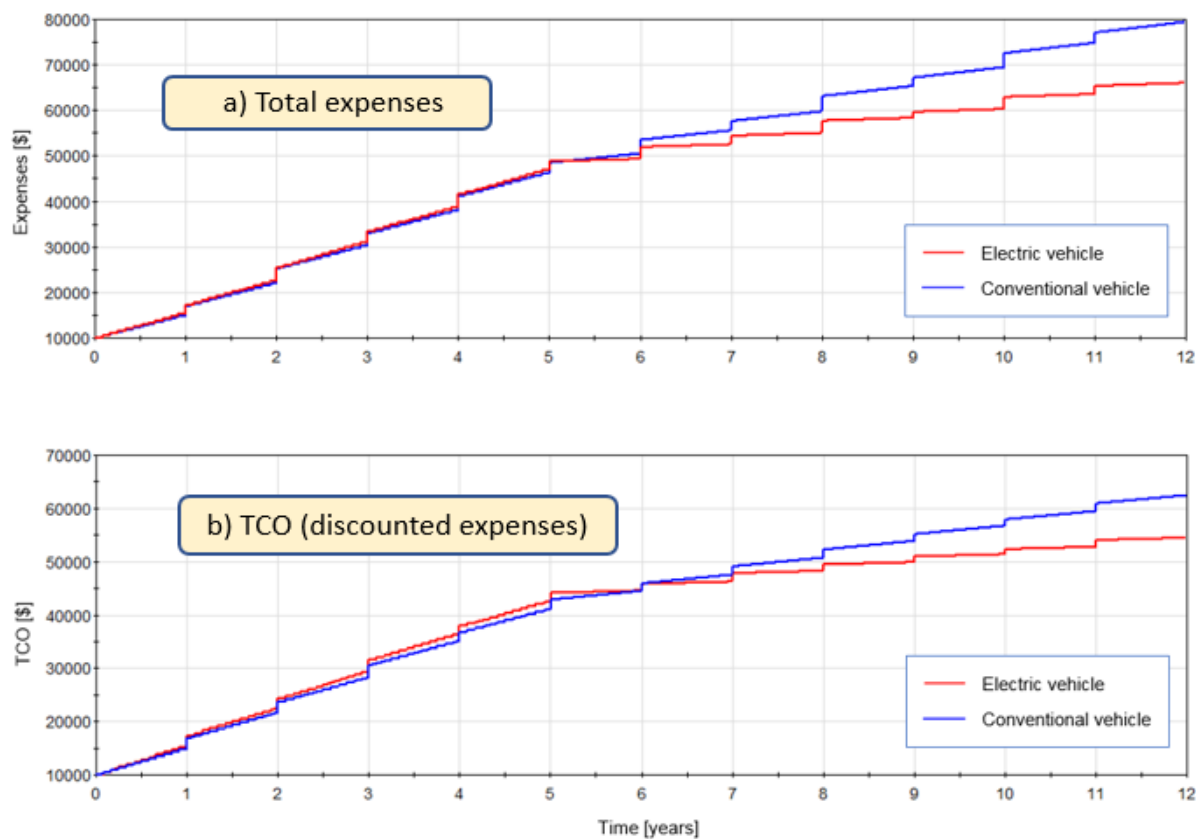


Figure 12 – Deterministic simulation results: a) sum of all expenses for both CV and EV; and b) TCO value (NPV of total expenses) for both CV and EV.

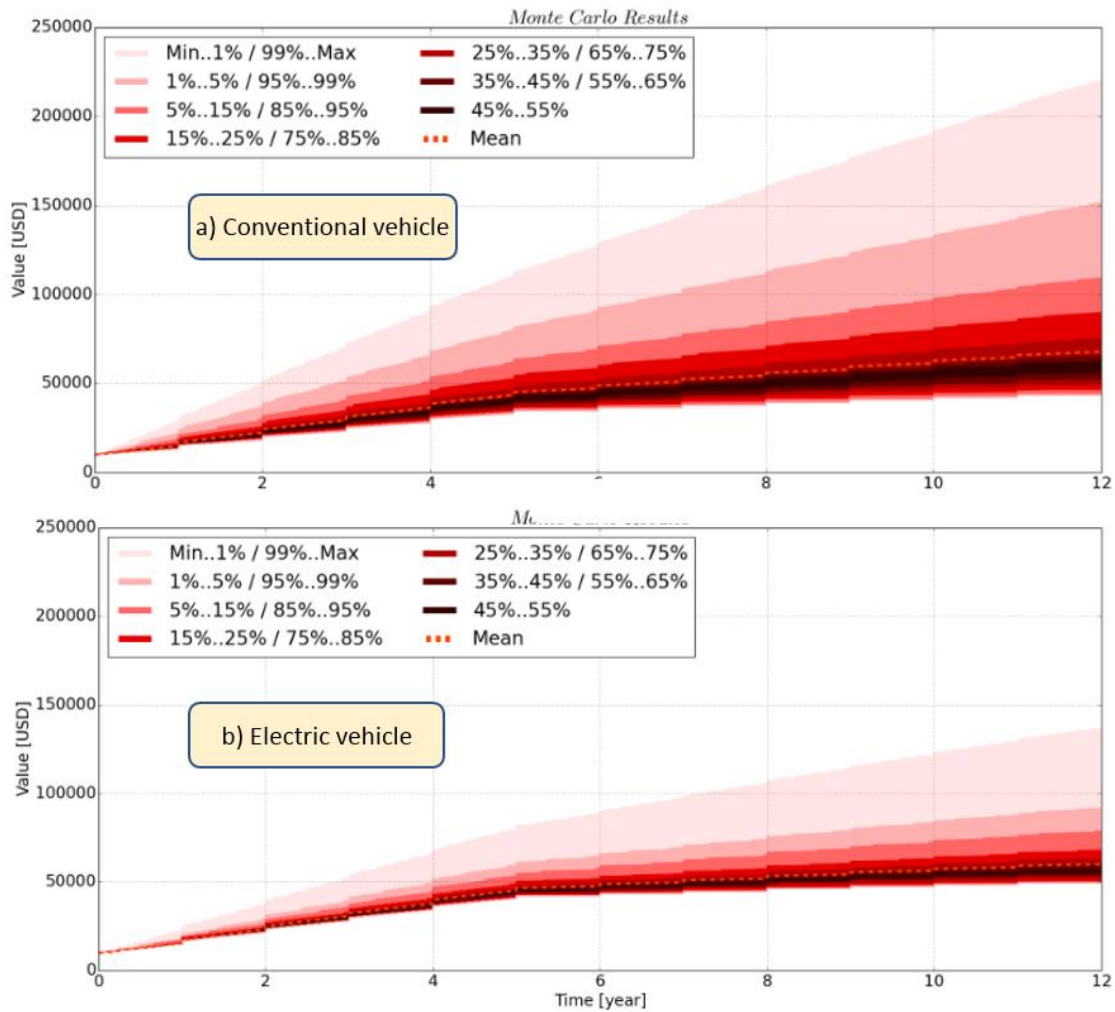


Figure 13 – Stochastic simulation results for: a) CV and b) EV.

5. CONCLUSIONS

The developed ICT tool for planning of city bus transportation electrification utilizes key modules needed for making and valorising decisions related to fleet electrification. With its first module, DPPM, it provides functionality of preprocessing and statistical analysis of raw driving cycle data that is collected from existing bus fleet. The second module, EBSM, includes integrated simulation models of different types of electrified buses (HEV, PHEV, and BEV) as well as of conventional ones, which allows user to parametrize models and conduct related comparative analyses and valorisation of different fleets. The third module, COM, uses driving cycles and bus models prepared in DPPM and EBSM, respectively, for city bus fleet simulation under realistic conditions and driving schedules. These results are used within this module for city bus fleet charging optimisation including determining the number of chargers and buses. The fourth module, TEAM, deals with the electrification techno-economic analysis, and at the end it provides value of Total Cost of Ownership for a given bus fleet.

In the last section, results of TCO calculation for an illustrative example of conventional and electrified (PHEV-type) vehicles were given to provide a sense of what would be final visualisation of the developed tool. It showed time propagation of costs that average conventional vehicle generates, as well as its electrified counterpart. Also, it is showed that variations of future prices (or any other parameter) can be taken into account through stochastic simulation.

6. ACKNOWLEDGEMENTS

This work was supported by the EU European Regional Development Fund through Interreg CE project SOLEZ (“Smart Solutions supporting Low Emission Zones and other low-carbon mobility policies in EU cities”) [12].

7. ABBREVIATIONS

BEV	– Battery electric vehicle
COM	– Charging Optimisation Module
CSV	– Comma-separated values
DP	– Dynamic programming
DPPM	– Data Post-Processing Module
EBSM	– E-Bus Simulation Module
EV	– Electric vehicle
FEV	– Fully electric vehicle (analogous to the BEV)
GPRS	– General Packet Radio Service
GPS	– Global Positioning System
HEV	– Hybrid electric vehicle
ICE	– Internal combustion engine
ICT	– Information and communications technology
JSON	– JavaScript Object Notation
LP	– Linear programming
M/G, MG	– (electric) Motor/Generator
NPV	– Net Present Value
PHEV	– Plug-in hybrid electric vehicle
QP	– Quadratic programming
RB	– Rule-based
SoC	– State-of-Charge
TCO	– Total Cost of Ownership
TEAM	– Techno-Economic Analysis Module
TPM	– Transition probability matrix

8. REFERENCES

- [1] Nyman, J., Olsson, O., Grauers, A., Ostling, J., Ohlin, G., Petterson, S. A user-friendly method to analyse cost effectiveness of different electric bus systems. EVS30 Symposium, Stuttgart, Germany, 2017.
- [2] Web: <http://www.volvobuses.co.uk/en-gb/our-offering/buses.html> 13.04.2018.
- [3] Web: <http://media.greenhighway.nu/2013/05/Edward-Jobson-Volvo-Buses.pdf> 13.04.2018.

- [4] Škugor, B., Hrgetić, M., Deur, J. GPS Measurement-based road grade reconstruction with application to electric vehicle simulation and analysis. SDEWES, Dubrovnik, Croatia, 2015.
- [5] Škugor, B., Deur, J., Cipek, M., Pavković, D. Design of a Power-split Hybrid Electric Vehicle Control System Utilizing a Rule-based Controller and an Equivalent Consumption Minimization Strategy, Proceedings of Mechanical Engineerings, Part D, Journal of Automobile Engineering, Vol. 228, No. 6, pp. 631-648, 2014.
- [6] Ourabdollah, M., Murgovski, N., Grauers, A., Eghart B., Optimal Sizing of a Parallel PHEV Powertrain, IEEE Transactions on Vehicular Technology, Vol. 62, No. 6, pp. 2469-2480, 2013.
- [7] Škugor, B., Topić, J., Deur, J. Quadratic Programming-based Electric Vehicle Charging Optimisation combining Charging Cost and Grid Power Peak Minimisation, 12th Conference on Sustainable Development of Energy, Water and Environment Systems (SDEWES), Dubrovnik, Croatia, 2017.
- [8] Alexander, M., Davis, M. Total Cost of Ownership Model for Current Plug-in Electric Vehicles. Electric Power Research Institute (EPRI) 2013 Technical Report.
- [9] Al-Alawi, B., Bradley, T. Total cost of ownership, payback, and consumer preference modelling of plug in HEVs. Applied Energy, 2013;102:488-506.
- [10] Web: <https://www.goldsim.com/web/home/> 13.04.2018.
- [11] Miller, S.P., Granata, J.E., Stein, J.S. The Comparison of Three Photovoltaic System Designs Using the Photovoltaic Reliability and Performance Model (PV-RPM), Sandia National Laboratories, report SAND2012-10342, December 2012
- [12] Web: <http://www.interreg-central.eu/Content.Node/SOLEZ.html> 13.04.2018.