energies

MDPI

Article

Minimisation of the Energy Expenditure of Electric Vehicles in Municipal Service Companies, Taking into Account the Uncertainty of Charging Point Operation

Mariusz Izdebski , Marianna Jacyna * and Jerzy Bogdański

Faculty of Transport, Warsaw University of Technology, 00-662 Warsaw, Poland; mariusz.izdebski@pw.edu.pl (M.I.); jerzy.bogdanski@pw.edu.pl (J.B.)
* Correspondence: marianna.jacyna@pw.edu.pl

Abstract: This article presents an original method for minimising the energy expenditure of electric vehicles used in municipal service undertakings, taking into account the uncertainty in the functioning of their charging points. The uncertainty of the charging points' operation was presented as the probability of the occurrence of an emergency situation hindering a point's operation, e.g., a breakdown or lack of energy supply. The problem is how to calculate the driving routes of electric vehicles so that they will arrive at charging points at times at which there is a minimal probability of breakdowns. The second aspect of this problem to be solved is that the designated routes are supposed to ensure the minimum energy expenditure that is needed for the vehicles to complete the tasks assigned. The developed method is based on two heuristic algorithms, i.e., the ant algorithm and genetic algorithms. These algorithms work in a hybrid combination, i.e., the ant algorithm generates the initial population for the genetic algorithm. An important element of this method is the decision-making model for defining the driving routes of electric vehicles with various restrictions, e.g., their battery capacity or the permissible risk of charging point breakdown along the routes of the vehicles. The criterion function of the model was defined as the minimisation of the energy expenditure needed by the vehicles to perform their transport tasks. The method was verified against real-life data, and its effectiveness was confirmed. The authors presented a method of calibrating the developed optimisation algorithms. Theoretical distributions of the probability of charging point failure were determined based on the Statistica 13 program, while a graphical implementation of the method was carried out using the PTV Visum 23 software.

Keywords: electric vehicles; energy expenditure; ant algorithm; genetic algorithm

Citation: Izdebski, M.; Jacyna, M.; Bogdański, J. Minimisation of the Energy Expenditure of Electric Vehicles in Municipal Service Companies, Taking into Account the Uncertainty of Charging Point Operation. *Energies* **2024**, *17*, 2179. https://doi.org/10.3390/en17092179

Academic Editors: Giovanni Lutzemberger and Alberto Dolara

Received: 13 March 2024
Revised: 18 April 2024
Accepted: 29 April 2024
Published: 2 May 2024

1. Introduction

The use of ecological means of transport characterized by low costs and levels of emissions of harmful exhaust gases, such as electric and hybrid cars, is of key importance for developing various modes of transport. Electric mobility seems to be one of the best solutions, enabling transport development without endangering future generations and the environment [1]. Many studies indicate the efficiency of electric cars [2] as they have zero pollutant emissions, which is a huge advantage when using them in populated cities [3]. Due to restrictions on the entry of conventional vehicles into city centres, service companies are analysing the possibility of introducing electric vehicles. Compared to conventional vehicles, electric vehicles require constant recharging due to their limited battery capacity. This involves developing effective vehicle routes that include loading and unloading points and battery charging stations [4].

The research carried out in this article focuses on the subject of calculating the energy expenditure of electric vehicles performing transport tasks in municipal service companies, such as municipal utilities [5] or courier companies [6]. These types of issues are very challenging to analyse due to the complexity of the tasks—customer service in densely built-up areas and the occurrence of breakdowns or lack of energy supply at charging points. The transport task for these types of companies was defined in two ways as part of the research presented herein. In the first case, it is the driving route of the electric vehicle from the base to the first loading point, the route between the loading points carried out until the entire capacity of the vehicle is used, and the driving route to the collective unloading point. In the second way of defining the transport task, the electric vehicle starts the route from the first loading point directly, after leaving the collective unloading point.

The main objective of our research was to develop a method for calculating the energy expenditure of electric vehicles that takes into account the uncertainty [7,8] of charging point operation. The developed method consists of a decision-making model calculating the energy expenditure of vehicles over their routes and optimisation algorithms minimising this consumption. The uncertainty of charging point operation was presented as the probability of a random situation hindering the functioning of this point, e.g., a failure occurring or a lack of energy supply. The probability of emergencies hindering the operation of the charging point, e.g., a failure, was determined based on a defined random variable, which is the moment of the occurrence of an undesirable event in the operation of the charging station. This probability is known from the perspective of the operation of the charging station. Taking into account the fact that the research undertaken aims to minimize the energy expenditure of electric vehicles, which depends on the designated driving route of these vehicles, the uncertainty of the operation of charging stations is seen from the point of view of electric vehicles performing transport tasks, not from the point of view of the operation of the station itself. For the electric vehicles, the moment a vehicle appears at the charging station determines the probability of the station failing. The moments when the vehicles appear at stations are not known until the driving routes of these vehicles are determined. Without designated vehicle driving routes, it is impossible to determine the probability of adverse events at each charging point seen from the perspective of an electric vehicle, not the station itself. Therefore, the authors use the concept of the uncertainty of charging point operation. The uncertainty of station operation seen from the vehicle's point of view is a measurable value and is defined by the probability of an emergency occurring at the station. This probability can be determined after determining the vehicle's driving routes.

Bearing in mind the complexity of the problem of calculating energy expenditure and taking into account the uncertainty of charging point operation, the authors developed an original decision-making model and solved it using artificial intelligence algorithms. In the driving route model, the routes of electric vehicles are calculated in such a way that they appear at charging points at times when the probability of a point breakdown is minimal. These routes are supposed to entail the minimum energy expenditure required by vehicles to carry out the transport tasks assigned. In order to control the level of uncertainty in the functioning of the charging point, the decision model was developed to limit the permissible level of the risk of charging point breakdown along vehicle driving routes. A function minimising the energy expenditure of all electric vehicles executing transport tasks was defined as the criterion function. In addition to the typical limitations encountered in this type of model, e.g., the time for the vehicles to complete tasks, the model takes into account the limitations typical of electric vehicles, e.g., the maximum distance covered without charging the battery.

Two optimisation algorithms were used to minimize the energy expenditure of electric vehicles, i.e., the ant algorithm and the genetic algorithm. These algorithms display different modes of operation, so they were mutually used for the verification of our results. The specificity of the genetic algorithm operation requires generating initial solutions, which are modified in further iterations of this algorithm. In classic approaches, initial solutions are generated randomly. In this study, a combination of the ant and genetic algorithm was employed, which created a hybrid genetic algorithm. The initial population for the genetic algorithm was generated by the ant algorithm. Genetic or ant algorithms are often used and recommended for calculating vehicle driving routes [9–11]. Their main advantage is the short amount of time needed to generate solutions.

The developed method was verified against real-life data, and its effectiveness was confirmed. The article presents a method of calibrating the developed optimisation algorithms. The theoretical distributions of the probability of charging point breakdown were determined based on the Statistica 13 program, whereas a graphical implementation of the method was carried out using the PTV Visum software.

The article proposes a new approach to determining the driving routes of electric vehicles in urban service enterprises, taking into account the uncertainty of the operation of vehicle battery charging stations. Determining driving routes for electric vehicles is a complex optimization problem based on the VRP (vehicle routing problem) with pick-up and delivery [12]. In this problem, vehicles visit individual customers, pick up or deliver the load, and return to the collection point. The authors focused on determining the energy expenditure of electric vehicles by using a hybrid genetic algorithm. A literature analysis has shown that using electric vehicles in urban service enterprises, e.g., courier companies or municipal enterprises, is still a big challenge for researchers.

The research in this work enabled the development of a new decision-making model defining the energy expenditure of electric vehicles performing transport tasks in the context of the operating uncertainty of battery charging stations and the development of a practical algorithm minimizing this expenditure.

This study is divided into five sections. The first section describes the research problem and the purpose of the research. The second section indicates the research gap and our premise to address this subject. The decision model calculating the energy expenditure of electric vehicles is presented in the third section, while the optimisation algorithms employed to minimize the expenditure are presented in the fourth section. The verification of the developed method against real-life data is described in the fifth section.

2. Analysis of the Literature

Electric vehicles play a vital role in transportation companies due to the development of sustainable transport systems [2,13,14]. In these companies, minimising the energy expenditure of electric vehicles involves calculating the shortest driving routes for vehicles executing transport tasks. In the work of [15], the authors determined the energy expenditure in municipal enterprises based on a decision-making model in which the criterion function was defined as the amount of energy needed to overcome rolling forces and aerodynamic resistance. An ant algorithm and a genetic algorithm were used to calculate the shortest driving routes of vehicles. A verification of the algorithms confirmed their high level of effectiveness.

The problem of minimising the energy expenditure of electric vehicles belongs to the group of problems described in the literature as electric vehicle routing problems (E-VRPs) [16–18]. This problem is a version of the vehicle routing problem (VRP) extended to issues related to electric vehicles. The classic vehicle routing problem consists in designating optimal transportation routes for a strictly defined number of vehicles, which are tasked with serving a set of customers located at various points, while adhering to a series of constraints, such as vehicle capacity and task completion time [19]. Various types of this problem occur, such as the capacitated VRP (CVRP), which incorporates vehicle carrying capacity constraints, the VRP with time windows (VRPTW), and the VRP with pickup and delivery (VRPPD). The vehicle routing problem is an NP-hard optimisation problem. Heuristic algorithms, primarily genetic [20] or ant algorithms, are commonly applied to solve it [21,22].

The electric vehicle routing problem, just like the classic VRP, has various variants and draws upon the travelling salesman problem [23,24]. Setting routes for electric vehicles depends on the location and number of available charging points. In the course of this study, mathematical models were developed to set vehicle routes, taking into account the location of both individual charging points [25] and multiple ones [26–28]. The time windows for customer service by electric vehicles have been described in the works of [29–31].

The problem of minimising the energy expenditure of electric vehicles is a complex decision-making problem, and therefore, artificial intelligence algorithms are used to solve it. In the work of [32], a novel energy management strategy based on machine learning was proposed for a hybrid electric bus. On the other hand, in the work of [33], a battery charging strategy was defined while meeting the operational constraints of vehicles by the consideration of dynamic programming and a genetic algorithm. The particle swarm optimisation algorithm for energy management in plug-in hybrid electric vehicles (PHEVs) was presented in the publication of [34]. Their verification against real-life data confirmed its high level of effectiveness. A comprehensive analysis of artificial intelligence algorithms in managing the efficiency of battery consumption in electric vehicles was presented in the work of [35]. Machine learning algorithms based on a feed forward neural network (FFNN) for diagnosing defects in electric vehicle batteries were presented in the work of [36]. A neuro-fuzzy inference system for estimating the state of charge of lithium-ion batteries was presented in the work of [37]. Advanced research on optimal energy management in electric vehicles using machine learning techniques was presented in the publications of [38–42]. In the works of [43,44], the classic electric vehicle routing problem was solved using the simulated annealing algorithm. The ant algorithm was applied to the same problem in the paper of [45], while the genetic algorithm was used in the paper of [46,47].

After a literature analysis, it can be concluded that energy expenditure is minimized in two ways. The first approach involves optimal energy management and its appropriate selection suited to the prevailing conditions along the route. In the second case, minimal driving routes for vehicles are set in order to reduce the vehicle's involvement in performing transportation tasks. Considering that the energy expenditure of electric vehicles in service companies depends on the routes travelled by these vehicles, and that heuristic algorithms are recommended and commonly used for vehicle routing problems, two algorithms were applied to minimize expenditure: the ant algorithm and the genetic algorithm. These algorithms are effective optimisation algorithms that are commonly applied in complex decision-making problems. Our literature analysis also confirmed the lack of publications regarding the coverage of regions by electric vehicles with the consideration of the reliability of vehicle charging points.

3. Decision-Making Model Determining the Energy Expenditure of Electric Vehicles

3.1. Assumptions

An essential aspect in determining the energy expenditure of electric vehicles in municipal service companies, considering the uncertainty of charging point operation, is to define routes characterized by the minimum distance travelled to accomplish all transportation tasks. Additionally, an electric vehicle performs battery-charging operations when the probability of a charging point breakdown or unavailability due to energy supply shortages is minimal. It was also assumed that the minimisation of the distance travelled along vehicle routes is proportional to the minimisation of energy expenditure. The minimisation of the energy expenditure of electric vehicles in municipal service companies was adopted as the quality assessment of the solution to the decision-making model for setting the minimum driving routes for electric vehicles. The faulty process of the operation of vehicle charging points and their unavailability on a given workday were presented using theoretical distribution models for the probability of the uncertainty of charging point operation. The random variable representing the probability distribution of the uncertainty of charging point operation was defined as the moment of point malfunctions, power supply interruptions, or any other random situations affecting its correct operation. Therefore, the routes of electric vehicles should be set in such a way that the probability of vehicles appearing at charging points during the time of their unavailability is below the permissible level of risk. In the model, it was assumed that there are no delays over sections of the transport network due to traffic congestion, and electric vehicles move along the designated lanes of the road. Additional assumptions of the model include the following [15]:

- The volume of the cargo in the given loading places is not greater than the capacity of the vehicle.
- A battery charging station can be located either at transportation bases or at particular places of a transport network.
- The criterion function determining the energy consumption takes into account the energy required to overcome air resistance and rolling resistance arising from road surface resistance. It was assumed that the vehicle travels over route sections in a uniform motion, and the forces generating vehicle acceleration were disregarded. It was assumed that the vehicle travels over a flat surface, and the resistance forces arising from overcoming inclined route sections were disregarded;
- The electric vehicle departs from the transportation base with a 100% charged battery;
- The transportation task was defined in two ways: (1) the departure of a vehicle from the base to the loading points and, after filling up its entire capacity, the transportation of its cargo to the unloading point; or (2) the departure of the vehicle from the unloading point, which loads its cargo at the loading points and returns to the unloading point;
- In a single transportation task, it was assumed that the electric vehicle may charge its battery only once due to the vehicle's capacity limitation;
- The trip from the unloading point to the transportation base was not included in the model. The route of this trip does not contain loading points and is not determined.

3.2. Input Data of the Decision-Making Model and Decision Variables

In the model, there are several types of data, e.g., sets and parameters. The sets include the identification of characteristic types of points, such as the starting and ending points of vehicle work, intersections, charging points, and vehicle types, as well as the tasks being performed. A summary of the sets is presented in Table 1. In addition, the parameters characteristic of the transportation network sections were defined, e.g., the distances between points in the network, time required for loading, unloading, and travel, and those taking into account the risk of damage to the vehicle charging points. A summary of the parameters is presented in Table 2.

Table 1. The sets used in the decision model.

The Elements of Sets	The Description
b	Transport base number, $b\epsilon \boldsymbol{B}$
pz	Loading point number, $pz\epsilon \boldsymbol{PZ}$
p	Intermediate point number, e.g., intersection, $p\epsilon \boldsymbol{P}$
s	Charging point number, $s\epsilon \boldsymbol{S}$
pw	Unloading point number, $pw\epsilon \boldsymbol{PW}$
v	Electric vehicle number, $v\epsilon \boldsymbol{V}$
z	Transport task number, $z\epsilon \boldsymbol{Z}$

Table 2. The parameters used in the decision model.

The Parameters	The Description
tz^{pz}	Loading time at the loading point
$t1^{v,b,p}$	Driving time between the base and an intermediate point
$t2^{v,p,p'}$	Driving time between intermediate points
$t3^{v,p,pw}$	Driving time between an intermediate point and unloading point
$t4^{v,pw,p}$	Driving time between an unloading point and intermediate point
$s1^{b,p}$	Distance between the base and an intermediate point
$s2^{p,p'}$	Distance between intermediate points
$s3^{p,pw}$	Distance between an intermediate point and unloading point
$s4^{pw,p}$	Distance between an unloading point and intermediate point

Table 2. *Cont.*

The Parameters	The Description
c^v	Vehicle capacity
$q1^{pz,b,p}$	Cargo volume at a loading point between the base and intermediate point
$q2^{pz,p,p'}$	Cargo volume at a loading point between intermediate points
$q3^{pz,p,pw}$	Cargo volume at a loading point between an intermediate point and unloading point
$q4^{pz,pw,p}$	Cargo volume at a loading point between an unloading point and intermediate point
T^{max}	Maximum time to complete a task by a vehicle
ΔT	Operating time of the unloading point
d^v	Permissible distance after which the electric vehicle heads to the charging point
$t^{v,s}$	Charging time for the electric vehicle at a charging point
$pE^{s,t}$	Probability of the uncertainty of charging point operation, where $E^{s,t}$ is a random variable determining the moment t of a charging point breakdown, etc.
R	Permissible risk of uncertainty in the operation of the charging point along the entire vehicle route
$m1^{v,b,p}$	Vehicle weight between the base and intermediate point
$m2^{v,p,p'}$	Vehicle weight between intermediate points
$m3^{v,p,pw}$	Vehicle weight between an intermediate point and unloading point
$m4^{v,pw,p}$	Vehicle weight between an unloading point and intermediate point
ρ	Air density ρ = 1.225 kg/m^3
μ	The coefficient of road friction μ = 2.02 × 10^{-5}
cx	The drag coefficient cx = 0.2
A	The vehicle frontal area A = 20 m^2

The energy expenditure depends on the length of the route covered by a vehicle. It is necessary to set vehicles' routes in such a way as to minimize their expenditure. The energy expenditure is determined by the decision variables determining the route of electric vehicles, which take the following form:

- $x1^{v,b,p,z}$—a transport link carried out by an electric vehicle between the base and an intermediate point in a given transportation task, if $x1^{v,b,p,z}$ = 1 is a transport link;
- $x2^{v,p,p',z}$—a transport link carried out by an electric vehicle between intermediate points in a given transport task, if $x2^{v,p,p',z}$ = 1 is a transport link;
- $x3^{v,p,pw,z}$—a transport link carried out by an electric vehicle between an intermediate point and unloading point in a given transport task, if $x3^{v,p,pw,z}$ = 1 is a transport link;
- $x4^{v,pw,p,z}$—a transport link carried out by an electric vehicle between an unloading point and intermediate point in a given transportation task, if $x4^{v,pw,p,z}$ = 1 is a transport link.

In addition, a decision variable representing the interpretation of the choice of a given charging point by the electric vehicle was introduced: if $x^{v,s,z}$ = 1, then a given charging point is used by a given vehicle for a given task.

3.3. Model Limitations

The following limitations were taken into account in the decision model:

- not exceeding the maximum time of task completion by an electric vehicle. The task type: bases—loading points—unloading points is shown in Formula (1). The task type: unloading points—loading points—unloading points is shown in Formula (2) (***LPP***—a set of transport links between intermediate points, and n—the number of loading points in the task).

$$\forall\ v\epsilon \boldsymbol{V},\ b\epsilon \boldsymbol{B},\ p\epsilon \boldsymbol{P},\ pz\epsilon \boldsymbol{PZ},\ z\epsilon \boldsymbol{Z},\ s\epsilon \boldsymbol{S},\ pw\epsilon \boldsymbol{PW}$$

$$x1^{v,b,p,z}\cdot t1^{v,b,p} + \sum_{(p',p'')\in \boldsymbol{LPP}} x2^{v,p',p'',z}\cdot t2^{v,p',p''} + x3^{v,p,pw,z}\cdot t3^{v,p,pw} + x^{v,s,z}\cdot t^{v,s} + n\cdot tz^{pz} \leq T^{max} \quad (1)$$

$$x4^{v,pw,p,z} \cdot t4^{v,\mathrm{pw},p} + \sum_{(p',p'') \in \boldsymbol{LPP}} x2^{v,p',p'',z} \cdot t2^{v,p',p''} + x3^{v,p,pw,z} \cdot t3^{v,p,pw} + x^{v,s,z} \cdot t^{v,s} + n \cdot tz^{pz} \leq T^{max} \quad (2)$$

- not exceeding the operating time of the unloading point by a single vehicle ($T1^{z,v}$—the completion time of the type one task calculated from the left part of the inequality (1); $T2^{z,v}$—the completion time of the type two task calculated from the left part of the inequality (2)):

$$\forall\, v \epsilon \boldsymbol{V}$$

$$\sum_{z \in \mathbf{Z}} \mathrm{T1}^{z,v} + \sum_{z \in \mathbf{Z}} \mathrm{T2}^{z,v} \leq \Delta T \quad (3)$$

- not exceeding the permissible risk related to the uncertainty of the charging point's operation (damage to the charging point, lack of energy supply, etc.) along each electric vehicle route:

$$\forall\, v\ \epsilon \boldsymbol{V}$$

$$\prod_{s \in \boldsymbol{S}} \prod_{z \in \mathbf{Z}} x^{v,s,z} \cdot pE^{s,t} \leq R \quad (4)$$

  where t is the time of arrival of the electric vehicle at a given charging point.
- not exceeding the maximum distance after which the electric vehicle should be routed to the charging point in a type one task (5) and in a type two task (6):

$$\forall\, v \epsilon \boldsymbol{V},\, b \epsilon \boldsymbol{B},\, p \epsilon \boldsymbol{P},\, pz \epsilon \boldsymbol{PZ},\, z \epsilon \boldsymbol{Z},\, pw \epsilon \boldsymbol{PW}$$

$$x1^{v,b,p,z} \cdot s1^{b,p} + \sum_{(p',p'') \in \boldsymbol{LPP}} x2^{v,p',p'',z} \cdot s2^{p,p'} + x3^{v,p,pw,z} \cdot s3^{p,pw} \leq d^v \quad (5)$$

$$x4^{v,pw,p,z} \cdot s4^{pw,p} + \sum_{(p',p'') \in \boldsymbol{LPP}} x2^{v,p',p'',z} \cdot s2^{p,p'} + x3^{v,p,pw,z} \cdot s3^{p,pw} \leq d^v \quad (6)$$

- volumetric limitation of the vehicle when collecting cargo from the loading points in a type one task (7) and in a type two task (8):

$$\forall\, v \epsilon \boldsymbol{V},\, b \epsilon \boldsymbol{B},\, p \epsilon \boldsymbol{P},\, pz \epsilon \boldsymbol{PZ},\, z \epsilon \boldsymbol{Z},\, pw \epsilon \boldsymbol{PW}$$

$$x1^{v,b,p,z} \cdot q1^{pz,b,p} + \sum_{(p',p'') \in \boldsymbol{LPP}} x2^{v,p',p'',z} \cdot q2^{pz,p',p''} + x3^{v,p,pw,z} \cdot q3^{pz,p,pw} \leq c^v \quad (7)$$

$$x4^{v,pw,p,z} \cdot q4^{pz,pw,p} + \sum_{(p',p'') \in \boldsymbol{LPP}} x2^{v,p',p'',z} \cdot q2^{pz,p',p''} + x3^{v,p,pw,z} \cdot q3^{pz,p,pw} \leq c^v \quad (8)$$

3.4. Criterion Function

The criterion function minimises the energy expenditure of all vehicles carrying out transportation tasks. This function takes into account the energy expenditure needed to overcome road resistance forces and aerodynamic forces. The components of the formula include the following (9): (10)—the expenditure for the sections between the base and the intermediate point, where ***LBP***—a set of transport links between the base and the intermediate point; (11)—the expenditure for the sections between the intermediate points; (12)—the expenditure for the sections between the intermediate point and the unloading point, where ***LPW***—a set of transport links between the intermediate point and the unloading point; and (13)—the expenditure for the sections between the unloading point and the intermediate point, where ***LWP***—a set of transport links between the unloading point and the intermediate point:

$$F = F1^{v,b,p,z} + F2^{v,p,p',z} + F3^{v,p,pw,z} + F4^{v,pw,p,z} \rightarrow min \quad (9)$$

$$F1^{v,b,p,z} = \sum_{v \in \boldsymbol{V}} \sum_{(b,p) \in \boldsymbol{LBP}} \sum_{z \in \mathbf{Z}} x1^{v,b,p,z} \cdot s1^{b,p} \cdot \left(F_{air}{}^{v,b,p,z} + F_r{}^{v,b,p,z} \right) \quad (10)$$

$$F2^{v,p,p',z} = \sum_{v\in \boldsymbol{V}} \sum_{(p,p')\in \boldsymbol{LPP}} \sum_{z\in \mathbf{Z}} x2^{v,p,p',z} \cdot s2^{p,p'} \cdot \left(F_{air}{}^{v,p,p'z} + F_r{}^{v,p,p',z} \right) \tag{11}$$

$$F3^{v,p,pw,z} = \sum_{v\in \boldsymbol{V}} \sum_{(p,pw)\in \boldsymbol{LPW}} \sum_{z\in \mathbf{Z}} x3^{v,p,pw,z} \cdot s3^{p,pw} \cdot \left(F_{air}{}^{v,p,pw,z} + F_r{}^{v,p,pw,z} \right) \tag{12}$$

$$F4^{v,pw,p,z} = \sum_{v\in \boldsymbol{V}} \sum_{(pw,p)\in \boldsymbol{LWP}} \sum_{z\in \mathbf{Z}} x4^{v,pw,p,z} \cdot s4^{pw,p} \cdot \left(F_{air}{}^{v,pw,p,z} + F_r{}^{v,pw,p,z} \right) \tag{13}$$

where:

- The air resistance force is as follows:

$$F_{air}{}^{v,b,p,z} = \frac{1}{2} \cdot \rho \cdot cx \cdot A \cdot \left(\frac{s1^{b,p}}{t1^{v,b,p}} \right)^2 \tag{14}$$

- The rolling resistance force is as follows:

$$F_r{}^{v,b,p,z} = \mu \cdot m1^{v,b,p} \cdot g \cdot \cos\alpha \tag{15}$$

4. Algorithms Minimising the Energy Expenditure of Electric Vehicles

4.1. Ant Algorithm

Bearing in mind the fact that the energy expenditure of electric vehicles depends on the length of the driving routes of these vehicles, it is important to determine the vehicle driving routes that are characterised by the minimum distance travelled for cargo pickup. In addition, these routes should comply with the limitations of the developed decision-making model. The ant algorithm uses the so-called artificial ants to set the driving routes of electric vehicles. An ant creates its own route (Figure 1), which is the driving route of all the vehicles completing transportation tasks.

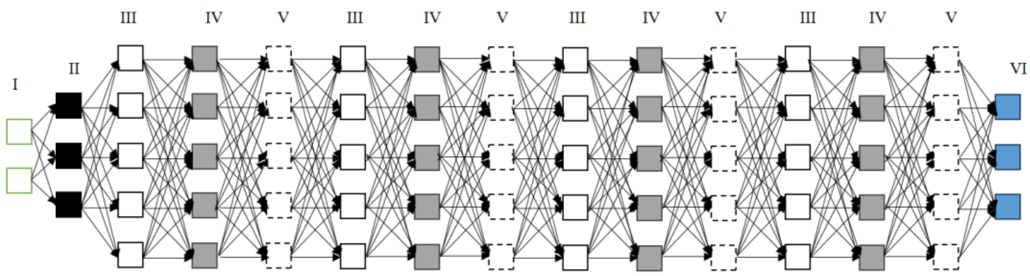


Figure 1. The elements of the ant's route.

Six types of layers were distinguished in the ant route as follows: layer I represents the transport base from which the electric vehicles depart to the initial loading points; layer II represents the points determining the electric vehicles that are assigned to tasks; layer III represents the intermediate points of the ant's route, i.e., intersections; layer IV represents electric vehicle charging points; layer V represents loading points; and layer VI represents collective unloading points. The number of intermediate points along an ant's route, the number of points interpreted as a charging point, and the number of unloading points are known only after the ant has created the entire route. The frequency of unloading points along the ant's route depends on the size of the collected cargo and the capacity of the electric vehicles. On the other hand, the frequency of the occurrence of points interpreted as a charging point depends on the length of the route generated by the ant. The points from layer I in the ant's route appear when the ant leaves the transport base, and the number of loading points is known. The ant returns to the base when all loading points have been visited, or when the operating time of the unloading point is exceeded (restriction (3)). In the event that all loading points are not visited, the ant sets off from the base again to visit these points. The process of selecting further route points by the ant is repeated until all the loading points have been visited. In any case, when the ant leaves the base, the moment of departure of the ant from the base is always determined as the moment (time) of commencing operation in the service company. The departure of the ant from the base represents the departure of another vehicle to perform tasks. An example of an ant's route is shown in Figure 2. Along this route, the ant has set driving routes for two electric vehicles.

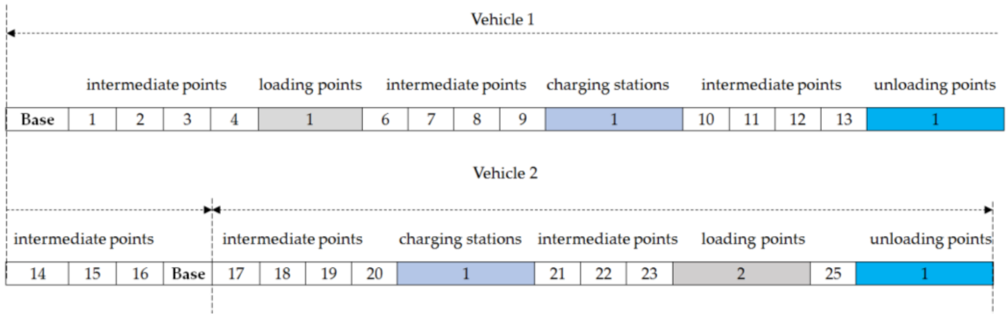


Figure 2. An example of an ant's route.

The starting point of each ant's route is the transport base from which the vehicles depart to the loading points. The ant proceeds to the following route points in accordance with the established probability.

$$\mathrm{PR}^{mr}{}_{ab}(t) = \begin{cases} \frac{[\tau_{ab}(t)]^{\alpha} \cdot [\eta_{ab}(t)]^{\beta}}{\sum_{l \in \Omega^{mr}} [\tau_{al}(t)]^{\alpha} \cdot [\eta_{al}(t)]^{\beta}} & b \in \Omega^{mr} \\ 0 & b \notin \Omega^{mr} \end{cases} \tag{16}$$

where:

$\tau_{ab}(t)$—the intensity of the pheromone trace between the a-th point of the ant's route and the b-th point in the t-iteration of the algorithm implemented by the mr ant;

$\eta_{\mathrm{ab}}(t)$—heuristic information:

$$\eta_{a,b}(t) = \frac{1}{d1(a,b) + d2(a,pz)} \tag{17}$$

where:

$d1(a,b)$—the distance between the selected points of the ant's route;

$d2(a,pz)$—the distance between the selected point of the ant's route and the loading point;

α, β—the influence of pheromones and heuristic data on the behaviour of the ants;

Ω^{mr}—a set of all the elements of the ant's route;

l—potential points of the ant's route that are taken into account when choosing the next point of the ant's route.

The heuristic information takes into account both the distance between the route points $d1(a,b)$ and the distance between the route point and the loading point $d2(a,pz)$. The parameter $d2(a,pz)$ was introduced in order to guide the ant to a given loading point to avoid ant accidentally wandering through all the points of its route. The distance $d2(a,pz)$ is the Euclidean distance calculated based on the location coordinates of the midpoints in the ant's route and each loading point. In the event that the ant proceeds to a charging point, base, or unloading point, the Euclidean distances are determined between these points and the intermediate points of the ant's route.

Each ant in the population determines its individual route. After completing these routes, the pheromone trace along them is updated. At the beginning, it is assumed that the trace on the transport links between the route points is equally strong. In the next iterations, the pheromone trace is calculated according to the following formula:

$$\tau_{a,b}(t+1) = (1-\rho)\tau_{a,b}(t) + \sum_{mr \epsilon \boldsymbol{MR}} \Delta\tau_{a,b}{}^{mr}(t) \tag{18}$$

The first component of formula (18) determines the pheromone volatilisation rate, while the second one determines the pheromone amplification and takes on a specific value when the segment (*a*,*b*) is used by the ant; otherwise, it is 0, i.e.:

$$\Delta\tau_{a,b}{}^{mr}(t) = \begin{cases} \frac{1}{L^{mr}(t)} - K1^{mr}(t) - K2^{mr}(t) \\ 0 \end{cases} \tag{19}$$

where:

$L^{mr}(t)$—the length of the entire route determined by the ant in a given iteration;

$K1^{mr}(t)$—a penalty for exceeding the maximum time of task implementation by an electric vehicle in the designated routes (1) and (2). It is assumed that this penalty is half of the pheromone accumulated along the route;

$K2^{mr}(t)$—a penalty for exceeding the permissible risk related to the uncertainty of charging point operation by the electric vehicle along the designated route (4). It is assumed that this penalty is half of the pheromone accumulated along the route;

The ant algorithm is an iterative algorithm and works until a fixed number of iterations has been reached. The algorithm diagram is shown in Figure 3. The number of ants in the population and the number of iterations are determined at the beginning of the algorithm's implementation. The operation of the ant algorithm is presented in the following steps:

- Step 1. An ant in the population randomly selects the transport base from which it starts its route, and a vehicle number is assigned to the ant;
- Step 2. The selection of the loading point located nearest to the transport base. The movement of the ant to the intermediate points is shown in Formula (16). After the ant arrives at the loading point, it picks up the load and selects the next closest loading point. The ant collects its cargo until the vehicle capacity is exceeded (limitation (7)). After exceeding this capacity, the ant goes to the nearest unloading point. During each passage of the ant to the subsequent points, it is checked whether the distance limit is exceeded, after which the electric vehicle should be directed to the charging point (5);
- Step 3. After unloading, the ant goes to the next closest loading point, taking into account the volumetric limit (8). The cargo collection process is carried out until the electric vehicle (3) exceeds the maximum time for completing tasks or until all loading points have been visited. After exceeding this limit, the ant returns to the base and then step 1 is implemented again. The ant is assigned to another electric vehicle of a given capacity. The departure of each ant from the base takes place the moment the service company starts work;
- Step 4. Repetition of steps 1–3 to complete all loading points;
- Step 5. Another ant from the population sets its own route, repeating steps 1–4 until the routes have been completed by all the ants in the population;
- Step 6. Updating the pheromone according to Formula (18);
- Step 7. Repeat steps 1–6 until the stop condition is reached;
- Step 8. The route of the ant with the highest pheromone value among all the routes generated in the population is the final solution.

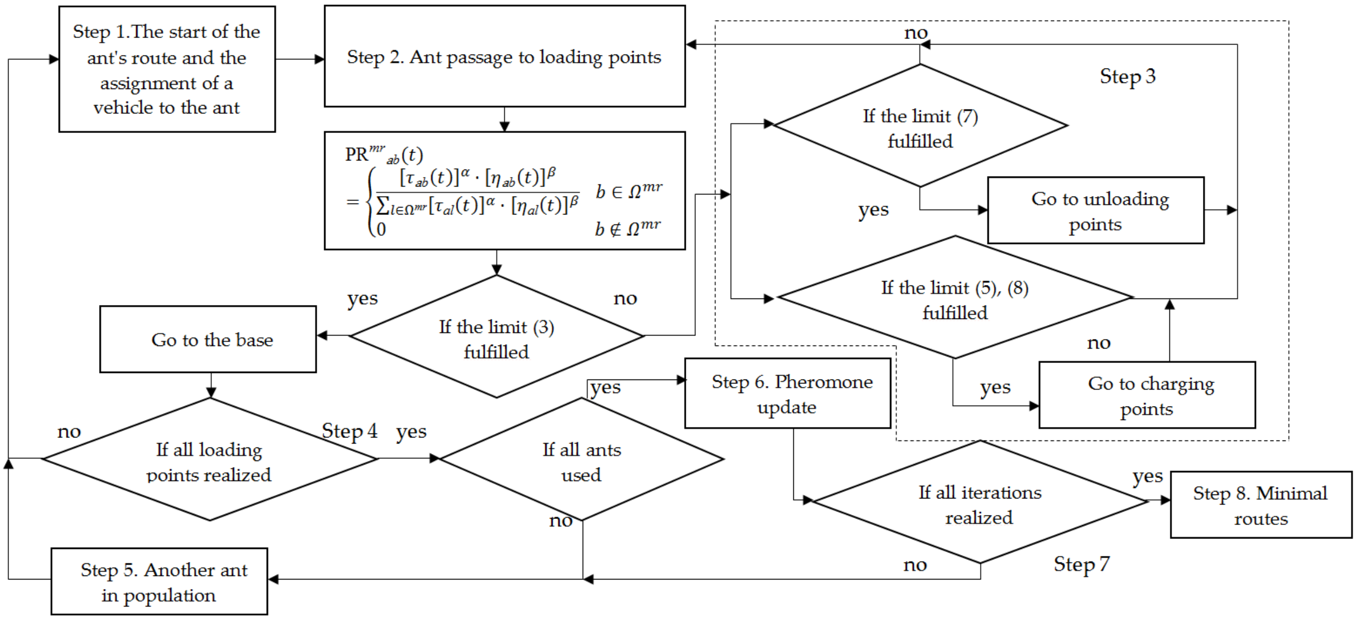


Figure 3. Diagram of the ant algorithm's operation.

4.2. Hybrid Genetic Algorithm

The first step in the operation of the genetic algorithm is to generate the initial population of the algorithm. The initial population consists of chromosomes representing the driving routes of electric vehicles. The initial population was established by the ant algorithm. The following stages were distinguished in the genetic algorithm: chromosome evaluation, reproduction, and crossbreeding. Chromosome mutation is not carried out due to its negative impact on the correctness of the generated solutions. The evaluation of the chromosome is carried out on the basis of the adaptation function. The best chromosomes with the greatest adaptation function are multiplied in the reproduction process. Reproduction generates new populations according to the principle of the roulette method [15,48], in which linear scaling was used to counteract the premature convergence of the algorithm in initial iterations. The algorithm for selecting chromosomes for crossbreeding randomly pairs two chromosomes and randomly selects chromosome cut-points. The adaptation function for the k-th M chromosome (t, k) can be presented as follows (where $K = \{1, \ldots, k, \ldots, K\}$—a set of chromosomes in the population, and t—iteration of the algorithm):

$$F(k,t) = \frac{1}{L(k,t)} - K1(k,t) - K2(k,t) \rightarrow \max \tag{20}$$

where:

$L(k,t)$—the length of the entire chromosome route in a given iteration;

$K1(k,t)$—the penalty for exceeding the maximum time for the implementation of the task by an electric vehicle in chromosomes (1) and (2). It is assumed that the penalty for exceeding this is that the generated value of the adaptation function for the chromosome is reduced by half;

$K2(k,t)$—the penalty for exceeding the acceptable risk associated with the uncertainty of charging point operation by an electric vehicle in chromosome (4); it is assumed that the penalty for exceeding this is that the generated value of the adaptation function for the chromosome is reduced by half.

The process of chromosome crossbreeding is shown in Figure 4 and involves the exchange of gene sequences between two chromosome cut-points. In both chromosomes, the cut-points must be identical.

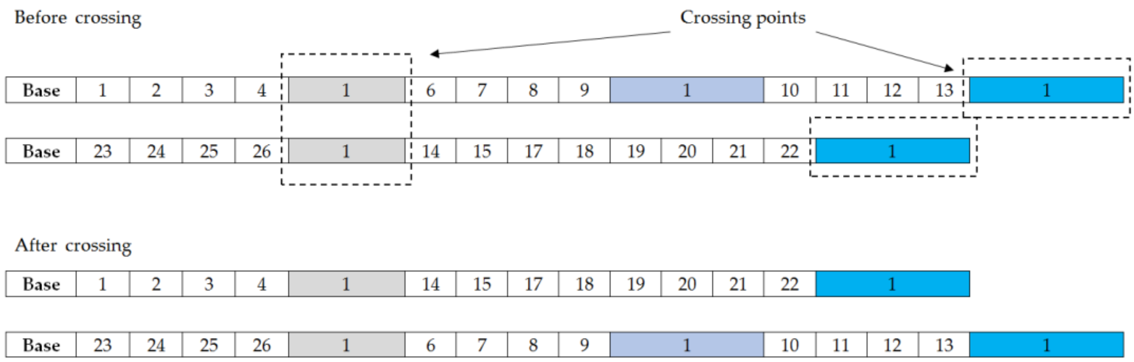


Figure 4. Chromosome crossbreeding.

The hybrid genetic algorithm is an iterative algorithm, and its solution is improved in subsequent iterations. The principle of the algorithm is presented in the following steps:

- Step 1. Generation of the initial population by the ant algorithm;
- Step 2. Calculation of the adaptation function for each chromosome;
- Step 3. Reproduction;
- Step 4. Crossbreeding;
- Step 5. Repeat steps 2–4 until the stop condition is reached;
- Step 6. The chromosome with the highest value of adaptation function in the population is the final solution.

5. The Case Study

5.1. Input Data

A service company carries out the collection of municipal waste from a given region. It was assumed that the waste loading time at each loading point is 5 min, and the unloading time at the unloading points was also set at 5 min. The company owns five DAF CF electric vehicles with a gross permissible weight of 28 tons, load-carrying capacity of 3 tons, battery capacity of 170 kWh, maximum driving distance without charging of 70 km in urban conditions, and charging time of 1 h. The permissible duration of a single task combined with the battery charging time is 3 h. The maximum operating time of the unloading point was set at 4 h. The service company starts work at 8:00 a.m. The accepted risk related to the uncertainty of charging point operation along each designated route was set at 0.40. The distances between the route points, driving times, and location coordinates of all points were generated using the PTV Visum software. The volume of cargo at the loading points is shown in Table 3.

Table 3. The size of the waste.

No.	Size (kg)	No.	Size (kg)	No.	Size (kg)
1	400	7	400	13	400
2	500	8	400	14	300
3	550	9	550	15	550
4	150	10	500	16	400
5	600	11	650	17	600
6	1450	12	450	18	450

The location of the base, waste collection points, unloading point, charging point, and linear infrastructure of the transport network are shown in Figure 5.

Figure 5. Transport network of a service company.

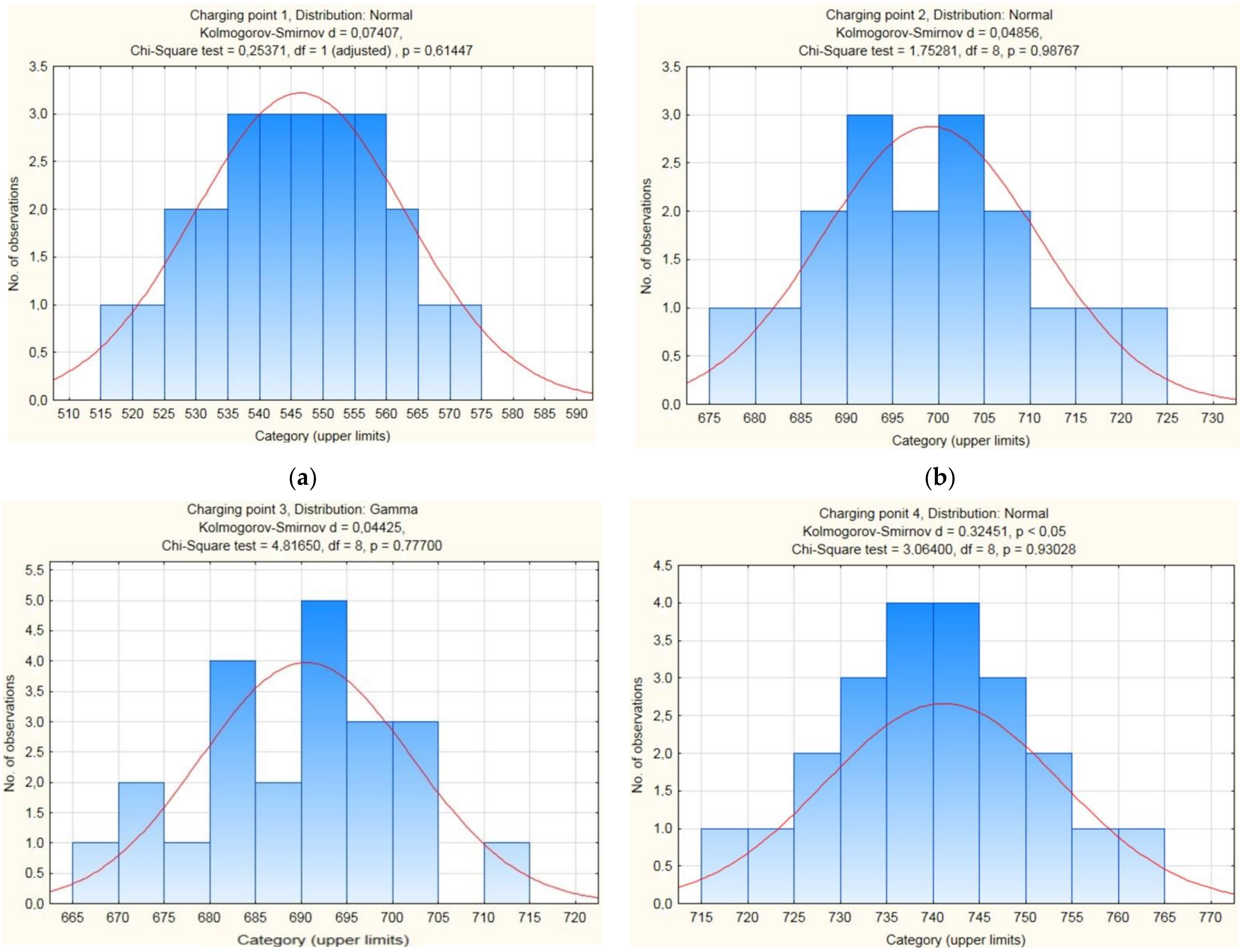
5.2. Distributions of the Probability of Uncertainty in Charging Point Operation

The location of the battery charging points is shown in Figure 6. Theoretical distributions of the probability of uncertainty in charging point operation were determined for these points. The time of the occurrence of malfunctions at each point is shown in Table 4. The time of damages, breakdowns, or other events that disrupt the operation of the charging point are presented in a format totalling the number of minutes, e.g., 8:20 a.m., that is 500 min, 8 times 60 min plus 20 min.

Table 4. Charging point breakdown moments (minutes).

Point 1	Point 2	Point 3	Point 4
521/516	680/707	670/693	720/751
526/550	683/711	671/694	721/752
534/551	687/717	672/695	745/760
535/552	690/723	680/696	731/761
537/556	691/-	681/697	733/726
538/557	692/-	686/698	734/727
541/558	694/-	683/702	741/736
544/561	696/-	684/703	748/737
545/563	697/-	685/704	747/738
548/567	703/-	690/711	744/739
549/572	704/-	691/-	745/-
527/539	706/-	692/-	746/-

Bearing in mind that the shapes of the histograms determining the frequency of charging point failures are similar to normal distributions, the Chi-squared test was used to determine the type of distribution. The samples are small, so in addition to the Chi-squared test, the Kolmogorov–Smirnov test was also employed. The use of the Kolmogorov–Smirnov test is only an additional step to help support the final decision regarding the type of distribution. This test detects only large deviations from the assumed distributions. The null hypothesis referring to the assumed type of distribution is rejected when the calculated value of the statistics belongs to the critical area determined by the assumed level of significance $\alpha = 0.05$ (when $p < \alpha$, p—the probability determined in the tests). The values of the Chi-squared and Kolmogorov–Smirnov concordance tests and the parameters of the distributions investigated are presented in Table 5. Adjustments of the theoretical distributions for the random variable of the time when disruptions in the operation of the charging point occur are shown in Figure 6.



(**a**) (**b**) (**c**) (**d**)

Figure 6. Theoretical distributions of the uncertainty of charging point operation, (**a**) point 1, (**b**) point 2, (**c**) point 3, and (**d**) point 4.

Table 5. Concordance tests and distribution parameters.

Charging Points	Statistic	Chi-Square Test Probability	Statistic	K-S Test Probability	Parameters of Distribution	Distribution
1	0.253	0.61	0.07	-	$\mu = 546.40$; $s^2 = 279.63$	normal
2	1.752	0.98	0.04	-	$\mu = 699.11$; $s^2 = 138.48$	normal
3	4.816	0.77	0.04	-	$\theta = 0.16$; $k = 4111.173$	gamma
4	3.064	0.93	0.32	-	$\mu = 741.11$; $s^2 = 162.23$	normal

5.3. Calibration and Verification of Algorithms

The calibration of the algorithm consists of finding the settings for the algorithm parameters that generate the best solution. The following values were adopted for the parameter α: 1, 3, 5, 10, and 20; parameter β: 0.5, 1, and 5; and parameter ρ: 0.2, 0.4, 0.6, and 0.8 [48] in order to calibrate the ant algorithm. For this number of specific parameters, 60 possible test settings were created: (5 (parameter α) × 3 (parameter β) × 4 (parameter ρ) = 60). The combinations of the ant algorithm settings that were tested are shown in Table 6. Table 7 presents a cumulative summary of the ant algorithm results for each test, i.e., the value of the energy expenditure for all vehicles (kWh), the number of vehicles performing tasks (V), and the breakdown probability for the charging points determined collectively along all routes (P). The number of iterations of the algorithm was set at 200 repetitions and the population size was set at 50 ants in an experimental way.

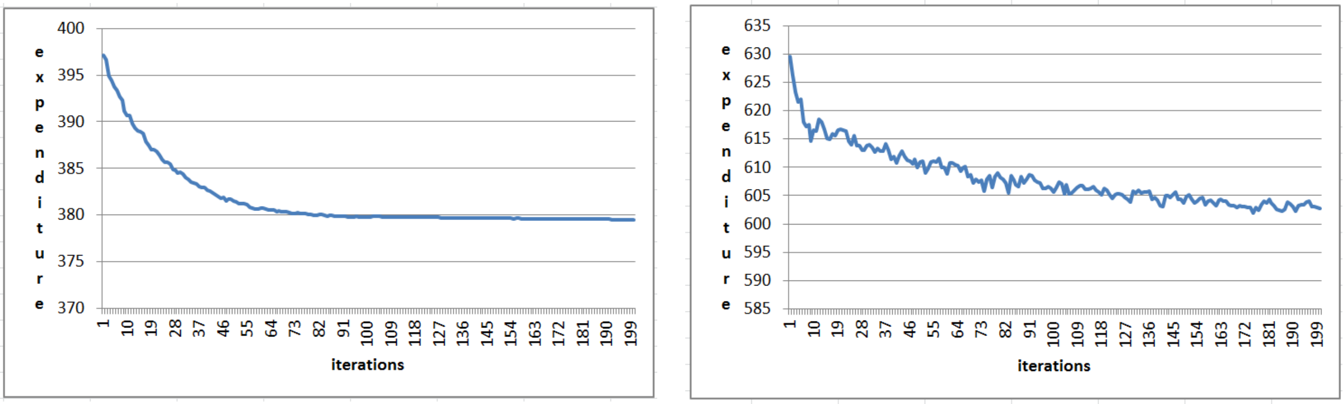
Table 6. Test settings of the ant algorithm parameters.

Test	α	β	ρ	Test	α	β	ρ	Test	α	β	ρ
1	1	0.5	0.2	21	1	1	0.2	41	1	5	0.2
2	1	0.5	0.4	22	1	1	0.4	42	1	5	0.4
3	1	0.5	0.6	23	1	1	0.6	43	1	5	0.6
4	1	0.5	0.8	24	1	1	0.8	44	1	5	0.8
5	3	0.5	0.2	25	3	1	0.2	45	3	5	0.2
6	3	0.5	0.4	26	3	1	0.4	46	3	5	0.4
7	3	0.5	0.6	27	3	1	0.6	47	3	5	0.6
8	3	0.5	0.8	28	3	1	0.8	48	3	5	0.8
9	5	0.5	0.2	29	5	1	0.2	49	5	5	0.2
10	5	0.5	0.4	30	5	1	0.4	50	5	5	0.4
11	5	0.5	0.6	31	5	1	0.6	51	5	5	0.6
12	5	0.5	0.8	32	5	1	0.8	52	5	5	0.8
13	10	0.5	0.2	33	10	1	0.2	53	10	5	0.2
14	10	0.5	0.4	34	10	1	0.4	54	10	5	0.4
15	10	0.5	0.6	35	10	1	0.6	55	10	5	0.6
16	10	0.5	0.8	36	10	1	0.8	56	10	5	0.8
17	20	0.5	0.2	37	20	1	0.2	57	20	5	0.2
18	20	0.5	0.4	38	20	1	0.4	58	20	5	0.4
19	20	0.5	0.6	39	20	1	0.6	59	20	5	0.6
20	20	0.5	0.8	40	20	1	0.8	60	20	5	0.8

Table 7. Expenditure, number of vehicles and breakdown probability for test settings.

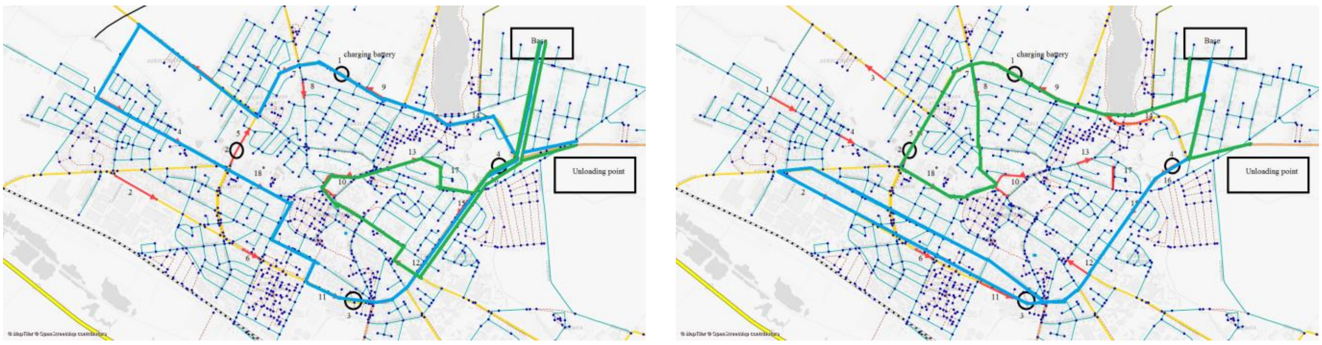
Test	(kWh)	(V)	(P)	Test	(kWh)	(V)	(P)	Test	(kWh)	(V)	(P)
1	489	2	0.12	21	523	2	0.04	41	398	2	0.06
2	477	2	0.20	22	500	2	0.05	42	467	2	0.09
3	643	2	0.12	23	380	2	0.04	43	395	2	0.10
4	386	2	0.12	24	410	2	0.07	44	465	2	0.09
5	399	2	0.23	25	541	2	0.08	45	460	2	0.11
6	603	2	0.14	26	534	2	0.11	46	499	2	0.15
7	678	2	0.21	27	555	2	0.12	47	512	2	0.13
8	612	2	0.22	28	532	2	0.13	48	532	2	0.16
9	600	2	0.14	29	567	2	0.11	49	612	2	0.18
10	632	2	0.17	30	543	2	0.14	50	611	2	0.19
11	611	2	0.21	31	653	2	0.12	51	600	2	0.20
12	636	2	0.20	32	632	2	0.15	52	623	2	0.22
13	611	3	0.19	33	612	3	0.22	53	614	3	0.24
14	676	3	0.14	34	600	3	0.21	54	632	3	0.21
15	688	3	0.23	35	632	3	0.23	55	655	3	0.20
16	704	3	0.14	36	668	3	0.12	56	663	3	0.22
17	743	3	0.12	37	704	3	0.14	57	776	3	0.32
18	789	3	0.43	38	777	3	0.32	58	843	3	0.31
19	801	3	0.33	39	754	3	0.14	59	883	3	0.21
20	898	3	0.22	40	756	3	0.32	60	804	3	0.25

The smallest value of energy expenditure reaching 380 (kWh) was generated for test number 23 with the following parameters for the algorithm: $\alpha = 1$, $\beta = 1$, and $\rho = 0.6$. The method of operation of the algorithm for test 23 and an example featuring test 6 are presented in Figure 7. A graphical presentation of the driving routes of the two vehicles generated in test 23 is presented in Figure 8. The energy expenditure for the first vehicle was 200 (kWh), the route travelled was 82 km, the breakdown uncertainty en route was 0.2, there was a single charging stop at charging point 4, and the loading points were as follows: 14, 9, 7, 3, 1, 4, 18, 16, 15, 12, 10, 13, and 17. The energy expenditure for the second vehicle was 180 (kWh), the route travelled was 75 km, the breakdown uncertainty en route was 0.2, there was a single charging stop at charging point 3, and the loading points were as follows: 8, 5, 2, 6, and 11.



(**a**) (**b**)

Figure 7. Operation of the ant algorithm: (**a**) test 23; (**b**) test 6.

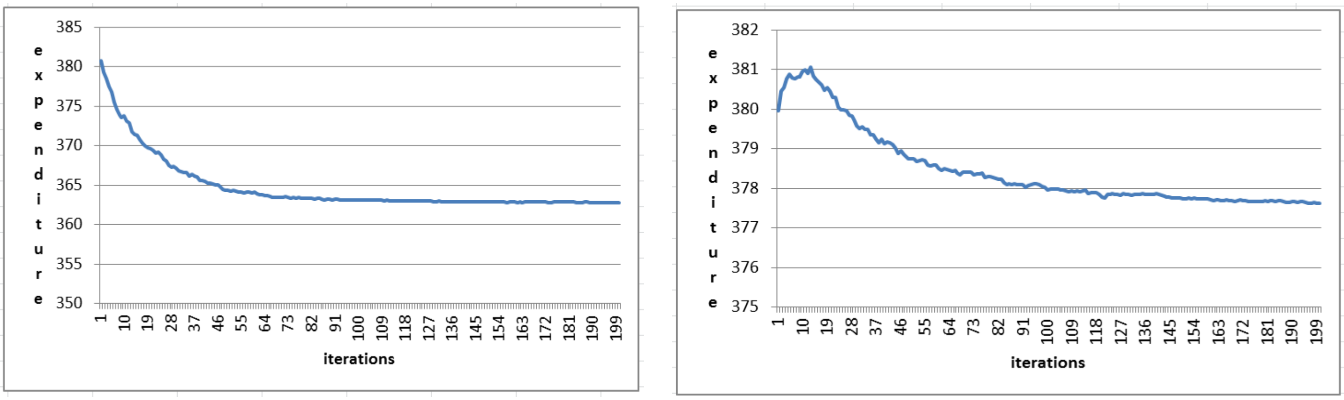


(**a**) (**b**)

Figure 8. The driving route of the vehicles created by the ant algorithm: (**a**) the first vehicle; (**b**) the second vehicle.

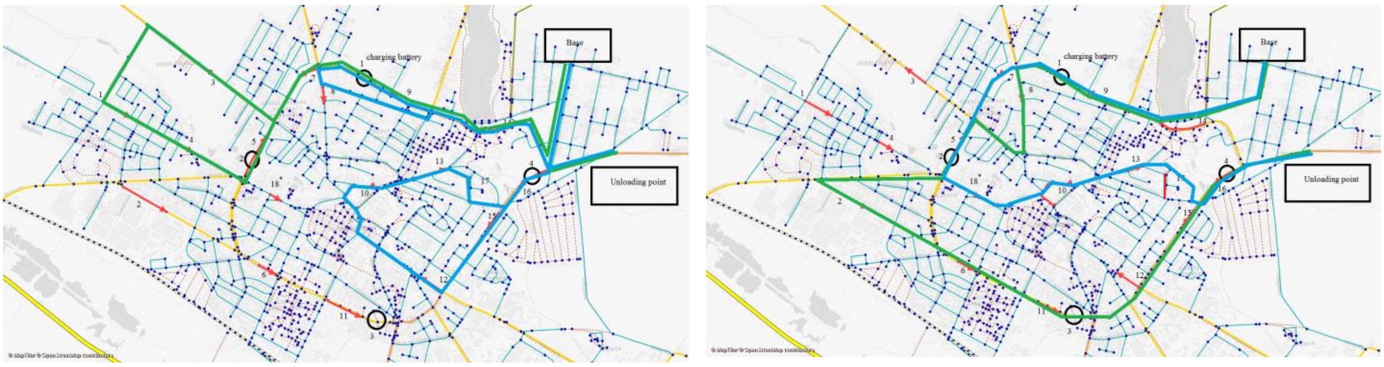
The initial population for the calibration of the genetic algorithm was generated using the ant algorithm based on the set of parameters from test 23. The crossbreeding operator, using $p = 0.2, 0.4, 0.6, 0.8$, and 1, is a parameter of the genetic algorithm [48]. Experimentally, the number of algorithm iterations was set to 200 repetitions and the population size was set to 50 chromosomes. The lowest value of energy expenditure for the parameter $p = 0.8$ amounted to 362 (kWh), and the uncertainty of charging point operation along the route of two vehicles was 0.04. The method of operation of the algorithm is presented in Figure 9. A visual presentation of the driving routes of two vehicles with the minimum energy expenditure is presented in Figure 10. The energy expenditure for the first vehicle was 180 (kWh), the distance travelled was 75 km, the breakdown uncertainty en route was 0.22, there was a single charging stop at charging point 2, and the loading points were as follows: 16, 15, 12, 10, 13, 9, 7, 3, 1, 4, and 5. The energy expenditure for the second vehicle was

182 (kWh), the distance travelled was 76 km, the breakdown uncertainty en route was 0.21, there was a single charging stop at charging point 4, and the loading points were as follows: 2, 6, 11, 8, and 18.



(**a**) (**b**)

Figure 9. Operation of the hybrid genetic algorithm: (**a**) p = 0.8; (**b**) p = 0.2.



(**a**) (**b**)

Figure 10. The driving route of the vehicles created by the hybrid genetic algorithm: (**a**) the first vehicle; (**b**) the second vehicle.

The ant and genetic algorithms are probabilistic algorithms, so each time they are run, they can generate different solutions. In order to verify the accuracy of the ant algorithm (A) and the hybrid genetic algorithm (G), 60 solutions were generated. Subsequently, the energy expenditure of the vehicles (E) generated by these algorithms and the probability associated with the uncertainty of charging point operation along these routes (P) were compared. Although the driving routes were determined in accordance with a limitation on the permissible risk related to the uncertainty of charging point operation (4), in the test column of Table 8, the time of the arrival of the vehicles at the loading points was compared with the time of the charging points' breakdowns presented in Table 2. If the time of the vehicle's arrival at a given point is inconsistent with the time of a charging point malfunction, the status OK is entered; in the case of both events being aligned in time, the point at which this alignment occurred is indicated. The average time required to generate a solution with the ant algorithm is seven minutes, while the hybrid genetic algorithm takes four minutes. The algorithms were run according to the best set of parameters established in the calibration process, i.e., $\alpha = 1$, $\beta = 1$, $\rho = 0.6$, and $p = 0.8$.

Table 8. Verification of the ant and hybrid genetic algorithms.

No.	A/G (E)	A/G (P)	A/G Test	No.	A/G (E)	A/G (P)	A/G Test	No.	A/G (E)	A/G (P)	A/G Test
1	380/364	0.09/0.08	OK/OK	21	377/365	0.08/0.12	OK/OK	41	398/373	0.07/0.12	OK/OK
2	370/353	0.10/0.12	OK/OK	22	380/360	0.11/0.11	OK/OK	42	467/380	0.10/0.11	OK/OK
3	391/372	0.12/0.13	OK/OK	23	380/376	0.12/0.10	OK/OK	43	395/377	0.12/0.13	OK/OK
4	386/370	0.07/0.06	OK/OK	24	410/370	0.06/0.08	OK/OK	44	365/376	0.16/0.14	OK/OK
5	399/369	0.12/0.15	OK/OK	25	441/373	0.12/0.06	OK/OK	45	360/350	0.12/0.13	OK/OK
6	403/380	0.14/0.12	OK/OK	26	434/367	0.14/0.09	OK/OK	46	399/371	0.14/0.05	OK/OK
7	378/377	0.15/0.09	OK/OK	27	455/360	0.13/0.05	OK/OK	47	412/345	0.12/0.06	OK/OK
8	412/393	0.11/0.13	OK/OK	28	432/345	0.12/0.12	OK/OK	48	432/355	0.12/0.08	OK/OK
9	400/380	0.06/0.11	OK/OK	29	377/350	0.07/0.15	OK/OK	49	412/345	0.11/0.10	OK/OK
10	392/380	0.07/0.14	OK/OK	30	443/355	0.07/0.05	OK/OK	50	411/360	0.10/0.11	OK/OK
11	380/360	0.11/0.13	OK/OK	31	412/367	0.05/0.04	OK/OK	51	400/355	0.14/0.13	OK/OK
12	436/379	0.12/0.08	OK/OK	32	432/369	0.12/0.06	OK/OK	52	423/370	0.13/0.11	OK/OK
13	411/366	0.13/0.05	OK/OK	33	412/370	0.09/0.05	OK/OK	53	414/345	0.12/0.08	OK/OK
14	376/350	0.11/0.13	OK/OK	34	398/369	0.10/0.12	OK/OK	54	432/367	0.06/0.11	OK/OK
15	388/365	0.12/0.14	OK/OK	35	389/350	0.11/0.14	OK/OK	55	365/345	0.06/0.12	OK/OK
16	404/360	0.08/0.16	OK/OK	36	368/340	0.07/0.11	OK/OK	56	363/344	0.19/0.13	OK/OK
17	443/367	0.04/0.14	OK/OK	37	404/350	0.05/0.14	OK/OK	57	376/333	0.10/0.14	OK/OK
18	389/359	0.05/0.16	OK/OK	38	377/345	0.05/0.12	OK/OK	58	443/356	0.11/0.11	OK/OK
19	401/380	0.05/0.08	OK/OK	39	354/340	0.05/0.06	OK/OK	59	383/345	0.07/0.08	OK/OK
20	380/372	0.10/0.09	OK/OK	40	456/347	0.14/0.08	OK/OK	60	404/380	0.12/0.07	OK/OK

Table 8 shows that the hybrid connection in which the ant algorithm generates the initial population for the genetic algorithm is an effective combination of the algorithms.

6. Discussion

The quality of the results obtained using the algorithms developed depends on the calibration process. In the calibration process, 60 test settings of the ant algorithm parameters and five crossbreeding parameter settings in the hybrid genetic algorithm were used. The space that allows for the search for an optimal solution is limited by the number of verified test combinations of these parameters. In order to expand this space, it is additionally necessary to check other parameter settings $\alpha = 1.5; 2$, whether $p = 0.5; 0.7$.

The best solution generated by the ant algorithm was determined for the small parameter values, e.g., $\alpha = 1$, $\beta = 1$, and $\rho = 0.6$. Maintaining a balance between the influence of the pheromone (α) and the heuristic information is important in the calibration of the ant algorithm (β). A large discrepancy between these two parameters means that the ant algorithm ceases to learn from the experiences of other ants and takes the form of a random search algorithm. The crossbreeding parameter plays a key role in the hybrid genetic algorithm. In the case of a small value of this parameter, the population of chromosomes is not diverse enough to generate new solutions. At a fast pace, the algorithm converges to the local optimum. In the case of a larger value of the crossing parameter, there is a strong level of competition between chromosomes in the population, and thus, there is an increase in the space allowing for the search for an optimal solution. The premature convergence of the ant algorithm in the initial phase of iterations is blocked by the continuous updating of the pheromone in each iteration of the algorithm.

The combination of the ant and genetic algorithms confirmed the effectiveness of the hybrid connection. In each of the tests conducted, the hybrid genetic algorithm found a better solution than the ant algorithm. The use of the genetic algorithm on its own is difficult due to the issue of generating an initial population. In the classic genetic algorithm, this population is randomly generated. The issue of determining vehicle driving routes requires designating a specific sequence of route points, which is difficult to achieve in a random manner. The use of a hybrid connection made it possible to implement a genetic algorithm and check its effectiveness in determining the energy expenditure of electric vehicles.

7. Conclusions

The aim of the conducted research was to develop a method that minimizes the energy expenditure of electric vehicles used in municipal service companies, taking into account the uncertainty of the operation of their charging points. Our approach to determining the routes of electric vehicles presented in this article shows that the use of appropriate algorithms reduces the energy expenditure of electric vehicles with the consideration of malfunctions in the operation of charging points. Our verification of the developed algorithms, i.e., the ant and hybrid genetic algorithms, confirmed their effectiveness. These algorithms can be an effective tool for assessing energy expenditure in service companies. The advantage of the presented algorithms is they are able to generate solutions in a short amount of time, which emphasizes their practical application. Our case study and its results provide valuable information on the feasibility of using ant and genetic algorithms to solve complex problems related to the routing of electric vehicles.

It should be emphasized that classic forms of the developed algorithms were implemented. For further research, their subsequent variations should be used, e.g., the use of ant hill systems, or research on other forms of selection in the genetic algorithm.

The decision-making model developed in this article can serve as a base model for testing other optimisation algorithms. The model developed was presented in a single-criterion approach. In further research, it should be expanded with other functions of the criterion, minimising the time of task implementation or its cost. Further research may also focus on combining the developed method with the charging problem of electric vehicles by optimal energy management for active distribution networks (ADNs) at electric vehicle charging stations [49].

For the proper operation of the heuristic algorithms used in this article, it is important to carry out the process of parameter calibration.

The developed hybrid combination of algorithms can be used to solve complex optimization problems in road transport and other transport branches, e.g., determining aircraft routes in air or rail transport, allocating a means of transport for certain tasks, or solving scheduling issues.

Author Contributions: Conceptualization, M.J. and M.I.; methodology, M.J.; software, J.B.; validation, M.J., M.I. and J.B.; formal analysis, M.J.; investigation, M.I.; resources, J.B.; data curation, J.B.; writing—original draft preparation, M.J.; writing—review and editing, M.I.; visualization, J.B.; supervision, M.J.; project administration, M.I.; funding acquisition, M.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data are contained within the article.

Acknowledgments: This research was funded by the National Science Centre, Poland (project no. 2022/04/Y/ST8/00134; project title: Energy optimal urban logistics as a service (E-LaaS)). The project was implemented as part of the call ERA-NET Cofund Urban Accessibility and Connectivity (EN-UAC China Call) organized by JPI Urban Europe and the National Natural Science Foundation of China (NSFC) funded by the European Union's Horizon 2020 research and innovation programme under grant agreement No. 875022.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Cieśla, M.; Sobota, A.; Jacyna, M. Multi-Criteria Decision Making Process in Metropolitan Transport Means Selection Based on the Sharing Mobility Idea. *Sustainability* **2020**, *12*, 7231. [CrossRef]
2. Pielecha, J.; Skobiej, K.; Kurtyka, K. Exhaust Emissions and Energy Consumption Analysis of Conventional, Hybrid, and Electric Vehicles in Real Driving Cycles. *Energies* **2020**, *13*, 6423. [CrossRef]
3. Zhou, G.; Hu, W.; Huang, W. Are Consumers Willing to Pay More for Sustainable Products? A Study of Eco-Labeled Tuna Steak. *Sustainability* **2016**, *8*, 494. [CrossRef]
4. Erickson, L.; Ma, S. Solar-Powered Charging Networks for Electric Vehicles. *Energies* **2021**, *14*, 966. [CrossRef]

5. Jiang, Y.; Leng, B.; Xi, J. Assessing the social cost of municipal solid waste management in Beijing: A systematic life cycle analysis. *Waste Manag.* **2024**, *173*, 62–74. [CrossRef] [PubMed]
6. Yıldız, B. Package routing problem with registered couriers and stochastic demand. *Transp. Res. Part E Logist. Transp. Rev.* **2021**, *147*, 102248. [CrossRef]
7. Jafar-Zanjani, H.; Zandieh, M.; Sharifi, M. Robust and resilient joint periodic maintenance planning and scheduling in a multi-factory network under uncertainty: A case study. *Reliab. Eng. Syst. Saf.* **2022**, *217*, 108113. [CrossRef]
8. Jacyna, M.; Semenov, I. Models of vehicle service system supply under information uncertainty. *Eksploat. I Niezawodn.—Maint. Reliab.* **2020**, *22*, 694–704. [CrossRef]
9. Kumar, S.N.; Panneerselvam, R. Development of an Efficient Genetic Algorithm for the Time Dependent Vehicle Routing Problem with Time Windows. *Am. J. Oper. Res.* **2017**, *7*, 1–25. [CrossRef]
10. Ibrahim, A.; Qader, H.; Latif, N. Use the Power of a Genetic Algorithm to Maximize and Minimize Cases to Solve Capacity Supplying Optimization and Travelling Salesman in Nested Problems. *J. Comput. Commun.* **2023**, *11*, 24–31. [CrossRef]
11. Adebayo, K.; Aderibigbe, F.; Dele-Rotimi, A. On the Development of a Hybridized Ant Colony Optimization (HACO) Algorithm. *Am. J. Comput. Math.* **2019**, *9*, 358–372. [CrossRef]
12. Liu, R.; Xie, X.; Augusto, V.; Rodriguez, C. Heuristic algorithms for a vehicle routing problem with simultaneous delivery and pickup and time windows in home health care. *Eur. J. Oper. Res.* **2013**, *230*, 475–486. [CrossRef]
13. Li, J.; Wang, F.; He, Y. Electric Vehicle Routing Problem with Battery Swapping Considering Energy Consumption and Carbon Emissions. *Sustainability* **2020**, *12*, 10537. [CrossRef]
14. Quak, H.; Nesterova, N.; van Rooijen, T.; Dong, Y. Zero Emission City Logistics: Current Practices in Freight Electromobility and Feasibility in the near Future. *Transp. Res. Procedia* **2016**, *14*, 1506–1515. [CrossRef]
15. Izdebski, M.; Jacyna, M. An Efficient Hybrid Algorithm for Energy Expenditure Estimation for Electric Vehicles in Urban Service Enterprises. *Energies* **2021**, *14*, 2004. [CrossRef]
16. Erdelić, T.; Carić, T. A Survey on the Electric Vehicle Routing Problem: Variants and Solution Approaches. *J. Adv. Transp.* **2019**, *54*, 1–48. [CrossRef]
17. Juan, A.; Mendez, C.; Faulin, J.; de Armas, J.; Grasman, S. Electric vehicles in logistics and transportation: A survey on emerging environmental, strategic, and operational challenges. *Energies* **2016**, *9*, 86. [CrossRef]
18. Keskin, M.; Çatay, B. Partial recharge strategies for the electric vehicle routing problem with time windows. *Transp. Res. Part C Emerg. Technol.* **2016**, *65*, 111–127. [CrossRef]
19. Vidal, T.; Crainic, T.G.; Gendreau, M.; Prins, C. Heuristics for multi-attribute vehicle routing problems: A survey and synthesis. *Eur. J. Oper. Res.* **2013**, *231*, 1–21. [CrossRef]
20. Agrawal, A.K.; Yadav, S.; Gupta, A.A.; Pandey, S. A genetic algorithm model for optimizing vehicle routing problems with perishable products under time-window and quality requirements. *Decis. Anal. J.* **2022**, *5*, 100139. [CrossRef]
21. Phuc, K.; Nguyen, P.; Thao, N.L.P. Ant Colony Optimization for Multiple Pickup and Multiple Delivery Vehicle Routing Problem with Time Window and Heterogeneous Fleets. *Logistics* **2021**, *5*, 28. [CrossRef]
22. Reed, M.; Yiannakou, A.; Evering, R. An ant colony algorithm for the multi-compartment vehicle routing problem. *Appl. Soft Comput.* **2014**, *15*, 169–176. [CrossRef]
23. Doppstadt, C.; Koberstein, A.; Vigo, D. The hybrid electric vehicle—Traveling salesman problem. *Eur. J. Oper. Res.* **2016**, *253*, 825–842. [CrossRef]
24. Roberti, R.; Wen, M. The electric traveling salesman problem with time windows. *Transp. Res. Part E Logist. Transp. Rev.* **2016**, *89*, 32–52. [CrossRef]
25. Barco, J.; Guerra, A.; Muñoz, L.; Quijano, N. Optimal routing and scheduling of charge for electric vehicles: A case study. *Math. Probl. Eng.* **2017**, *2017*, 8509783. [CrossRef]
26. Erdelić, T.; Carić, T.; Erdelić, M.; Tišljarić, L. Electric vehicle routing problem with single or multiple recharges. *Transp. Res. Procedia* **2019**, *40*, 217–224. [CrossRef]
27. Hiermann, G.; Puchinger, J.; Ropke, S.; Hartl, R.F. The electric fleet size and mix vehicle routing problem with time windows and recharging stations. *Eur. J. Oper. Res.* **2016**, *252*, 995–1018. [CrossRef]
28. Zhang, S.; Gajpal, Y.; Appadoo, S.S.; Abdulkader, M.M.S. Electric vehicle routing problem with recharging stations for minimizing energy consumption. *Int. J. Prod. Econ.* **2018**, *203*, 404–413. [CrossRef]
29. Macrina, G.; Pugliese, L.D.P.; Guerriero, F.; Laporte, G. The green mixed fleet vehicle routing problem with partial battery recharging and time windows. *Comput. Oper. Res.* **2019**, *101*, 183–199. [CrossRef]
30. Bruglieri, M.; Pezzella, F.; Pisacane, O.; Suraci, S. A variable neighborhood search branching for the electric vehicle routing problem with time windows. *Electron. Notes Discret. Math.* **2015**, *47*, 221–228. [CrossRef]
31. Desaulniers, G.; Errico, F.; Irnich, S.; Schneider, M. Exact algorithms for electric vehicle-routing problems with time windows. *Oper. Res.* **2016**, *64*, 1388–1405. [CrossRef]
32. Wu, J.; Wei, Z.; Liu, K.; Quan, Z.; Li, Y. Battery-involved Energy Management for Hybrid Electric Bus Based on Expert-assistance Deep Deterministic Policy Gradient Algorithm. *IEEE Trans. Veh. Technol.* **2020**, *69*, 12786–12796. [CrossRef]
33. Basma, H.; Mansour, C.; Haddad, M.; Nemer, M.; Stabat, P. A novel method for co-optimizing battery sizing and charging strategy of battery electric bus fleets: An application to the city of Paris. *Energy* **2023**, *285*, 129459. [CrossRef]

34. Abd-Elhaleem, S.; Shoeib, W.; Sobaih, A. Improved Power Management Under Uncertain Driving Conditions for Plug-In Hybrid Electric Vehicles via Intelligent Controller. *IEEE Trans. Intell. Transp. Syst.* **2023**, *99*, 1–15. [CrossRef]
35. Manoj, D.; Josh, F.T. A Comprehensive Review on Optimization and Artificial Intelligence Algorithms for Effective Battery Management in EVs. *Int. J. Electr. Electron. Eng. Telecommun.* **2023**, *12*, 334–341. [CrossRef]
36. Caylak, O.; Yaman, A.; Baumeier, B.R. Evolutionary approach to constructing a deep feedforward neural network for prediction of electronic coupling elements in molecular materials. *J. Chem. Theory Comput.* **2019**, *15*, 1777–1784. [CrossRef] [PubMed]
37. Chaoufi, I.; Abdelkhalek, O.; Gasbaoui, B. State of charge estimation of lithium-ion batteries using adaptive neuro fuzzy inference system. *IAES Int. J. Artif. Intell.* **2022**, *11*, 473–484. [CrossRef]
38. Hu, X.; Liu, T.; Qi, X.; Barth, M. Reinforcement learning for hybrid and plug-in hybrid electric vehicle energy management: Recent advances and prospects. *IEEE Ind. Electron. Mag.* **2019**, *13*, 16–25. [CrossRef]
39. Samanta, A.; Chowdhuri, S.; Williamson, S.S. Machine learning-based data-driven fault detection/diagnosis of lithium-ion battery: A critical review. *Electronics* **2021**, *10*, 1309. [CrossRef]
40. Lucas, A.; Barranco, R.; Refa, N. EV idle time estimation on charging infrastructure, comparing supervised machine learning regressions. *Energies* **2019**, *12*, 269. [CrossRef]
41. Li, Y.; Wang, Z.; Xu, W.; Gao, W.; Xu, Y.; Xiao, F. Modeling and energy dynamic control for a ZEH via hybrid model-based deep reinforcement learning. *Energy* **2023**, *277*, 127627. [CrossRef]
42. Sun, X.; Fu, J.; Yang, H.; Xie, M.; Liu, J. An energy management strategy for plug-in hybrid electric vehicles based on deep learning and improved model predictive control. *Energy* **2023**, *269*, 126772. [CrossRef]
43. Normasari, N.M.; Yu, V.F.; Bachtiyar, C. Sukoyo A simulated annealing heuristic for the capacitated green vehicle routing problem. *Math. Probl. Eng.* **2019**, *2019*, 2358258. [CrossRef]
44. Vincent, F.Y.; Redi, A.A.N.P.; Hidayat, Y.A.; Wibowo, O.J. A simulated annealing heuristic for the hybrid vehicle routing problem. *Appl. Soft Comput.* **2017**, *53*, 119–132. [CrossRef]
45. Joo, H.; Lim, Y. Ant colony optimized routing strategy for electric vehicles. *J. Adv. Transp.* **2018**, *2018*, 5741982. [CrossRef]
46. Alesiani, F.; Maslekar, N. Optimization of Charging Stops for Fleet of Electric Vehicles: A Genetic Approach. *IEEE Intell. Transp. Syst. Mag.* **2014**, *6*, 10–21. [CrossRef]
47. Gołda, P.; Zawisza, T.; Izdebski, M. Evaluation of efficiency and reliability of airport processes using simulation tools. *Eksploat. I Niezawodn.—Maint. Reliab.* **2021**, *23*, 659–669. [CrossRef]
48. Izdebski, M.; Jacyna-Gołda, I.; Gołda, P. Minimisation of the probability of serious road accidents in the transport of dangerous goods. *Reliab. Eng. Syst. Saf.* **2022**, *217*, 108093. [CrossRef]
49. Zening, L.; Su, S.; Xiaolong, J.; Mingchao, X.; Qifang, C.; Koji, Y. Stochastic and distributed optimal energy management of active distribution network with integrated office buildings. *CSEE J. Power Energy Syst.* **2024**, *10*, 504–517. [CrossRef]