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A MODELLING SYSTEM FOR EVALUATING OPTIONS FOR BUILDING AND USING A FLEET OF BATTERY ELECTRIC TRUCKS

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Many shipping companies tackle the challenge of potentially replacing conventional trucks with electric ones in economically developed countries. The aim of this work is to describe the principle of scaling models for analysing the operation of a fleet of vehicles, when the decision to use a particular type of model is made considering the accuracy and completeness of the initial data, as well as the goals of modelling. At the end of the report, information is provided on the TraPodSim simulation system developed by the authors, which is based on a multi-agent simulation model created using AnyLogic software.

The paper considers modelling methods aimed at assessing the physical indicators of the transportation process. Various aspects of using three types of mathematical models are discussed: a) analytical deterministic models, b) analytical models using the Monte Carlo method and c) simulation models.

Keywords: Electric trucks, Fleet modelling, Physical indicators, Multi-agent simulation

1. Introduction

The problem of evaluating options for building and using a fleet of electric trucks is relevant to all actors who are the creators, owners, operators, or users of the relevant transport system. There is still not generally accepted definition for the concept of transport system to this day. The shortest definition would be if a transport system is any system in which the transportation process is realised. The essence is the movement of goods or passengers from one point to another. The components of the transport system are its infrastructure, means of transport and the rules of conduct for all participants in the transport process. All components of the road transport system are well known and need no additional explanation.

The emergence of electric vehicles (EVs) encourages all the above-mentioned subjects to find a solution for the problem of placing charging stations. The creators, owners and operators of the transport system solve the problem for a certain territory, choosing the number and location of charging stations of various capacities based on data on existing or expected traffic of electric vehicles. Users of the transport system (who operate a fleet of electric freight vehicles) often make the decision to build their own high-capacity charging stations.

The review (Wang *et al*., 2018) notes that the existing literature on the use of electric commercial vehicles in urban freight transport reflects four main research areas. These are feasibility, adaptations of logistics concept, adaptations of vehicle concept, and support of stakeholders. The authors in (Wang *et al*., 2018) formulate 15 specific problems that are part of these four areas of research. It is important to mention that only computer simulation is noted as a method for solving significant number of problems. Specialists who use simulation in practice understand it is possible to obtain sufficiently reliable and useful simulation results only if sufficiently complete and accurate initial data are used. The first stage of work with the developed model ends with the receipt of primary simulation results in the form of such physical indicators of the transportation process as the volume of transportation performed, the amount of energy consumed, etc.

Currently there are no scientifically based technical parameters that characterize energy consumption in various driving modes for many types of cargo electric vehicles (Taefi *et al*., 2017). This set of parameters can be considered complete if the dependences of energy consumption indicators on factors are known (such as the mass of the transported cargo, speed, air temperature, road slope, road surface, wind strength and direction). Since a complete set of parameters is generally not available to model developers, they use only a subset of these parameters, most often in the form of averages.

The second step in using the simulation results is usually to calculate two types of secondary indicators: a) the costs according to the chosen economic model and b) the greenhouse gas emissions according to the chosen environmental model (Martins-Turner *et al*., 2020). The initial data for such calculations are characterized by an even greater degree of uncertainty, since they depend on the economic situation not only in a particular country, but throughout the world.

The purpose of this work is to describe the principle of model scaling for the analysis of the operation of a fleet of electric vehicles, when the type of mathematical model is selected from several models that starts with simple deterministic calculation models and ends with arbitrarily complex simulation models. The decision to apply a specific type of model is made considering the accuracy and completeness of the initial data, as well as the goals of modelling.

2. Critical analysis of relevant models

Relevant in the sense of this work, we must consider mathematical models that allow us to evaluate the above-mentioned physical, economic and environmental indicators of the process of using a specific given fleet of cargo electric vehicles. Although models do not have to be simulation models, it has already been noted above that models of other classes are very rare in publications (Wang *et al*., 2018).

A notable event for this review is the “MathWorks Math Modelling Challenge 2020: U.S. Big Rigs Turnover from Diesel to Electric” (FleetOwner, 2022). This event was hosted by Michael Roeth on the FleetOwner’s page. He is best known as the Executive Director of the North American Council for Freight Efficiency. The main results of the study are published at (Qi *et al*., 2020). Mathematicians predicted the appearance of electrical semi-trucks on US roads over time for the next 25 years using differential equations. The number of charging stations and the number of chargers were calculated for five transport corridors ranging in length from 390 to 702 miles by algebraic models. Since the number of chargers at one station reaches 2535, the authors concluded: “Thus, electric trucks with their current capabilities in charging speed and range are not feasible for long haul driving”. In addition, they formulated the condition at the beginning of the study in 2020: “No energy shocks that would drive the price of gas or electricity up/down. This assumption is because imperative attempting to account for volatile factors such as future energy shocks would make model development nearly impossible” (Qi *et al*., 2020). These models cannot be considered fully relevant, since they are too abstract, and they consider the total flow of electric freight vehicles, which, in principle, can be observed in the selected transport corridor. A sign that professional mathematicians do not pay much attention to the problem under consideration is the fact that 760 teams of 3,500 students were invited to participate in challenge (FleetOwner, 2022). The authors of a large new review (Bhardwaj and Mostofi, 2022) used keywords electric trucks, battery-electric trucks, battery swapping, and fast charging stations when processing 106 publications. In this review, there is no information on the application of any mathematical models.

Example of a purely mathematical (more precisely, arithmetic) and quite adequate model, we can name the Range Simulator (Renault, 2022). The user selects one of the offered types of Renault cars, and then sets the parameter values: cargo type (dry or fridge), transportation environment (urban or regional), external temperature and load percentage. An online “calculator” instantly computes the expected range of a given truck, i.e. the distance it can travel when starting with a fully charged battery. It is well known that mathematical models are almost always used in solving routing problems, but these kinds of problems are not the subject of this article.

The authors of this article have extensive experience in modelling traffic flows in transport systems. Therefore, at the beginning of work they had to switch their thinking from transport system modelling to transportation process modelling on the task of modelling a specific fleet. In the first case, many “anonymous” vehicles are generated in the model. And in the second, the freight demand is set and a specific fleet is set or determined during the modelling process, which can fulfil all this demand or part of it. The authors reported their first experience of modelling the operation of a specific transport enterprise using the System Dynamics method in (Tolujevs *et al*., 2018).

In the following, examples of the use of simulation modelling to analyse the use cases of a fleet of electric trucks in the conditions of Urban Freight Transport will be considered. The authors proceed a lot from the assumption that the car battery is charged only during the night parking in the depot. Planning long-distance transportation seems to be an almost trivial task, since for their implementation it is enough to have charging stations located at a minimum distance from each other, which can be easily calculated (Renault, 2022).

(Lebeau *et al*., 2013) considers three scenarios for shipping goods from an Urban Distribution Center (UDC). In the first baseline scenario, no electric vehicles are used, and goods are shipped using a regular 16m³ diesel truck. In the second scenario, an electric van of 4.5m³ loading capacity, that range is limited to 100km, was used instead of a diesel truck. In the third scenario, an electric truck with the same payload as a diesel truck was chosen. The simulation model was implemented using ARENA software. It was discovered by the simulation that when using an electric van, the number of trips per day increases. But the entire task can be completed with only one charge at the depot. If electric trucks have a battery with enough capacity to carry out the entire day's program, then its introduction does not affect the logistics performance of UDC. To criticise it should be noted that a rather complex UDC model was selected for experiments with only one vehicle. The authors discuss only the logistical performance of the UDC and do not pay attention to either energy or economic performance.

In (Taefi *et al*., 2017) the application of energy models in solving electric vehicle routing problems (VRP) is considered. The main part of the work is devoted to methods for calculating the total cost of ownership (TCO). Using numeric simulation, the authors try to determine which average daily mileage is the most cost effective for a particular EV model compared to a similar diesel model. Unfortunately, the TCO calculation model considers only the costs of acquiring and operating an EV and does not take into account the commercial effect of using an EV. The authors demonstrate a large amount of numerical information in their work, but do not explain the details of the applied numeric simulation.

Serious research has been carried out on modelling a specific fleet of electric trucks using MATSim software for several years at the Technical University of Berlin (TU Berlin). The development of the MATSim project was started at ETH Zürich, but after one of the authors of the project moved to Berlin in 2004, the work was continued at TU Berlin (Axhausen *et al*., 2016). MATSim is an activity-based, extendable, multi-agent simulation framework implemented in Java. It is open-source and can be downloaded (MATSim, 2022).

An example of using MATSim is considered in (Martins-Turner *et al*., 2020), where the authors use the *jsprit* system to solve the VRP along with MATSim. The object of study is a system for transporting goods to the shops of the food retailing industry for the city of Berlin. The demand of 15 retailing companies in Berlin with 17 distribution centres located in and around Berlin is modelled. These companies serve 1057 food retailing shops with 1928 demand requests. The shops' demand is the demand of an average day. The simulation could use either current internal combustion engine vehicles (ICEVs) or battery electric vehicles (BEVs). For each fleet, four types of vehicles were assigned with a carrying capacity from 7.5 to 40 tons. The number of vehicles of the different available types are not limited for each carrier. As a result of solving the VRP problem, 283 ICEVs or 279 BEVs were used in the model during one typical workday. Around 75% are vehicles with a carrying capacity of 26 tons. Using simulations, it was discovered that using BEVs, 56% of all tours can be completed without recharging during the day and 90% of tours on a single charge during the day (Martins-Turner *et al*., 2020). Based on a large amount of regulatory data, total costs for the carriers are determined. Indicators of greenhouse gas (GHG) emissions were also calculated, including an orientation towards the future production of renewable energy in Germany.

The work (Jahn *et al*., 2021) considers the results of a study (Martins-Turner *et al*., 2020) and, based on them, proposes a methodology for placing a charging infrastructure for BEVs in a given area. One of the specific findings of the work is that if 279 BEVs belonging to 16 different depots share their charging stations, then 71 400 kW fast charging stations will be enough to run 90% of the tours. If you create 29 additional fast charging stations in the city, then 100% of the tours can be operated by BEVs.

Another example (AnyLogic, 2022a) contains information about using AnyLogic software to simulate delivery by electric trucks (ETs) in Paris and its suburbs. It is assumed that the maximum route length is 100 km and each ET charges the battery only at the charging station in its depot. The simulation was used to optimize the delivery route. The model provided the collection of traffic statistics and made it possible to observe the transport process using animation. Using the model, the optimal number of ETs with different types of batteries was calculated, as well as the number and power of chargers, which will ensure stable delivery of goods to customers.

(AnyLogic, 2022b) provides information about General Electric Company (GE) using AnyLogic software to predict market demand for EVs and evaluate the impact of this process on the electricity distribution network. By EVs, we mean cars, which are bought in large quantities by the population of the country. A group of researchers were asked general questions regarding the fundamental applicability of the simulation method for solving problems of forecasting and decision making. To this end, demonstration prototypes were built using AnyLogic's multimethod modelling capabilities and built-in graphical visualization capabilities.

3. Factors that determine choice of model

Consider the important factors when deciding whether to create a simulation model. The purpose of modelling is to obtain primary and secondary indicators of the process of using EVs for the transport of goods. Primary metrics typically reflect the physical results of using one EV on its assigned itinerary for one day. Secondary indicators of an economic or environmental nature are obtained by interpreting the primary indicators using various normative data. As a rule, such figures refer to the whole year of operation of one EV or fleet of EVs.

The choice of how to solve the problem of modelling the operation of a fleet of EVs is determined by two main factors:

a) the use of a static or dynamic approach to solving the VRP;
b) the use of a deterministic or stochastic approach to modelling the operation of a particular EV in a real transport network.

In a static solution approach, VRP software such as Route Planning assigns each EV a specific daily route that starts and ends at the depot. An example of such software is *jsprit* (Martins-Turner *et al.*, 2020). The dynamic approach assumes that a particular EV receives a new destination address from the dispatcher after completing the loading/unloading operations in the previous point. As is usually done in a taxi service. An example of a scientific article on this topic is (Luo *et al.*, 2018). Almost all the publications reviewed use a static approach to solving VRP, which should consider five fundamentally possible ways of placing charging stations (Figure 1).

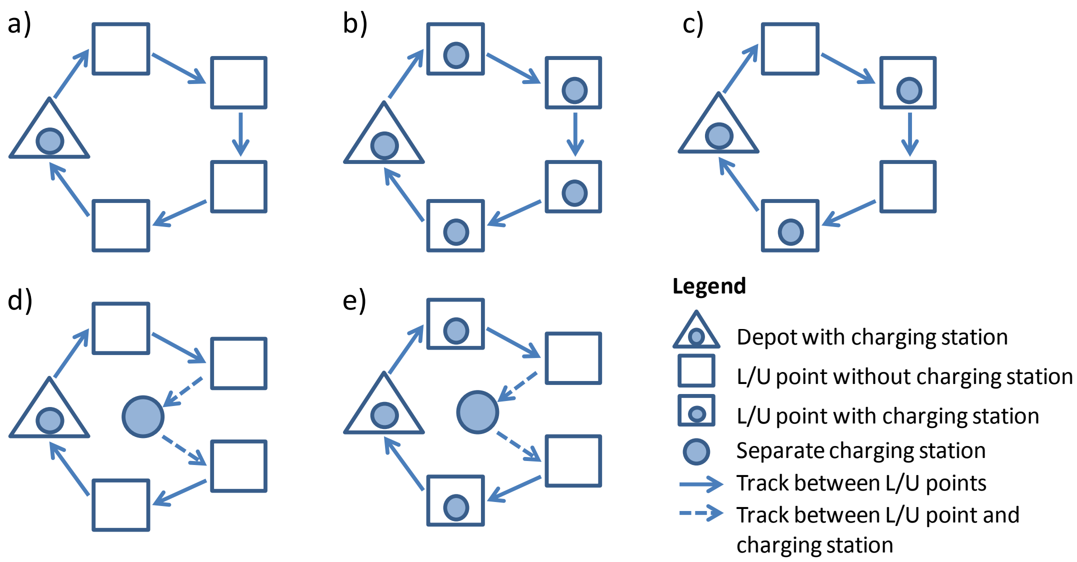

Figure 1. Five Ways to Place Charging Stations

Case *a*. The charging station is available only in the depot. The total length of the daily route must not exceed the maximum value, which is determined by the amount of energy of a fully charged battery. Such a case is often found in existing Urban Freight Transport systems.

Case *b*. There is a charging station at every loading/unloading point (L/U point). Such a condition can only be met when the carrier visits only those L/U points that belong to specific regular customers. These customers install chargers, for example, at each place on the unloading ramp. An important issue is the power of these chargers. Ideally, it should be such that during the loading/unloading time the battery has time to replenish the amount of energy spent since the last charge, or to reach a specified minimum percentage of its capacity. Delays may occur that exceed the loading/unloading time with low power chargers. And when installing high power chargers, it will be necessary to solve the corresponding technical and financial problems.

Case *c*. Charging stations are only placed at certain L/U points. This solution is possible under the condition that EVs will only move along certain routes, which include L/U points equipped with chargers. The choice of specific L/U points is made by analysing all route options that will be performed for one client or a group of clients located in the same geographical area.

Case *d*. The carrier itself equips one or more high-capacity charging stations to operate in the geographical area in which it will serve customers. The disadvantage of the solution is the costs noted above, which the carrier will have to bear. More, the routes will include additional sections of the path associated with visiting charging stations.

Case *e*. This case is a combination of cases *c* and *d*. The positive feature of this solution is the reduction of additional path sections compared to case d, but at the same time the complexity of the VRP solution increases.

Let us now consider the features of applying a deterministic or stochastic approach to modelling the operation of a specific EV in a real transport network. If dynamic scheduling is used, like that used in a taxi service, the model will necessarily be stochastic, and computer simulation will have to be used to implement it. In the case of the static route planning approach discussed above, the decision to use computer simulation depends on what random factors must be taken into account when developing a model of the EV operation process. Three types of models are listed below, which are presented in order of increasing complexity of their computer implementation.

4. Analytical deterministic models

The models of this class do not consider any random factors, and all calculations are carried out using the average values of the input parameters. Let the main primary indicators of the model be two indicators:

a) the total time that EV spends to follow the given route

$T_{route} = \sum T_{L/U-L/U} + \sum T_{L/U-CS-L/U} + \sum T_{charging} + \sum T_{L/U}$,

b) the amount of energy that EV expends to follow a given route

$E_{expended} = \sum E_{empty} + \sum E_{with\,cargo} + \sum E_{L/U\,time}$.

If all waypoints and the distances between them are given, then for each segment of the path it is necessary to set the value of the average speed and calculate the values of the travel time. $T_{L/U-L/U}$ values are calculated for paths connecting L/U points to each other, and $T_{L/U-L/U}$ values are calculated for paths connecting L/U points with charging stations (see Figure 1). To calculate each $T_{charging}$, you need to know the battery charge rate (kWh/h) depending on the power of the charger, as well as the amount of energy that should be received at this charging point. The values of $T_{L/U}$ are the duration of loading/unloading operations at the corresponding points of the route.

To calculate $E_{expended}$ it is necessary to know the average values for the following power consumption behaviors:

a) energy consumption (empty) (kWh/m);
b) energy consumption (per weight unit) (kWh/kg/m);
c) energy consumption (idling) (kW).

All components of the $E_{expended}$ formula are easy to calculate, since the route description specifies not only the distance between points, but also the amount of cargo carried on each segment. To calculate $E_{L/U\,time}$, it is again necessary to take into account the duration of loading/unloading operations at the corresponding points of the route.

The TraPodSim simulation system described below includes an Excel program supplemented with VBA macros. This program performs the procedure presented here for the deterministic calculation of some primary indicators of the process of completing a route by one EV. The full set of output indicators is created by the simulation model, and when it works in deterministic mode, the values of the T_{route} and $E_{residual}$ indicators must match those shown by the Excel program. This fact is used to verify the simulation model.

Figure 2 shows an example of a deterministic calculation of the T_{route} and $E_{residual}$ indicators. The route uses four points numbered 1, 2, 3 and 4. The complete sequence of waypoints is: 1-2-3-2-3-3-4-3-4-1. Starting the trip at point 1, the EV transported the cargo from point 2 to point 3 twice. Then it loaded at point 3 and transported the cargo from point 3 to point 4 twice, after which it went to depot 1. It is assumed that in all L/U points there are charging stations that provide a battery charge level of up to 50% of its capacity, i.e. equal to 450 kWh. The final values $T_{route} = 14.54\ h$ and $E_{residual} = 317.27\ kWh$ can also be obtained with absolute accuracy using the simulation model.

no	current geoPoint	operation typ	residual kWh	segment distance	cruise distance	segment time	idling time	cruise time
1	1		900,00					
2	2	1	813,49	60,08	60,08	0,83	0,17	1,00
3	3	2	566,08	132,16	192,24	1,84	0,17	3,00
4	2	1	450,00	129,96	322,19	1,80	0,47	5,28
5	3	2	450,00	132,16	454,36	1,84	1,46	8,58
6	3	1	450,00	0,00	454,36	0,00	0,17	8,74
7	4	2	450,00	60,36	514,72	0,84	0,75	10,34
8	3	1	450,00	60,36	575,09	0,84	0,58	11,75
9	4	2	450,00	60,36	635,45	0,84	0,67	13,26
10	1		317,27	92,17	727,62	1,28	0,00	14,54

Figure 2. Fragment of an Excel table with the results of a deterministic calculation

Tables like those shown in Figure 2 can be computed for any number of routes and any set of different types of EVs that make up the simulated fleet.

5. Analytical models using the Monte Carlo method

The formulas described above for calculating T_{route} and $E_{expended}$, as well as any other mathematical expressions that form an analytical model of the process of using a fleet of EVs, could form the core of a stochastic model that is designed to be studied using the Monte Carlo method. To turn the transformation of a deterministic model into a stochastic one, it is necessary to make two types of changes in the original analytical model:

a) instead of the average values of some input parameters of the model, describe the corresponding theoretical or empirical distribution laws;

b) for all output indicators of the model, create opportunities for their representation in the form distribution histograms.

To obtain statistical results of modelling one day of operation of the EVs fleet, it is necessary to repeat the calculation of the model many times, i.e., to implement the so-called parallel runs. The number of such runs is determined considering the required accuracy of the simulation results, usually using the confidence interval method (Rees, 2001). The Monte Carlo model is easiest to create in Excel by adding new macros to the deterministic model.

Model developer decides which input parameters of the model should be declared random variables, who should have information about the possible real values range for each of the parameters.

One should have information about the possible real range of values for each of the properties. These parameters can be more accurately selected by conducting special experiments with the model, which are called sensitivity analysis (Cadence, 2022). Let's consider some input parameters of the model, which sometimes it is expedient to declare random variables.

The energy consumption indicators depend on such factors as the mass of the transported cargo, the speed of movement, air temperature, the angle of the road, the nature of the road surface, the strength and direction of the wind. If the model developer does not have reliable empirical dependences of energy consumption indicators on these factors, or he will not display any of these factors in the model at all, then any of the indicators can be declared a random variable with a given mathematical expectation and boundaries of the distribution area.

The average movement speed on a certain section of the route is determined as the result of dividing the length of the section by the time of its passage. It is this time that depends on the permitted and actual speed of movement, which, in turn, depends on many factors such as time of day and weather conditions. In addition, there are sections of roads where the likelihood of traffic jams is high. Since the length of the section is a constant value, in the model it is possible to declare either the average speed of movement or the average time for passing this section as a random variable.

If the ***battery charging time*** is not static but depends on the desired level of charge at which recharging stops, then this time is in fact a random variable. If the battery is charging from level L1 to level L2, then the exact duration of this process can only be determined if there is a Charging Characteristic for this type of battery, as shown, for example, in (Taefi *et al*., 2017). In addition, the duration of the charging process depends on the capacity of the charger.

The execution time of the loading/unloading operation can be a stable deterministic value if it is set for each type of cargo. And the operation itself is performed using technical means with a high level of automation. The operation time will have a significant variation in the case of manual labour or, for example, manually operated forklifts.

Random ***delay periods*** may occur in a real system. Usually, they are not considered by the route planner. If we keep in mind only the participants in the transportation process, then they can form queues in front of two types of shared resources: in front of L/U operations (for example, with a small capacity of the unloading ramp) or in front of high-capacity autonomous charging stations. In an analytical model using the Monte Carlo method, it is practically impossible to take into account such effects, but, if necessary, this can be done using a simulation model.

6. Simulation models

Simulation models for analyzing the operation of a fleet of electric vehicles can be created both using universal simulation packages (see the examples of using the ARENA and AnyLogic packages described above) and using specialized packages such as MATSim (Axhausen *et al*., 2016). Since the basis of the model is the process of performing a daily task by a group of specific EVs, the most adequate process modeling paradigm is multi-agent simulation. To simulate the interaction of agents when using shared resources, fragments are added to the model that work on the principle of discrete event simulation.

The main purpose of modeling remains the calculation of indicators, examples of which are shown in the form of formulas for calculating T_{route} and $E_{expended}$. The model implements a sequence of states associated with the execution of a given route for each EV. For each state, numerical values of time, distance, energy, etc. are calculated and added to the current statistical data, which are necessary to calculate the final primary indicators of the model. The model can be either purely deterministic or include any of the above random factors. There are only two fundamental differences between simulation models in relation to models using the Monte Carlo method: a) they can display in more detail the processes of performing L/U operations and charging batteries, as well as the processes of interaction of EVs with each other and b) in the composition of the simulation model, a GIS model is included, with the help of which the movement of the fleet of EVs is visualized in a real transport network.

The TraPodSim simulation system developed by the authors of the article is briefly described in the next chapter; the system core is a multi-agent simulation model created using AnyLogic software.

7. TraPodSim simulation system

The TraPodSim system is designed to create simulation models of the process of transporting goods by conventional or electric vehicles along the routes of the transport network specified for a particular region.

The system includes three software products:

a) route Planning program implemented in the VBA programming language in the Excel environment;
b) auxiliary model GIS Model implemented on AnyLogic;
c) the main executable Mail Model implemented on AnyLogic.

The system also uses two sets of Excel tables named User Database and Model Database (Figure 3).

Structures on Figure 3 indicate the sequence of user actions when preparing and implementing experiments on models in the TraPodSim system. It was decided not to use a GIS map, which requires online connection for the OpenStreetMap service, to ensure the repeatability of simulation experiments and reduce the processing time of the model. Its graphical representation is stored as a PNG image instead of a GIS map in the executable model. The movement of vehicles is modelled using space markup elements of the “point” and “path” types, which the user manually applies to the graphic copy of the GIS map.

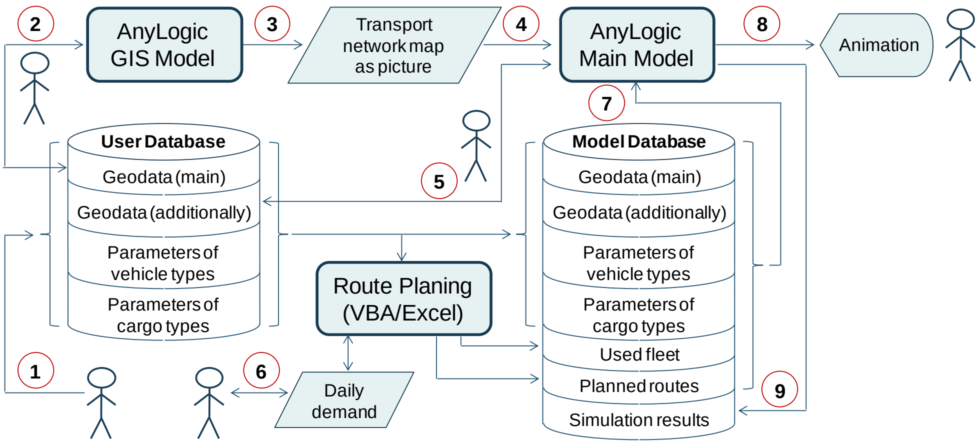

Figure 3. Structure and application method of the simulation system TraPodSim

Two models were created using AnyLogic:

a) an auxiliary model based on a GIS map (AnyLogic GIS Model) for placing geographic points and selecting sections of real roads that will be included in the simulated transport network;

b) the main executable model (AnyLogic Main Model) based on a graphical copy of the GIS map obtained using the auxiliary model described above.

The main source data of the model is stored in the User Database tables. When a user works with the Route Planning program, this data is transferred to Model Database tables. Additionally, data on the simulated scenarios is recorded in the Model Database: Used fleet and Planned routes. After the data preparation is completed, the user starts the AnyLogic Main Model program. During the execution of this program, the user can observe an animated picture of the movement of all simulated EVs in a real transport network. When the model run is completed, the Simulation results are written to the Model Database.

Figure 4 projects an example of the Simulation results table, which corresponds to the data contained in the table in Figure 2. After running the model in the deterministic simulation mode, in columns 9 and 21 you can see the previously calculated values $T_{route} = 14.54\ h$ and $E_{residual} = 317.27\ kWh$, respectively. Column 17 shows that the battery has been charged five times. In the table in Figure 2 it can also be seen that the EV left the location five times with the remaining energy $E_{residual} = 450.00\ kWh$.

1	2	3	4	5	6	7	8	9	10	11
Day No.	Cruise No.	Route name	Start time, h	Truck type No.	Route length, km	Volume of transpor-ted cargo, tons	Volume of freight traffic, tons*km	Total trip duration, h	Empty drive, h	Empty drive, kWh
1	1	route_1	6	1	727,62	9	465,71	14,54	6,59	493,30

12	13	14	15	16	17	18	19	20	21
Drive with cargo, h	Drive with cargo, kWh	L/U time, h	L/U time, kWh	Charging duration, h	Number of charging	Initial energy, kWh	Energy added, kWh	Energy expended, kWh	Residual energy, kWh
5,35	679,24	1,00	1,00	3,93	5	900	589,81	1172,54	317,27

Figure 4. Example of model outputs in the Simulation results table

The model outputs the values of 16 primary indicators of the process of performing a daily route by one EV as described in Figure 4, columns 6 to 21. A table with indicators for conventional vehicles has a similar structure, the amount of fuel (Litres) is displayed instead of the amount of electric energy (kWh).

The user of the TraPodSim system should choose a methodology for preparing and conducting experiments with the model, which can be divided into two groups:

a) experiments without changing infrastructure elements;

b) experiments to determine the optimal number and location of separate Charging stations.

Experiments are prepared only with the help of the Route Planning program in the first case. The AnyLogic Main Model program serves only to implement model runs, i.e., no actions are provided to change the composition of additional points of the transport network.

In the second case, the user must change some graphical elements of the AnyLogic Main Model if one wants to experimentally find the number and location of separated Charging stations.

8. Conclusion

The analyst should proceed considering the fact three types of mathematical models can be applied for the purpose when deciding how to evaluate the physical performance of a particular fleet of electric or conventional trucks:

a) analytical deterministic models;
b) analytical models using the Monte Carlo method;
c) simulation models.

It is necessary to have almost the same set of conditionally constant initial data for all types of models including geographic data, technical parameters of vehicles, data on the consumption of electric energy or liquid fuel in various operating modes as well as the physical parameters of the transported goods. Data provided on the chosen fleet and planned transportation routes for each vehicle during the working day are as the input of the models in almost the same format. Any proper model belonging to one of the three types can be used to obtain the main performance indicators of the fleet of vehicles. An example is displayed on Figure 4.

The analyst should first create an analytical deterministic model to create a model that uses the Monte Carlo method. The decision to apply the Monte Carlo method should be based on the desire to obtain the values of the main performance indicators of the fleet of vehicles not in the form of numbers shown in Figure 4. rather in the form of corresponding histograms. Next, information should be available about random factors that affect the operation of vehicles when using this type of simulation.

Simulation modelling supplies the analyst with a wide range of opportunities for a more detailed display of individual technological operations of the cargo transportation process. The model can operate in both deterministic and stochastic modes. The ability to animate of a vehicles fleet movement in a transport network outlined on a geographic map is the advantage of simulation models.

A particular model type should be chosen taking into account the accuracy and completeness of initial data, modelling goals and expected time spent on the model creation.

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