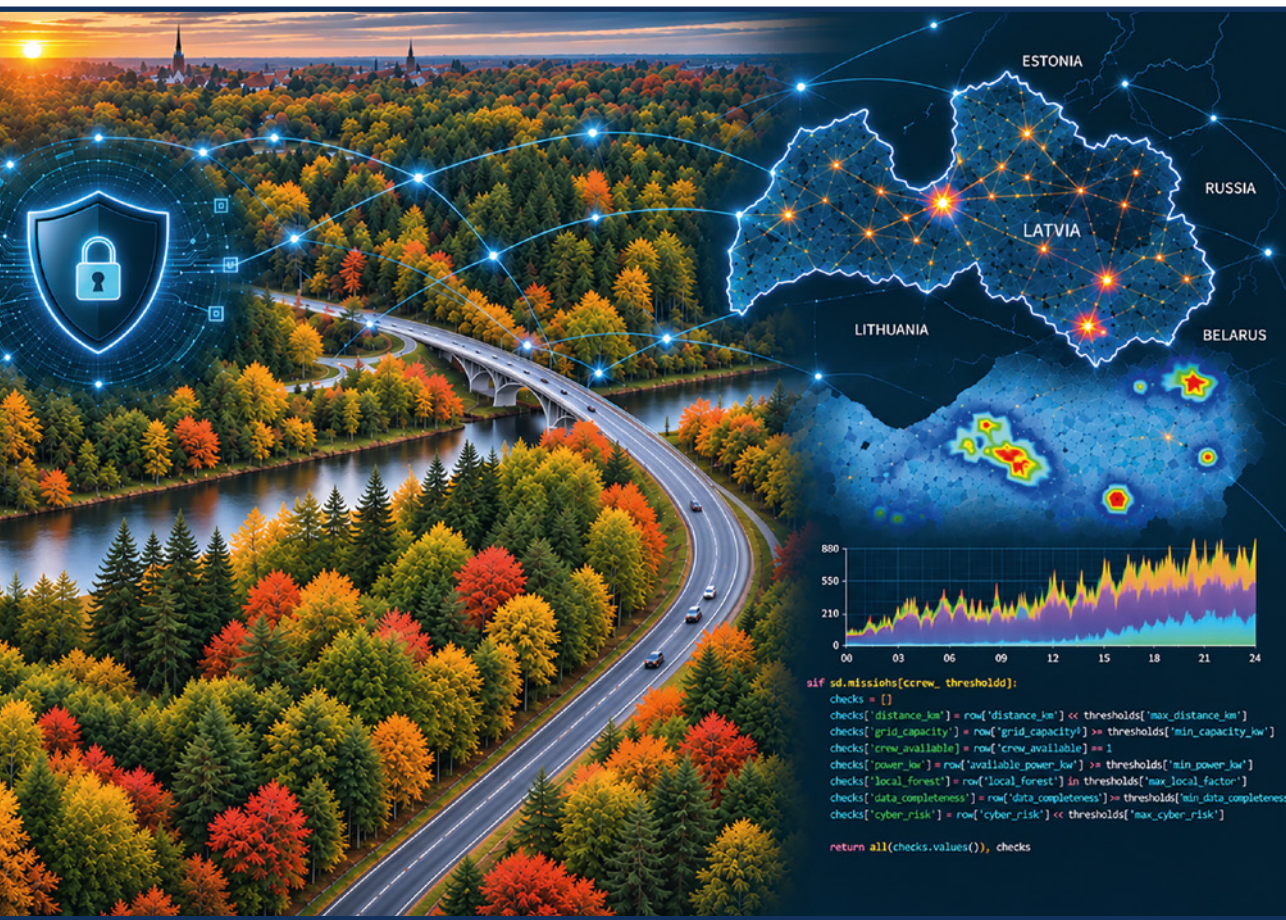
RIGA TECHNICAL UNIVERSITY

Roberts Grants

DECISION SUPPORT SYSTEM DEVELOPMENT FOR RELIABILITY-ORIENTED DYNAMIC ELECTRIC VEHICLE CHARGING POINT ASSIGNMENT

Summary of the Doctoral Thesis



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Faculty of Computer Science, Information Technology and Energy
Institute of Industrial Electronics, Electrical Engineering and Energy

Roberts Grants
Doctoral Student of the Study Programme "Computerised Control of Electrical Technologies"

DECISION SUPPORT SYSTEM DEVELOPMENT FOR RELIABILITY-ORIENTED DYNAMIC ELECTRIC VEHICLE CHARGING POINT ASSIGNMENT

Summary of the Doctoral Thesis

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DOCTORAL THESIS PROPOSED TO RIGA TECHNICAL UNIVERSITY FOR PROMOTION TO THE SCIENTIFIC DEGREE OF DOCTOR OF SCIENCE

To be granted the scientific degree of Doctor of Science (PhD), the present Doctoral Thesis has been submitted for defence at an open meeting of the RTU Promotion Council on 21 December 2026 at 13:00, at the Institute of Industrial Electronics, Electrical Engineering and Energy, Riga Technical University, Āzenes Street 12/1, Room 525, Riga, Latvia.

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DECLARATION OF ACADEMIC INTEGRITY

I hereby declare that the Doctoral Thesis submitted for review to Riga Technical University for promotion to the scientific degree of Doctor of Science (PhD) is my own. I confirm that this Doctoral Thesis has not been submitted to any other university for promotion to a scientific degree.

Roberts Grants ……. (signature)
Date: ……

The Doctoral Thesis has been prepared as a monographic doctoral thesis presenting an original scientific study on reliability-oriented dynamic electric vehicle charging point assignment. The Thesis consistently presents the theoretical basis of the research, the developed multi-criteria decision-making model, its algorithmic implementation, the validation data and scenario environment, the analysis of results and the possibilities for practical implementation.

The results of the Doctoral Thesis have been approbated in 18 publications by the author and co-authors.

The Doctoral Thesis has been written in Latvian. It consists of an Introduction, six chapters, Conclusions, Proposals and a Bibliography. The Thesis includes 26 figures, 74 tables and 115 equations. The total number of pages is 198, not including appendices. The Bibliography contains 62 titles.

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GENERAL DESCRIPTION OF THE DOCTORAL THESIS

Relevance of the research

The growth in the number of electric vehicles (EVs) worldwide and in Europe is substantially changing the interaction between the transport and energy sectors. Electromobility is becoming an important element of sustainable mobility, decarbonisation, energy efficiency and the transformation of electricity systems [1]–[5]. As the number of electric vehicles increases, so do the requirements for publicly accessible, technically safe, user-friendly charging infrastructure that is acceptable to the distribution network [1], [2], [6].

Electric vehicle charging demand is uneven in space and time. It is influenced by users' travel habits, the battery state of charge, the charging power, the availability of charging points, the loading of the local distribution network, the availability of renewable energy resources and the operation of digital management systems [7]–[11]. Uncoordinated or simultaneous charging can increase the local distribution network load, create overload risk, voltage deviations and growing electricity losses [7], [10], [11]. Therefore, EV integration into the distribution network is not only a question of connection or building charging infrastructure, but a complex problem of interaction between the power system, the transport system, digital management, user behaviour, data quality and cybersecurity [7], [8], [12]–[14].

At the practical level, the question is becoming increasingly important not only of where to place charging stations, but also of how to select the most suitable charging point for a particular electric vehicle at a particular time. This choice cannot be reduced to a single criterion – the nearest station, the shortest waiting time, the lowest price or the highest nominal charging power. The most suitable alternative is determined by the vehicle's state, the required amount of energy, the actual availability of the charging point, the waiting time, the distribution network load, the power reserve, the user's requirements, the data quality, the reliability and the cybersecurity risk [7]–[14]. Since modern charging infrastructure is a cyber-physical system, the choice of charging point must be not only convenient for the user and technically feasible, but also reliable from the data, communication, distribution network and cybersecurity perspective [9], [13]–[15].

Research problem and research gap

Existing studies in the field of electric vehicle charging extensively address charging station siting, capacity selection, smart charging strategies, user behaviour, aggregator control and the integration of charging infrastructure into the electricity system [7], [8], [10], [11], [15]–[23]. These studies are important for infrastructure development, but they mostly address long-term planning, location selection or charging process control problems, rather than the operational assignment of a charging point to a specific EV at a specific time.

The research gap of the Doctoral Thesis is associated with the insufficient development of an operational and dynamic charging point assignment approach. Practical solutions are often dominated by the logic of selecting the nearest station, a free charging point, the shortest waiting time or the largest available power, which is not sufficient when the suitability of alternatives is determined by several mutually conflicting criteria [7], [10], [12]–[14]. In the Doctoral Thesis, this problem is addressed by developing a reliability-oriented dynamic multi-criteria decision-making methodology that makes it possible to compare several charging alternatives, integrate user, charging infrastructure, distribution network, data quality, reliability and cybersecurity criteria, and obtain an interpretable ranking of charging points and a sequence of backup alternatives.

The need for a multi-criteria decision-making approach

Dynamic electric vehicle charging point assignment is essentially a multi-criteria decision-making problem. For the user, the most suitable alternative may be the nearest or cheapest charging location, whereas from the distribution network perspective, the more suitable alternative may be one with a lower local network load or a larger power reserve. Similarly, a high-charging-power alternative is not always the best if it has low data quality, a high cybersecurity risk or an unstable operating status [7], [10], [12]–[14].

Multi-criteria decision-making methods are suitable for situations in which it is necessary to structure a complex decision space, combine quantitative and qualitative criteria, ensure transparent comparison of alternatives and justify a compromise decision among differing interests [24]–[26]. The Doctoral Thesis uses the Analytic Hierarchy Process (AHP) and the PROMETHEE method. AHP is used to determine the criteria hierarchy and relative importance, whereas PROMETHEE is used to prioritise the admissible charging alternatives and obtain a complete ranking [25], [27], [28]. Such a division of methods makes it possible to separate the structuring of criteria weights from the operational ranking of the alternatives available at a particular decision moment.

An essential feature of the Doctoral Thesis is its dynamic view of charging point suitability. The evaluation of charging alternatives is not static, because charging demand, station availability, distribution network load, available power, user priorities, data quality and security status change over time [29]. Therefore, the study develops dynamic filtering and recalculation logic that makes it possible to update the set of alternatives and the ranking in accordance with changing operating conditions.

Research object and subject

The research object of the Doctoral Thesis is electric vehicle charging infrastructure in the context of distribution networks and cyber-physical management.

The research subject of the Doctoral Thesis is a multi-criteria decision-making methodology for reliability-oriented dynamic electric vehicle charging point assignment.

Aim and tasks of the Doctoral Thesis

The Doctoral Thesis aims to develop and validate a multi-criteria decision-making-based model for reliability-oriented dynamic electric vehicle charging point assignment, using operational data on the electric vehicle's state, charging infrastructure availability, distribution network parameters, renewable energy availability, data quality and cybersecurity risk.

To achieve this aim, the following tasks were set:

1) to analyse the development trends of electric vehicle charging infrastructure, its impact on distribution networks and the research context of charging management;
2) to assess the suitability of multi-criteria decision-making methods, particularly AHP and PROMETHEE, for the dynamic electric vehicle charging point assignment task;
3) to identify and structure the criteria that influence charging point suitability, including vehicle, charging point, user, distribution network, economic, renewable energy, reliability, data quality and cybersecurity criteria;
4) to develop a reliability-oriented criteria hierarchy and define the logic for using the criteria weights, based on the AHP approach;
5) to develop a PROMETHEE-based alternative prioritisation model for ranking the admissible charging points;
6) to develop a dynamic filtering and recalculation algorithm that makes it possible to exclude alternatives that are inadmissible in technical, operational, network, data quality or cybersecurity terms;

7) to create a data, scenario and experimental validation environment, using anonymised electric vehicle charging infrastructure objects, load profiles, network parameters, data quality indicators and cybersecurity scenarios;
8) to validate the developed model by comparing it with simplified assignment strategies;
9) to assess the contribution of the reliability, distribution network, data quality and cybersecurity criteria to the result of dynamic electric vehicle charging point assignment.

Research hypothesis

The hypothesis of the Doctoral Thesis: A reliability-oriented dynamic multi-criteria assignment approach that integrates, within a single model, the electric vehicle's state, charging infrastructure availability, distribution network parameters, user requirements, data quality and cybersecurity risk provides a more justified and more interpretable charging point selection than static or limited-criteria approaches.

The hypothesis is tested within the bounds of methodological and scenario-based validation. The work assesses whether the developed AHP–PROMETHEE model is able to integrate user, infrastructure, distribution network, data quality, reliability and cybersecurity criteria into the charging point selection in a structured, reproducible and interpretable way.

Research methods

The following research methods are used in the Doctoral Thesis:

- analysis of scientific literature, legal acts and industry sources;
- multi-criteria decision-making methods, particularly AHP and PROMETHEE;
- operationalisation of criteria;
- data preprocessing and normalisation;
- scenario modelling;
- algorithmic prototyping in a Python environment;
- comparative analysis with simplified charging point assignment approaches;
- sensitivity analysis with respect to changes in criteria weights and in the distribution network and cybersecurity criteria.

Scientific novelty

The scientific novelty of the Doctoral Thesis is expressed in the following aspects.

1. Dynamic electric vehicle charging point assignment is formalised as an operational multi-criteria decision-making problem, distinguishing it from classical charging station siting and capacity planning.
2. A reliability-oriented criteria system has been developed that combines, within a single model, the electric vehicle, charging point, user, distribution network, economic, renewable energy, data quality, reliability and cybersecurity criteria.
3. An AHP–PROMETHEE-based methodology has been developed in which AHP is used to determine the criteria hierarchy and weights, and PROMETHEE is used for prioritising the admissible alternatives and obtaining the complete ranking of charging points.
4. Reliability and cybersecurity are integrated into the charging point assignment model as full decision criteria, filtering conditions or final priority correction factors.

5. Dynamic filtering and recalculation logic has been developed that makes it possible to update the set of alternatives, the criteria values and the ranking in accordance with changing operating conditions.
6. A methodological validation environment has been created with anonymised electric vehicle charging infrastructure objects, load profiles, technical parameters, data quality indicators and cybersecurity scenarios.

Practical significance

The practical significance of the Doctoral Thesis is associated with the possibility of using the developed methodology as the computational core of a decision support system in electric vehicle charging infrastructure management. For charging infrastructure operators, this approach can help to assign users more suitable charging points, taking into account not only distance or the availability of free connections, but also charging power, waiting time, distribution network load, data quality, reliability and security criteria. For distribution system operators, the model offers a decision-making layer in which the charging point selection takes into account the operating regime of the distribution network, the local load, the available power reserve and the potential overload risk.

In the context of cybersecurity management, the developed approach makes it possible to include data quality, communication reliability, authentication, data integrity and cyberrisk indicators in the selection of charging alternatives. The developed model is not a commercial software product, but a methodologically validated computational core of a decision support system prototype, which can be further developed for the needs of charging infrastructure operators, distribution system operators, municipalities, cybersecurity management, smart charging and a charging infrastructure digital twin.

Data and code availability

To ensure reproducibility of the Doctoral Thesis calculations, the developed Python calculation code, the anonymised validation data, the scenario configurations and the result-generation scripts have been prepared as a separate research data and code appendix.

The appendix does not include non-anonymised infrastructure data, data that precisely identify objects, or sensitive cybersecurity information. The publishable dataset contains only anonymised input data, calculation results and scenario parameters necessary for methodological verification.

Data and code are available at: https://doi.org/10.5281/zenodo.20383316

Approbation of the research results

The results of the Doctoral Thesis have been approbated in the scientific publications of the author and co-authors, in international conference proceedings and in peer-reviewed journals. The publications cover EV charging infrastructure, distribution network integration, decision support systems, cybersecurity, digitalisation, data quality and cyber-physical system reliability.

Scientific publications of the author and previous works related to the Doctoral Thesis

Publications directly related to the topic of the Doctoral Thesis

1. **Grants, R**. Integration opportunities of electric vehicle charging stations in low-voltage power supply network construction projects. Engineering project. Riga: Riga Technical University, 2020.
2. Bisenieks, M.; **Grants, R**.; Krumins, O.; Zabasta, A. Fast Charging for Electric Vehicles Station Integration with Renewable Energy Sources. In: 2022 IEEE 7th

International Energy Conference (ENERGYCON), 2022. DOI: 10.1109/ENERGYCON53164.2022.9830155.

3. Kunicina, N.; Beliaev, V.; **Grants, R.**; Caiko, J.; Amanova, R.; Brūzgienė, R.; Mansurova, M. Decision-Making System for Electric Vehicle Management by Integrating Smart Technologies and Local Characteristics. Applied Sciences, 2024, 14, 11150. DOI: 10.3390/app142311150.
4. **Grants, R.**; Kunicina, N.; Brūzgienė, R.; Grigaliūnas, Š.; Romanovs, A. Decision-Support Framework for Cybersecurity Risk Assessment in EV Charging Infrastructure. Energies, 2026, 19, 1814. DOI: 10.3390/en19081814.

Publications on electricity systems, distribution network digitalisation, renewable energy sources and data analysis

5. **Grants, R.** Integration of an electric vehicle fast charging station with renewable energy sources. Master's thesis. Riga: Riga Technical University, 2020.
6. Bisenieks, M.; **Grants, R.**; Krumins, O.; Caiko, J.; Shuvarina, A.; Ziravecka, A. Operational Management for Grid Connections. In: 2023 IEEE 10th Jubilee Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE), 2023. DOI: 10.1109/AIEEE58915.2023.10134826.
7. Gauce, D.; Lektauers, A.; Solovjova, I.; **Grants, R.**; Kolosovs, D.; Litvinenko, A. Application of Digital Twin in Medium-Voltage Overhead Distribution Network Inspection. Remote Sensing, 2023, 15, 489. DOI: 10.3390/rs15020489.
8. **Grants, R.**; Baltputnis, K.; Junghāns, G.; Zāģere-Tihova, S.; Bruksle, B.; Groza, E. Forecasting Accuracy and Portfolio Effect Impact on Renewable Power Plant Imbalance Costs. In: 2025 IEEE 66th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), 2025. DOI: 10.1109/RTUCON67996.2025.11415022.
9. **Grants, R.** Enerģētikas nākotne 2025: globālās tendences un Latvijas pielāgošanās. Enerģija, 2025, Nr. 4, ISSN: #2592-9844

Publications on control systems, automation, reliability and cyber-physical systems

10. Beliaev, V.; Kunicina, N.; Ziravecka, A.; Bisenieks, M.; **Grants, R.**; Patlins, A. Development of Adaptive Control System for Aerial Vehicles. Applied Sciences, 2023, 13, 12940. DOI: 10.3390/app132312940.
11. Alizada, R.; Beliaev, V.; **Grants, R.**; Utesevs, I.; Ziravecka, A.; Romanovs, A. Conceptual Model of Control Reliability and Safety for Integrated Maritime Navigation through Cognitive Route Simulation. In: 2024 IEEE 11th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE), 2024. DOI: 10.1109/AIEEE62837.2024.10586716.
12. Beliaev, V.; Utesevs, I.; **Grants, R.**; Bisenieks, M.; Ziravecka, A.; Caiko, J. Extremum-Seeking Adaptive Controllers for Energy Efficient Unmanned Aerial Vehicles. In: 2024 IEEE 11th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE), 2024. DOI: 10.1109/AIEEE62837.2024.10586635.
13. Kunicina, N.; Bisenieks, M.; **Grants, R.**; Balodis, V. Automated Level Control System Development for Harbor Tank Storage for Smart Cities. In: 2025 IEEE 66th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), 2025. DOI: 10.1109/RTUCON67996.2025.11415052.

14. Zhao, B.; Zheng, D.; Yang, C.; Wang, S.; Mansurova, M.; Jomartova, S.; Kunicina, N.; Zabasta, A.; Beliaev, V.; Caiko, J.; **Grants, R.** Design and Optimization of an Internet of Things-Based Cloud Platform for Autonomous Agricultural Machinery Using Narrowband Internet of Things and 5G Dual-Channel Communication. Electronics, 2025, 14, 1672. DOI: 10.3390/electronics14081672.

Publications on MCDM, sustainability, education and smart methods

15. Hnatov, A.; Bisenieks, M.; Arhun, S.; **Grants, R.**; Mygal, V.; Ulianets, O. Prospects for the Use of Electric Drives in Urban Passenger Vehicle Transport in Ukraine. In: 2023 IEEE 64th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), 2023. DOI: 10.1109/RTUCON60080.2023.10413061.
16. Kunicina, N.; Caiko, J.; **Grants, R.** Cultivating Future-Ready Education: Striking a Balance with Personalized Empowerment in Electrical Engineering. In: 2023 IEEE 64th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), 2023. DOI: 10.1109/RTUCON60080.2023.10412931.
17. Kunicina, N.; Caiko, J.; **Grants, R.** Enhancing Student Motivation and Academic Success. Effective Strategies for Promoting Study Programs in Education. In: 2023 IEEE 64th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), 2023. DOI: 10.1109/RTUCON60080.2023.10413029.
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20. Lei, S.; Yang, C.; **Grants, R.**; Grunde, U.; Kunicina, N. PDGM-PINN: Partial Derivative Guided Multi-Branch Physics-Informed Neural Network. Mathematics, 2026, 14, 1349. DOI: 10.3390/math14081349.

Structure of the Doctoral Thesis

The Doctoral Thesis consists of an introduction, six chapters, conclusions, proposals, a list of references and appendices.

Chapter 1 analyses the development of electric vehicle charging infrastructure and the research context. Chapter 2 develops a theoretical model for reliability-oriented dynamic electric vehicle charging point assignment. Chapter 3 operationalises and algorithmically implements the multi-criteria decision-making (MCDM) methodology. Chapter 4 creates the data, scenario and experimental validation environment. Chapter 5 validates the developed model and analyses the results. Chapter 6 provides a discussion of the results, a comparison with the literature, an assessment of the scientific and practical contribution, implementation opportunities, research limitations and directions for further development.

At the end of the Doctoral Thesis, the main conclusions and proposals are formulated, as well as the theses put forward for defence.

Use of artificial intelligence tools in the preparation of the Doctoral Thesis

During the preparation of the Doctoral Thesis, artificial intelligence tools were used solely as auxiliary tools for the editorial and technical improvement of the text prepared by the author. Their use was limited to checking language, grammar and style, improving sentence clarity, harmonising terminology, reducing repetitions, and reviewing the structure and formatting of individual text fragments.

Artificial intelligence tools were not used to generate the scientific content of the Doctoral Thesis, develop the research methodology, perform calculations, process data, interpret results, or formulate conclusions or recommendations. The research idea, aim, tasks, methodological approach, data selection, model development, calculations, analysis of results, scientific novelty, conclusions and recommendations presented in the Doctoral Thesis are the result of the author's independent work.

All editorial suggestions provided by artificial intelligence tools were critically assessed, verified and, where necessary, corrected by the author. The author assumes full responsibility for the content of the Doctoral Thesis, its scientific accuracy, the methods applied, the results obtained, their interpretation and the final version of the work.

Artificial intelligence tools were not used as a source of scientific literature, and the information provided by such tools was not used as independent evidence or as a reference in the theoretical or empirical parts of the Doctoral Thesis.

1. DEVELOPMENT OF ELECTRIC VEHICLE CHARGING INFRASTRUCTURE AND RESEARCH CONTEXT

This chapter analyses the development of electric vehicle charging infrastructure and its research context. The aim of the chapter is to justify why the selection of an electric vehicle charging point should be viewed not as a simple choice of the nearest, cheapest or most powerful station, but as an operational, time-varying and multi-criteria decision-making problem. The chapter examines electromobility development trends, the impact of EV charging on the distribution network, the cyber-physical nature of charging infrastructure, the types of charging infrastructure and the use of MCDM approaches in the EV infrastructure literature.

1.1. Development of electric vehicles and their impact on electricity supply systems

The development of electric vehicles has in recent years become one of the most significant directions of change in the transport and energy sectors. The growth of electromobility is driven by transport sector decarbonisation goals, the reduction of fossil fuel consumption, increased energy efficiency, technological development in the field of batteries and charging infrastructure, and policy instruments that promote the use of zero-emission vehicles [1]–[5].

Global electromobility development has accelerated considerably over the past decade. Data from the International Energy Agency show that in 2024 more than 17 million electric cars were sold worldwide, while the share of electric cars in the new car market exceeded 20 % [1]. In the European Union, electromobility development is closely linked to climate policy, the reduction of transport emissions and the development of alternative fuels infrastructure [3]–[6].

At the same time, electromobility is changing the operating characteristics of electricity supply systems. An electric vehicle is not only a new type of vehicle, but also a mobile electricity consumer whose charging need depends on the user's travel habits, the battery state of charge, the selected charging power, the available infrastructure and the state of the particular electricity supply network. Consequently, EV charging increases the interdependence between transport and electricity systems, especially at the distribution network level [7], [10], [11].

The development of electromobility in Latvia has in recent years been moving from an initial deployment stage to a stage of faster growth and infrastructure expansion. According to data published by e-transports/CSDD, on 1 January 2026, there were 14 385 electric vehicles registered in Latvia, while on 1 April 2026, there were already 15 309 electric vehicles [30]. At the same time, in 2025, 1 606 new electric cars were registered in Latvia, which is 27.7 % more than in 2024 [31].

Latvia's public charging infrastructure is gradually transitioning from an initially dominant national fast charging network to a multi-operator environment, in which several alternatives with different power, price, availability, payment model and data quality may be available to a user within a specific area. The development of electromobility is taking place in parallel with changes in the electricity system. According to data from the Official Statistics Portal dataset ENB010m, in 2025, gross electricity production in Latvia was 5959 GWh, while supplies to the domestic market reached 7200 GWh. Electricity generation in solar power plants increased from 403 GWh in 2024 to 683 GWh in 2025 [32].

Under these conditions, EV charging infrastructure is becoming an important issue for electricity supply system flexibility, load management and reliability. EV charging load is spatially concentrated, time-varying and dependent on user behaviour; therefore, it can increase the loading of transformers and lines, load peaks, voltage deviations, phase unbalance and electricity losses [10], [11], [33]. At the same time, modern charging infrastructure is a cyber-

physical system in which electricity supply is linked to data exchange, authentication, payment systems, operator platforms, remote monitoring and cybersecurity risks [9], [13]–[15], [34].

1.2. Types and operating principles of EV charging infrastructure

Electric vehicle charging infrastructure is a heterogeneous technical and digital system that can be classified by energy supply type, charging power, access mode, operating environment and communication solutions. This classification is important because it determines not only the technical parameters of the charging process, but also the user experience, charging duration, infrastructure utilisation and interaction with the distribution network [2], [10], [11], [35].

By energy supply type, charging infrastructure is most commonly divided into alternating current (AC) and direct current (DC) charging solutions. In AC charging, the conversion of electricity into the direct current required for battery charging usually takes place in the vehicle's on-board charger; therefore, such solutions are generally associated with lower or medium charging power. In DC charging, power conversion takes place in the charging station itself, enabling higher charging power and shorter charging time [2], [35].

By power and charging duration, charging infrastructure can be divided into slow, fast and ultra-fast charging. In IEA analyses, public slow chargers are defined as devices with power up to 22 kW, fast chargers exceed 22 kW, and ultra-fast chargers reach 150 kW or more [2]. Higher charging power reduces charging time, but at the same time increases the instantaneous load on the network. Therefore, charging point suitability must be assessed not only by nominal power but also by connection capacity, local network loading, available power reserve and the intensity of charging sessions [10], [11].

By access mode, charging infrastructure can be divided into private, semi-public and public infrastructure. This distinction is significant in the context of dynamic charging point assignment, because the alternatives available to a user at a particular time may differ in technical parameters, access conditions, price, reservation options, operator data quality and actual utilisation [10], [35].

A modern charging point is a technical and digital node in which electricity supply, data exchange, user identification, payment processing, status monitoring, session management and communication with the operator's management system take place simultaneously. Therefore, in a dynamic charging point assignment model, the charging point must be described by a broader set of characteristics: distance, power, price, waiting time, availability, data timeliness, communication reliability, compatibility, network load profile and cybersecurity risk level.

1.3. Charging point selection as a multi-criteria decision problem

In practice, the selection of an electric vehicle charging point cannot be reduced to a single criterion, such as the geographically nearest, cheapest or nominally most powerful station. In a real operating situation, the most suitable charging alternative is simultaneously influenced by spatial reachability, actual station availability, waiting time, station utilisation, the vehicle's charging need, user flexibility, the technical state of the distribution network, data quality, service reliability and cybersecurity risk [7], [10], [12]–[14].

Unlike charging infrastructure planning tasks, in which the main question is station siting, capacity selection or ensuring network coverage, this Doctoral Thesis focuses on an operational decision: which charging point should be assigned to a particular EV at a particular time. This means that the decision problem is not only spatial but also dynamic. The set of available alternatives changes over time, the criteria values change over time, and the best alternative depends on the specific operating moment.

In charging point selection, the infrastructure availability shown on a map must be distinguished from real service availability at a particular time. A charging point may be located

in a convenient place for the user but may be occupied, non-operational, reserved, technically incompatible or associated with elevated network, data quality or cybersecurity risk. Therefore, charging point suitability cannot be determined only by nominal power or user convenience, but also by whether the local network is able to accommodate the additional load at the relevant moment.

With the digitalisation of charging infrastructure, charging point selection is influenced not only by physical and operational parameters but also by reliability, data quality and cybersecurity factors. The reliability dimension includes charging point operability, service continuity, data timeliness, communication stability and decision feasibility. The cybersecurity dimension includes authentication security, access control, data integrity, communication security, incident detection capability and service availability risk [13], [14].

From the perspective of charging point assignment, this means that an alternative may be technically feasible and spatially attractive but less desirable if it has a higher communication, data integrity or access control risk. In a reliability-oriented model, cybersecurity is not interpreted as an external audit after the decision has been made, but becomes one of the evaluation dimensions within the charging point selection process itself.

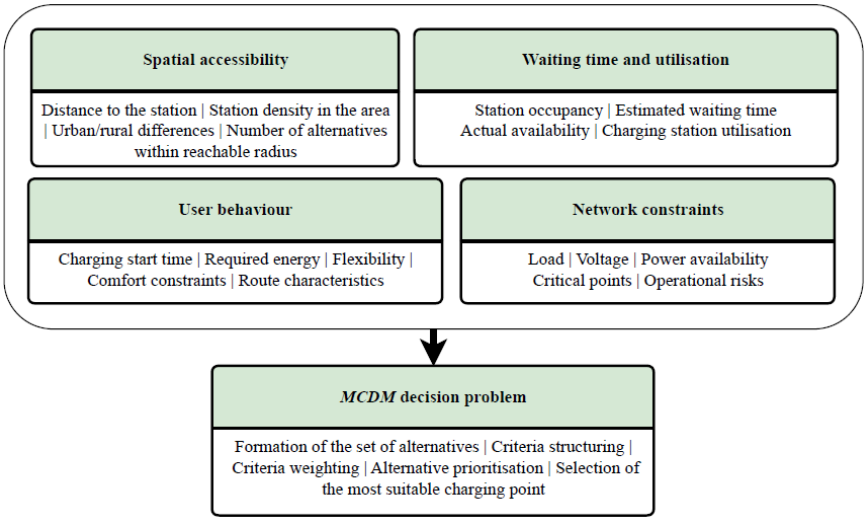

Fig. 1.1. Map of factors influencing EV charging point selection.
Source: Prepared by the author, based on a literature analysis [7], [10], [12]–[14], [25], [27].

Such a decision environment can be conceptually described by a set of alternatives, where each alternative is a specific charging point at a specific time. Each alternative is characterised by a set of criteria values, while the final priority depends on these values and their relative importance. Therefore, in this Doctoral Thesis, charging point selection is formalised as an MCDM problem, in which AHP is later used for criteria structuring and weighting, while PROMETHEE is used for prioritising admissible alternatives.

1.4. MCDM approaches in the EV charging infrastructure literature

In the EV charging infrastructure literature, decision-making models have developed from location and capacity selection models towards more integrated multi-criteria, multi-objective and hybrid approaches. Studies analyse station siting, charging power selection, transport demand, user behaviour, distribution network constraints, investment costs,

environmental impact, smart charging strategies and charging infrastructure management [8], [10], [16]–[22]. However, these research directions do not always directly address the operational task of dynamically assigning a specific charging point to a specific EV at a specific time.

One of the most extensively developed research lines in the EV charging infrastructure literature concerns charging station siting, location selection and capacity determination. To solve these problems, Geographic Information System–based Multi-Criteria Decision-Making (GIS-MCDM) approaches are widely used, as they make it possible to combine spatial analysis with multi-criteria evaluation by assessing candidate locations according to transport, energy, economic, social and environmental criteria [10], [16]–[19]. These studies are important for infrastructure development, but their main focus is long-term planning rather than the operational assignment of a specific vehicle to the most suitable charging point in a specific operating situation.

MCDM methods are used in EV charging infrastructure studies in situations where alternatives cannot be properly compared using a single indicator. Typical criteria include distance, travel time, investment costs, charging power, network capacity, waiting time, user demand, environmental impact and service quality [8], [10], [16], [18], [19]. AHP is suitable for determining the criteria hierarchy and relative importance [27], [28], whereas PROMETHEE enables alternative prioritisation using outranking logic and comparison of alternatives across multiple criteria [25].

An important methodological distinction in this work is the difference between charging infrastructure planning, smart charging and dynamic charging point assignment. In infrastructure planning tasks, the main question is where stations should be located, what capacity is required and how territorial coverage should be ensured [10], [16], [17]. In smart charging literature, the focus is usually on when and at what power a vehicle should be charged in order to reduce network load, use price signals or increase flexibility [7], [20], [21]. By contrast, dynamic charging point assignment answers a different question – which specific charging point should be selected for a specific EV at a specific time.

The approach developed in this Doctoral Thesis addresses the gap identified in the literature by integrating reliability and cybersecurity criteria directly into the MCDM model. This means that a charging point is assessed not only by distance, price, power and waiting time, but also by data quality, communication reliability, service availability, authentication security and cyberrisk level [13], [14].

1.5. The need for a decision support system for dynamic EV charging point assignment

In this Doctoral Thesis, the decision support system is not treated as an end in itself or as the main scientific result. It is interpreted as the practical implementation environment in which the developed MCDM approach is realised: criteria structuring, AHP-based weight determination, PROMETHEE-based alternative prioritisation, dynamic data updating and interpretation of decision results.

Dynamic EV charging point assignment requires several data layers: EV data, charging station data, distribution network data, user data, as well as security and reliability data. These data describe the vehicle's charging need, charging point availability and technical parameters, local network load, available power reserve, communication stability, data timeliness, authentication security and cyberrisk level [7], [10], [12]–[15]. The use of such data allows the model to operate not as a one-off static calculation, but as a repeatedly executable decision-making process in which alternative priorities are recalculated when charging point availability, network loading, data quality or cybersecurity risk changes.

2. THEORETICAL MODEL OF RELIABILITY-ORIENTED DYNAMIC CHARGING POINT ASSIGNMENT

This chapter develops a theoretical model for reliability-oriented dynamic electric vehicle charging point assignment. Dynamic charging point assignment is formalised as a multi-criteria decision-making problem in which the most suitable charging point must be selected for a particular EV at a particular moment in time from the set of admissible alternatives. This selection is not static, because charging point suitability changes depending on the vehicle state, required energy, charging point availability, waiting time, distribution network regime, user constraints, data quality, service reliability and cybersecurity risk [7], [10], [12]–[14].

2.1. Formulation of the dynamic EV charging point assignment problem

In this work, dynamic EV charging point assignment is interpreted as an operational decision-making process in which the most suitable charging point is determined for a particular vehicle at a particular time from a limited set of alternatives. This set of alternatives is not permanent, because it changes depending on the vehicle's location, the remaining range, the status of charging points, station load, the user's time constraints, the distribution network regime and data availability.

Dynamic charging point assignment must be distinguished from classical charging infrastructure planning. Charging infrastructure planning studies mainly analyse station siting, capacity selection, connection power determination, area coverage, investment efficiency, demand forecasting and the impact on distribution network development [10], [16]–[19]. The focus of this Doctoral Thesis, by contrast, is an operational decision: which of the already available or currently reachable charging points to choose for a particular EV in a particular operating situation.

Table 2.1

Comparison of station planning and dynamic charging point assignment

Aspect	Charging infrastructure planning	Dynamic charging point assignment
Decision object	Siting, capacity and coverage of charging stations	Selection of a specific charging point for a specific EV
Decision scale	Area, city, region or system level	Operational or charging-session level
Time horizon	Months, years, the infrastructure development period	Real-time or operational situations
Set of alternatives	Potential locations or station configurations	Reachable and available charging points at time (t)
Main criteria	Coverage, investments, demand forecast, connection power, network development	Availability, waiting time, SOC, required energy, network regime, reliability, cybersecurity risk
User role	Aggregated demand or mobility flow	Individual or partly individualised choice situation
Network role	Planning of connection and reinforcement needs	Assessment of the local regime and admissibility at the particular moment
Decision result	Infrastructure development or siting plan	Prioritised charging point ranking or selected charging point

Note: The table shows that dynamic charging point assignment cannot be reduced to classical station planning, since it is an operational multi-criteria choice problem with a short time horizon and changing input data [10], [12], [16]–[19].

In this work, the set of alternatives available at the moment in time t is denoted by

$$A_t = \{a_1, a_2, \dots, a_m\}, \tag{2.1}$$

where A_t is the set of charging points reachable or initially considered at the particular time, and m is the number of alternatives. Each alternative $a \in A_t$ is characterised by a vector of criteria values:

$$c(a,t) = [c_1(a,t), c_2(a,t), \dots, c_n(a,t)], \tag{2.2}$$

where $c_j(a,t)$ is the evaluation of alternative a by the j-th criterion at time t, and n is the number of criteria [13], [14].

The relative importance of the criteria is characterised by the weight vector:

$$w = [w_1, w_2, \dots, w_n], \sum_{j=1}^{n} w_j = 1\,, w_j \geq 0. \tag{2.3}$$

In this Doctoral Thesis, AHP logic is used to obtain the criteria weights, because it makes it possible to structure the decision problem hierarchically and to determine the relative importance of the criteria through expert pairwise comparisons [27]–[29]. For the final prioritisation of the alternatives, the PROMETHEE approach is used, because it makes it possible to compare alternatives pairwise by several criteria and to obtain an interpretable ranking of alternatives [25].

Before prioritising the alternatives, the initial set of alternatives, A_t, is selected:

$$A_t^{adm} \subseteq A_t. \tag{2.4}$$

The final selection can be defined as the alternative with the highest multi-criteria priority value in the set of admissible alternatives:

$$a_t^* = arg \max_{a \in A_t^{adm}} \phi(a,t). \tag{2.5}$$

This notation shows that dynamic charging point assignment is not a single-criterion optimisation task. It is a multi-criteria choice problem in which the suitability of an alternative depends on the values of several criteria, their relative importance and the situation at the particular moment in time [7], [10], [12], [14], [25], [27], [29].

2.2. Elements of the decision environment and the set of alternatives

In the MCDM model of dynamic EV charging point assignment, the decision is not made solely on the basis of the charging point's location or technical power. The decision environment includes several mutually related elements: the electric vehicle, the charging point, the local regime of the distribution network, the user requirements, the operator data environment, and the reliability and cybersecurity indicators [7], [10], [12]–[15].

The electric vehicle acts as the decision initiator, because its state, the battery state of charge, the required amount of energy and the user's mobility task determine when and why a charging point must be selected [7], [12]. The EV state at time t can be conceptually described by the vector:

$$x_{EV}(t) = [SOC(t), E_{req}(t), R_{rem}(t), P_{acc}(t), u_{pref}(t)]. \tag{2.6}$$

In the model, the charging point is the MCDM alternative $a \in A_t$, characterised by the available power, the waiting time, the location, connector compatibility, the operating status and the price:

$$x_{CP}(a,t) = [P_{ch}^{avail}(a,t), W(a,t), L(a), C_{conn}(a), S_{op}(a,t), p(a,t)]. \tag{2.7}$$

In this model, the distribution network is not an external background, but a full element of the decision environment. The selection of a charging point may be convenient for the user but technically undesirable if the particular connection point is located at an already loaded transformer, if voltage deviations exist in the local network, or if the additional charging load increases the peak-load risk [7], [10], [33]. The distribution network state can be described by the vector:

$$x_G(a,t) = [P_{load}(a,t), Q(a,t), U(a,t), I_\Phi(a,t), P_{avail}(a,t), e_G(a,t)]. \quad (2.8)$$

The operation of the dynamic MCDM model also depends on data availability, timeliness and reliability. The data and operator environment can be characterised by the vector:

$$x_D(a,t) = [D_{qual}(a,t), D_{age}(a,t), Com(a,t), Sec(a,t), O_{stat}(a,t)\ ]. \quad (2.9)$$

Combining these elements, the suitability of each alternative at time t can be interpreted as a function of four main state blocks:

$$s(a,t) = [x_{EV}(t), x_{CP}(a,t), x_G(a,t), x_D(a,t)\ ]. \quad (2.10)$$

The criteria values are derived from this state vector:

$$c(a,t) = g(s(a,t)), \quad (2.11)$$

where $g(\cdot)$ is the criteria-derivation or calculation function that transforms the original technical, operational, user, network and data parameters into the criteria values used in the MCDM model.

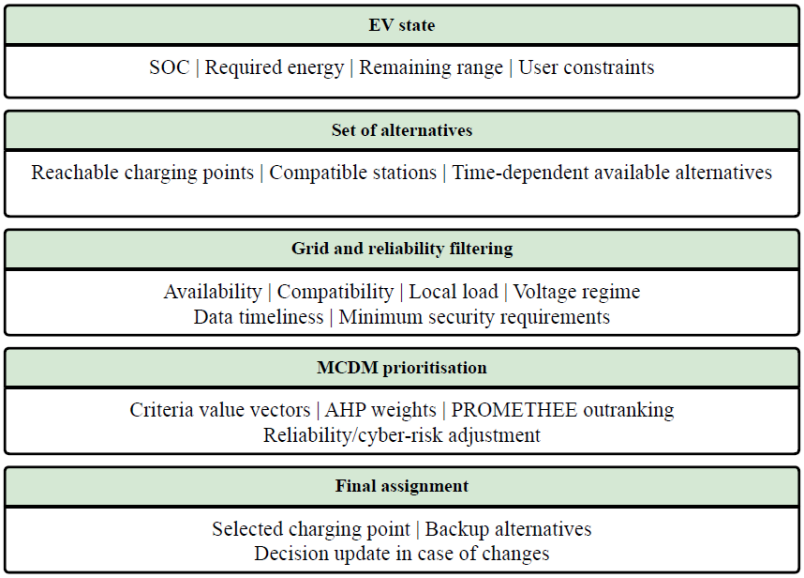

Fig. 2.1. Elements of the decision environment and their link with MCDM prioritisation.
Source: Prepared by the author, based on [9]–[13], [27], [29], [41], [49].

Such a formalisation separates three levels: the physical and digital data, the criteria calculated from them, and the MCDM prioritisation. At the first level are the security operations centre (SOC), the station power, the voltage or the communication status. At the second level,

criteria are calculated from these data, for example, the waiting time, the network load risk or data reliability. At the third level, the criteria are used in MCDM prioritisation, in which AHP determines the criteria weights, and PROMETHEE forms the ranking of alternatives [14], [25], [27], [29].

2.3. Criteria system for reliability-oriented charging point assignment

In the dynamic EV charging point assignment model, the criteria system is the central element that makes it possible to transform heterogeneous technical, user, network, economic, environmental, reliability and cybersecurity data into a comparable multi-criteria evaluation structure [7], [10], [12]–[14], [25].

The overall set of criteria is defined as the union of several criteria groups:

$$C = C_{EV} \cup C_{CP} \cup C_G \cup C_U \cup C_E \cup C_{ENV} \cup C_{SEC} \cup C_{REL}, \tag{2.12}$$

where C_{EV} are the vehicle criteria, C_{CP} – the charging point criteria, C_G – the distribution network criteria, C_U – the user and operational criteria, C_E – the economic criteria, C_{ENV} – the environmental, renewable energy systems (RES) and battery energy storage systems (BESS) criteria, C_{SEC} – the cybersecurity criteria, and C_{REL} –t he reliability criteria.

Criteria may be maximised, for example, available power, power reserve, data reliability or service availability, or minimised, for example, distance, waiting time, voltage deviation or the cyberrisk level. Therefore, the desired direction is defined for each criterion:

$$d_j = \begin{cases} +1, & \text{if a larger criterion value is preferable,} \\ -1, & \text{if a smaller criterion value is preferable.} \end{cases} \tag{2.13}$$

Table 2.2

Criteria system for dynamic EV charging point assignment

Criteria group	Typical subcriteria	Criterion direction	Role in the MCDM model	Main sources
Vehicle criteria	SOC, required energy, remaining range, acceptable charging power, compatibility	Depends on the criterion; SOC deficit minimised, compatibility mandatory	Determine the charging need, the admissible alternatives and the interpretation of criteria	[7], [12], [34], [35]
Charging point criteria	Available power, waiting time, occupancy, connector, status, reservation	Power and availability maximised; waiting time minimised	Characterise the quality and technical suitability of the charging service	[11], [12], [15], [35]
Distribution network criteria	Load coefficient, power reserve, voltage deviation, phase unbalance, peak-load risk	Power reserve maximised; load and deviations minimised	Enable assessment of the network regime admissibility and impact	[7], [10], [11], [33]
User and operational criteria	Distance, travel time, route deviation, acceptable waiting time, flexibility	Distance, delay and deviation minimised; flexibility maximised	Ensure the practical acceptability of the alternative to the user	[7], [10], [12]
Economic criteria	Charging price, tariff structure, reservation costs, cost predictability	Usually minimised	Differentiate alternatives by cost acceptability	[7], [10], [12]
Environmental and RES/BESS criteria	RES availability, BESS SOC, local energy flexibility, net load reduction	RES/BESS availability maximised; network impact minimised	Characterise the energy flexibility of the alternative and the potential to reduce network load	[11], [37]–[39]

Table 2.2 (continued)

Security/cybersecurity criteria	Authentication, access control, data integrity, communication security, incident risk	Security level maximised; risk minimised	Enable assessment of digital reliability and cyber-physical resilience	[9], [13], [14]
Reliability criteria	Availability, operability, service uptime, data timeliness, decision stability	Reliability maximised; failure risk minimised	Serve as a cross-cutting quality dimension and may affect the final priority	[9], [13]–[15]

The criteria system is designed so that the vehicle, charging point, distribution network, user, economic, environmental, security and reliability factors are integrated into a single MCDM evaluation space. The relative importance of the criteria is then determined with AHP, and the prioritisation of alternatives is done with PROMETHEE [25], [27], [29].

2.4. Integration of reliability and cybersecurity indicators into the MCDM model

In the dynamic EV charging point assignment model, reliability and cybersecurity are interpreted as factors influencing the decision environment, not as external additions assessed after the final selection. They may determine whether a particular charging point is admissible, how it is compared with other alternatives and how its final priority is interpreted [9], [13], [14], [40], [41].

Reliability includes charging point availability, service continuity, data timeliness, communication stability and the admissibility of the network regime. Cybersecurity indicators characterise the risks of the cyber-physical EV charging environment, involving EVs, EVSE, operator platforms, payment systems, communication protocols and the electricity supply system [9], [13], [14]. In the MCDM model, these indicators are used as filtering conditions, evaluation criteria and final priority correction factors.

The overall reliability indicator for alternative a at time *t* can be conceptually defined as a weighted sum of reliability subindicators:

$$R_{rel}(a,t) = \sum_{r=1}^{q} a_r \tilde{r}_r(a,t), \qquad \sum_{r=1}^{q} a_r = 1,\ a_r \geq 0. \tag{2.14}$$

The cybersecurity risk, in turn, can be formulated as a weighted sum of risk subindicators:

$$\rho_{cyb}(a,t) = \sum_{l=1}^{p} \beta_l \tilde{\rho}_l(a,t), \qquad \sum_{l=1}^{p} \beta_l = 1, \beta_l \geq 0, \tag{2.15}$$

where $\rho_{cyb}(a,t)$ is the cyber risk evaluation of the alternative, $\tilde{\rho}_l(a,t)$ is the normalised value of the l-th cyberrisk indicator, β_l is the relative weight of this indicator, and p is the number of cybersecurity risk subindicators.

Unlike the reliability indicator, a lower value is preferable for the cyberrisk indicator.

Since reliability and cybersecurity indicators may be expressed in different units and scales, normalisation is required before using them in the MCDM model.

For benefit-type indicators, in which a higher value is preferable, normalisation can be formulated as follows:

$$\tilde{x}_j(a,t) = \frac{x_j(a,t) - x_j^{\min}}{x_j^{\max}(t) - x_j^{\min}}. \tag{2.16}$$

For cost-type indicators, in which a lower value is preferable, normalisation can be formulated as follows:

$$\tilde{x}_j(a,t) = \frac{x_j^{\max}(t) - x_j(a,t)}{x_j^{\max} - x_j^{\min}}. \quad (2.17)$$

Reliability and cybersecurity indicators can be integrated into the MCDM model at three levels: as filtering conditions, as separate MCDM criteria, and as final priority correction factors. At the filtering level, an alternative is excluded from further evaluation if it does not meet the minimum technical, reliability or security conditions:

$$A_t^{adm} = \left\{ a \in A_t \middle| \begin{matrix} h_{tech}(a,t) = 1, h_G(a,t) = 1, \\ h_{rel}(a,t) = 1, h_{sec}(a,t) = 1 \end{matrix} \right\} \quad (2.18)$$

If the initial PROMETHEE net flow result is denoted by $(\phi(a,t))$, then the cyberrisk correction can be written as follows:

$$\Phi_{adj}(a,t) = \phi(a,t) - \lambda \rho_{cyb}(a,t). \quad (2.19)$$

If the reliability indicator is not directly included among the PROMETHEE criteria, an extended correction form can be used:

$$\Phi_{adj}(a,t) = \phi(a,t) + \mu R_{rel}(a,t) - \lambda \rho_{cyb}(a,t). \quad (2.20)$$

This formula should be used only if reliability and cyberrisk are not already fully included in the base set of criteria. Otherwise, there is a risk of double counting.

Table 2.3

Integration of reliability and cybersecurity indicators into the MCDM model

Integration level	Function in the model	Examples	Impact on the decision
Filtering	Excludes inadmissible alternatives	non-operational station, outdated data, inadmissible cyberrisk	The alternative is not included in A_t^{adm}
MCDM criteria	Compares admissible alternatives by reliability and security	data timeliness, communication stability, authentication security	Affects the PROMETHEE ranking
Final priority correction	Reduces or increases the final priority according to risk/reliability indicators	cyberrisk penalisation, reliability bonus	Changes the risk-adjusted ranking

2.5. AHP-based criteria hierarchy and the principle of weight determination

In this Doctoral Thesis, AHP is used as a method for structuring the criteria and determining their weights. It is not a method for selecting the final alternative, but provides the weight vector that is subsequently used in the PROMETHEE prioritisation of alternatives. Such a division of methods makes it possible to separate the structuring of expert preferences from the operational ranking of the alternatives available at a particular moment in time [25], [27]–[29].

In this work, the AHP hierarchy consists of four levels: the main goal – the reliability-oriented selection of the most suitable EV charging point at time *t*; the criteria groups; the subcriteria; and the alternatives, i.e. the charging points admissible at the particular time. The result of AHP is the criteria weight vector w, which is subsequently used in the PROMETHEE calculation.

The PROMETHEE method is used as the main mechanism for prioritising the admissible charging alternatives. It is suitable for the dynamic EV charging point assignment

task because it is based on the pairwise comparison of alternatives and makes it possible to take into account several mutually conflicting criteria simultaneously [25].

If the criterion is to be maximised, the criterion difference between alternatives a and b is defined as

$$d_j(a,b,t) = c_j(a,t) - c_j(b,t). \tag{2.21}$$

If the criterion is to be minimised, for example, waiting time, distance or the cyberrisk level, the difference can be defined in the opposite direction:

$$d_j(a,b,t) = c_j(b,t) - c_j(a,t). \tag{2.22}$$

The criterion difference is transformed into a preference value $P_j(a,b,t) \in [0;1]$. The overall preference index between alternatives is then calculated:

$$\pi(a,b,t) = \sum_{j=1}^{n} w_j P_j(a,b,t). \tag{2.23}$$

If the set of admissible alternatives A_t^{adm} contains m alternatives, the positive, negative and net flows are calculated for each alternative:

$$\phi^+(a,t) = \frac{1}{m-1} \sum_{\substack{b \in A^{adm} \\ b \neq a}} \pi(a,b,t), \tag{2.24}$$

$$\phi^-(a,t) = \frac{1}{m-1} \sum_{\substack{b \in A^{adm} \\ b \neq a}} \pi(b,a,t), \tag{2.25}$$

$$\phi(a,t) = \phi^+(a,t) - \phi^-(a,t). \tag{2.26}$$

As a result of PROMETHEE II, the alternatives are ordered according to the net flow value:

$$R_t = (a_{(1)}, a_{(2)}, \dots, a_{(m)}), \qquad \phi(a_{(1)},t) \geq \phi(a_{(2)},t) \geq \cdots \geq \phi(a_{(m)},t). \tag{2.27}$$

Such an approach is essential in the dynamic charging point assignment model, because it provides not only a single recommended charging point but also a complete sequence of backup alternatives. If the initially selected charging point becomes unavailable or no longer meets the minimum conditions, the next alternative in the ranking can be used.

Table 2.4

The AHP–PROMETHEE sequence in the dynamic charging point assignment model

Stage	Content	Result
Building the criteria hierarchy	Goal, criteria groups and subcriteria	Structured criteria system
AHP weight determination	Expert pairwise comparisons and weight calculation	Criteria weight vector
Building the set of admissible alternatives	Filters out alternatives that are inadmissible in technical, network, data and security terms	A_t^{adm}
PROMETHEE preference index	Uses the criteria values, AHP weights and preference functions	$\pi(a,b,t)$
Flow calculation	Calculates ϕ, ϕ^+, ϕ^-	Priorities of the alternatives
Ranking	Orders the alternatives by net flow	Final ranking and backup sequence

2.6. The principle of dynamic updating and filtering

In the dynamic EV charging point assignment model, the set of alternatives and the criteria values are not constant. They may change as the EV location, the SOC level, the load of charging stations, the waiting time, the distribution network regime, the data quality or the

cybersecurity status change. Therefore, the MCDM model must incorporate a principle of dynamic updating and filtering.

Initially, a candidate set of alternatives is formed:

$$A_t^0 = \{a_1, a_2, \dots, a_k\}, \tag{2.28}$$

where A_t^0 is the set of charging points reachable or initially considered at time t.

After filtering, the set of admissible alternatives is obtained:

$$A_t^{adm} \subseteq A_t^0. \tag{2.29}$$

It is exactly A_t^{adm} that is used in the PROMETHEE prioritisation. The filtering process includes checking the minimum conditions of reachability, technical compatibility, EVSE status, minimum available power, distribution network admissibility, user limits, data quality and cybersecurity [9], [13]–[15].

The filtering conditions can be written with indicator functions:

$$h_i(a,t) = \begin{cases} 1, & \text{if the condition is satisfied,} \\ 0, & \text{if the condition is not satisfied.} \end{cases} \tag{2.30}$$

Dynamic recalculation can be triggered periodically or event-based. In the case of event-based recalculation, the model is executed if the selected charging point becomes occupied, the network regime deteriorates, the user's SOC changes, the data quality decreases, or a security risk is detected [42], [43].

Decision stability can be characterised by the difference between the net flows of the first and second alternatives:

$$\Delta\phi_{12}(t) = \phi(a_{(1)}, t) - \phi(a_{(2)}, t). \tag{2.31}$$

If $\Delta\varphi_{12}(t)$ is large, the first alternative is clearly better than the second. If the difference is small, the first two alternatives are close, and the decision must be interpreted with caution. In such a case, the sequence of backup alternatives is of particular importance.

Table 2.5

Theoretical stages of dynamic filtering and updating

Stage	Content	Result
Building the candidate set	Reachable and initially suitable charging points	A_t^0
Filtering	Technical, user, network, data and security conditions	A_t^{adm}
Criteria updating	Updates the criteria values at time (t)	C_t
PROMETHEE recalculation	Calculates the flows and the net ranking	R_t
Final selection	Determines the first and backup alternatives	a_t^*, backup sequence
Stability check	Evaluates $\Delta\phi_{12}(t)$	Indicator of decision confidence

In Chapter 2, dynamic EV charging point assignment is formalised as a multi-criteria decision-making problem. The decision environment is defined, in which the EV acts as the decision initiator, the charging point as the MCDM alternative, the distribution network as the constraining and evaluated layer, and the data and operator environment as the source of criteria updating and reliability. A criteria system has been created that includes vehicle, charging point, distribution network, user, economic, RES/BESS, cybersecurity and reliability criteria. The AHP method is used to determine the criteria hierarchy and weights, and PROMETHEE is used to rank the admissible charging alternatives and determine the backup sequence. The principle of dynamic filtering and updating ensures that only the alternatives admissible at the particular time and the current criteria values are used in the prioritisation.

3. OPERATIONALISATION AND ALGORITHMIC IMPLEMENTATION OF THE MCDM METHODOLOGY

In Chapter 3, the reliability-oriented dynamic EV charging point assignment MCDM model developed in Chapter 2 is transferred into a practically executable calculation methodology. In this work, operationalisation means transforming the theoretical model elements into computable operations: the criteria are defined as measurable or scenario-determined indicators, the set of alternatives is narrowed by filtering conditions, the AHP weights are prepared for the PROMETHEE calculation, and the PROMETHEE ranking is used for charging point selection and for determining the sequence of backup alternatives. The calculation prototype and the result visualisation environment are used as tools for testing the methodology, ensuring reproducibility and interpreting the results.

3.1. Methodological logic of the research

Chapter 1 justified the research context of EV charging infrastructure and the multi-criteria nature of charging point selection, while Chapter 2 formalised the problem as a reliability-oriented MCDM model. The task of Chapter 3 is to transform this theoretical model into a calculation procedure: the criteria system is operationalised as computable indicators, a candidate set is formed from the available charging points, inadmissible alternatives are excluded by filtering conditions, the criteria weights are determined with AHP, and the admissible alternatives are ranked with PROMETHEE.

This sequence is based on the principles of AHP hierarchical structuring and pairwise comparisons [27], the measurement-theory considerations of AHP [28], the dynamic-priorities approach [29], the PROMETHEE methodology [25], as well as decision support system and energy management system development approaches [36], [44].

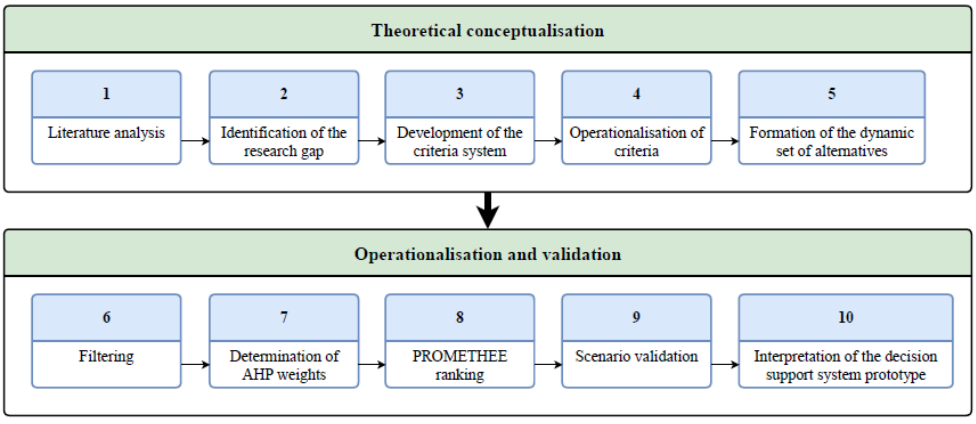

Fig. 3.1. Methodological flow of the research.

Source: Prepared by the author, based on the literature on AHP, PROMETHEE, dynamic priorities and decision support system methodology [25], [27]–[29], [36], [44].

The developed methodology is based on the assumption that the data necessary for decision-making on the EV state, the charging point status, the distribution network regime, user constraints, data quality and cybersecurity indicators are available operationally or are defined in scenario form. At the same time, the methodology has defined bounds: the work does not model the full transport flow, electricity market dynamics or the technical course of

EVSE cybersecurity incidents. The cybersecurity component is included as a risk and reliability layer that influences the decision [13], [14].

3.2. Operationalisation of criteria and the use of AHP weights

In Chapter 3, the criteria system defined in Chapter 2 is transferred into the calculation model. For each criterion, a practical interpretation is defined: the computable indicator, the possible data source, the direction in the MCDM model and the role in the algorithmic procedure.

In the calculation model, a criteria value vector is formed for each admissible alternative a_i at time t. If the set of admissible alternatives contains m alternatives and n criteria are used, the basic calculation structure is the criteria matrix:

$$C_t = \begin{bmatrix} c_1(a_1,t) & c_2(a_1,t) & \cdots & c_n(a_1,t) \\ c_1(a_2,t) & c_2(a_2,t) & \cdots & c_n(a_2,t) \\ \vdots & \vdots & \ddots & \vdots \\ c_1(a_m,t) & c_2(a_m,t) & \cdots & c_n(a_m,t) \end{bmatrix}. \tag{3.1}$$

This matrix aggregates all admissible alternatives and their values by the operationalised criteria. The criteria values may be obtained from EV data, electric vehicle supply equipment (EVSE) technical parameters, operator data, distribution network measurements, the user scenario, the data quality assessment or the cybersecurity risk indicator.

In the calculation model, the criteria may perform three functions: they may act as filtering conditions, as PROMETHEE ranking criteria, or as final priority correction and penalisation factors. This division is important because not all alternatives may proceed to the ranking stage – alternatives that are inadmissible in technical, network, data quality or cybersecurity terms must first be excluded.

Table 3.1

Operationalisation of criteria in the dynamic EV charging point assignment model

Criteria group	Computable indicator	Main data source	Direction in the MCDM model	Role in the model
Vehicle criteria	SOC, required energy, remaining range, EV acceptable charging power	EV/BMS data, user app, scenario data	Depends on the indicator	Filter and scenario-interpretation factor
Reachability and compatibility	Distance, travel time, connector and charging-type matching	Navigation data, EVSE technical data	Distance minimised; compatibility mandatory	Filter and ranking criterion
Charging point availability	Availability status, occupancy, reservation option, operability	Charge Point Operator (CPO) / Charging Station Operator (CSO) data, EVSE monitoring	Availability maximised; occupancy minimised	Filter and ranking criterion
Waiting time	Expected waiting time, queue length	Operator data, session history, scenario data	Minimised	Ranking criterion
Charging power	Available charging power, nominal power, EV power limit	EVSE data, operator data, EV technical data	Maximised up to the EV and network limits	Filter and ranking criterion
Distribution network load	Load coefficient, connection or transformer loading	Control meters, Distribution System Operator (DSO) data, local measurements	Minimised	Filter and ranking criterion
Power reserve	Available power reserve	Control meters, connection data	Maximised	Filter and ranking criterion

Table 3.1 (continued)

Voltage regime	Voltage deviation from the nominal value	Per-phase voltage measurements or average voltage	Minimised	Filter and ranking criterion
Phase unbalance	Phase-current unbalance indicator	Phase currents, local measurements	Minimised	Ranking criterion
Economic criteria	Charging price, tariff, reservation costs	CPO/CSO price data, scenario data	Usually minimised	Ranking criterion
RES/BESS criteria	PV availability, BESS SOC, local flexibility	EMS, BESS/BMS data, scenario data	Availability and flexibility maximised	Ranking criterion or scenario factor
Reliability criteria	Service uptime, operability, data completeness, event frequency	EVSE monitoring, event logs, data quality check	Reliability maximised; event frequency minimised	Filter, ranking criterion or correction
Cybersecurity criteria	Authentication, data integrity, communication security, incident risk	Security monitoring, risk model, expert assessments	Security level maximised; risk minimised	Filter, ranking criterion or penalisation
Data quality	Data completeness, data age, status reliability	Data preprocessing, operator system, measurement archive	Completeness maximised; data age minimised	Filter, ranking criterion or correction

Note: The table transfers the criteria system defined in Chapter 2 into the calculation model. The role of a criterion may change depending on the validation scenario; for example, voltage deviation may act as a ranking criterion under normal conditions and as a filtering condition in the case of a critical deviation.

After operationalising the criteria, their relative importance must be determined. For this purpose, the AHP method is used; it makes it possible to decompose a complex decision problem into a hierarchy and to determine the criteria priorities through pairwise comparisons [27]. In this Doctoral Thesis, AHP is not used as a method for selecting the final alternative but as a weight-determination instrument whose results are subsequently used in the PROMETHEE prioritisation.

AHP is used at three levels: the weights of the criteria groups, the local weights of the subcriteria, and the global weights used in the PROMETHEE calculation. The global subcriterion weight is calculated as follows:

$$w_{g,j} = w_G \times w_{j|G}, \tag{3.2}$$

where $w_{g,j}$ is the global weight of the j-th subcriterion, w_G is the weight of the relevant criteria group, and $w_{j|G}$ is the local weight of the subcriterion within this group.

In the context of dynamic charging point assignment, the AHP weights can be used as a base weight vector or as scenario-dependent weights. The scenario-adjusted weight can be described as follows:

$$w_j^{(s)} = \frac{\gamma_j^{(s)} w_j}{\Sigma_{k=1}^{n} \gamma_k^{(s)} w_k}, \tag{3.3}$$

where w_j is the initial AHP weight, $\gamma_j^{(s)}$ is the scenario s multiplier for the j-th criterion, and $w_j^{(s)}$ is the adjusted and normalised criterion weight in scenario s. This approach is later used for sensitivity analysis, examining how the ranking changes if the importance of the reliability, cybersecurity or network criteria increases.

3.3. The PROMETHEE prioritisation calculation procedure

After operationalising the criteria and preparing the AHP weights, the admissible charging points are prioritised using the PROMETHEE method. The PROMETHEE calculation uses three inputs: the set of admissible alternatives A_t^{adm}, the criteria matrix C_t and the AHP-determined weight vector w. This approach makes it possible to evaluate alternatives according to several mutually conflicting criteria and to obtain an interpretable ranking [25].

So that the preference calculation is equally interpretable for all criteria, the criterion difference between alternatives a and b is defined so that a positive value always denotes the advantage of alternative a over alternative b:

$$d_j(a,b,t) = \begin{cases} c_j(a,t) - c_j(b,t), & \text{if } c_j \text{ is a maximised criterion,} \\ c_j(b,t) - c_j(a,t), & \text{if } c_j \text{ is a minimised criterion.} \end{cases} \tag{3.4}$$

Next, the preference function $Pj(dj)$, the overall preference index, and the positive, negative and net flows are applied. These formulas are theoretically defined in Chapter 2, so in this chapter PROMETHEE is interpreted as a practical calculation procedure. The net flow $\phi(a,t)$ is the final priority indicator: the higher the net flow, the higher the priority of the alternative in the overall multi-criteria evaluation.

As a result of PROMETHEE, the admissible alternatives are arranged in a complete ranking:

$$R_t = (a_{(1)}, a_{(2)}, \dots, a_{(m)}), \tag{3.5}$$

where $a_{(1)}$ is the most highly evaluated alternative, while the following alternatives form the backup sequence. The sequence of backup alternatives is essential in reliability-oriented dynamic charging point assignment, because the initially selected point may become occupied, technically unavailable, less suitable in network terms or risky in security terms.

In addition to the final selection, the difference between the net flows of the first and second alternatives $\Delta\phi_{12}(t)$ is analysed. If this difference is large, the first alternative is clearly superior to the second. If it is small, the decision is more sensitive to changes in data, weights or scenario, and maintaining the sequence of backup alternatives becomes particularly important.

3.4. The dynamic filtering and assignment algorithm

The dynamic assignment algorithm is based on the assumption that charging point suitability is not constant over time. The EV state, user demand, charging point availability, waiting time, available power, distribution network load, data quality and cybersecurity indicators change. Therefore, the decision on the most suitable charging point is treated as a repeatable and updatable process.

Before the PROMETHEE prioritisation, the initial candidate set A_t^0 is formed. After filtering, the set of admissible alternatives A_t^{adm} is obtained. It includes only those alternatives that satisfy the mandatory filtering conditions:

$$A_t^{adm} = \left\{ \begin{matrix} a \in A_t^0 | h_{reach}(a,t) = 1, h_{comp}(a,t) = 1, \\ h_{EVSE}(a,t) = 1, h_P(a,t) = 1, h_G(a,t) = 1, \\ h_U(a,t) = 1, h_D(a,t) = 1, h_{SEC}(a,t) = 1, \end{matrix} \right\} \tag{3.6}$$

Here h_{reach} characterises reachability, h_{comp} – technical compatibility, h_{EVSE} – the charging point's operability and status conditions, h_P – the minimum available power, h_G – network admissibility, h_U – user limits, h_D – data quality, and h_{SEC} – fulfilment of the minimum cybersecurity requirements.

Each filtering condition is interpreted in binary form:

$$h_k(a,t) = \begin{cases} 1, \text{if the alternative satisfies the condition,} \\ 0, \text{if the alternative does not satisfy the condition'} \end{cases} \quad (3.7)$$

Table 3.2

Filtering conditions in the dynamic charging point assignment algorithm

Filtering condition	Essence of the check	If the condition is not met	Related criteria group
Reachability	Whether the point is reachable given the EV's remaining range, location and route	The alternative is excluded	Vehicle/user criteria
Compatibility	Whether the EV and EVSE are technically compatible by connector, charging type and power	The alternative is excluded	Vehicle/EVSE criteria
EVSE status	Whether the charging point is operational and not in an error or maintenance mode	The alternative is excluded	Charging point/reliability criteria
Minimum available power	Whether the available power is sufficient for the particular charging need	The alternative is excluded or downgraded in the scenario	Charging point/user criteria
Network admissibility	Whether the additional charging load does not cause an inadmissible network risk	The alternative is excluded or penalised	Distribution network criteria
User limits	Whether the maximum waiting time, distance and route deviation are observed	The alternative is excluded	User and operational criteria
Data quality	Whether the data are sufficiently complete, current and reliable	The alternative is excluded or downgraded in the ranking	Data quality/reliability criteria
Cybersecurity threshold	Whether there is no critical authentication, communication, data integrity or availability risk	The alternative is excluded or penalised	Cybersecurity/reliability criteria

Note: The filtering conditions ensure that only the alternatives usable at the particular moment in time proceed to the PROMETHEE ranking. Some conditions may be strict filters, while others may be scenario-dependent criteria or penalisation factors [10]–[12], [14], [15], [36].

Dynamic updating can be implemented periodically or event-based. Periodic updating means that the model is recalculated after a defined time interval. Event-based updating means that recalculation is triggered when the selected charging point becomes occupied, the network regime deteriorates, the data quality decreases, the cyberrisk increases or the parameters of the user demand change.

Dynamic updating can be described as a repeated calculation cycle:

$$D_t \longrightarrow A_t^0 \longrightarrow A_t^{adm} \longrightarrow C_t \longrightarrow R_t \longrightarrow a_t^*, \quad (3.8)$$

where D_t are the data available at time t, A_t^0 is the candidate set of alternatives, A_t^{adm} is the set of admissible alternatives, C_t is the criteria matrix, R_t is the PROMETHEE ranking, and a_t^* is the selected charging point.

Algorithm 3.1. Reliability-oriented dynamic charging point assignment with AHP–PROMETHEE

Input: EV state data; user constraints; charging point data; distribution network data; data quality indicators; cybersecurity indicators; AHP weight vector; PROMETHEE preference functions; calculation step Δt.

Output: Recommended charging point a_t^*; complete ranking of alternatives R_t; sequence of backup alternatives; justification of the filtering and prioritisation.

1. Determine whether a charging point selection or a recalculation of the previous decision is needed.
2. Obtain or update the EV, user, EVSE, network, data quality and cybersecurity data.
3. Prepare the data for the selected calculation step Δt.
4. Build the initial candidate set A_t^0, including reachable and theoretically suitable charging points.
5. Check the reachability condition.
6. Check the technical compatibility of the EV and EVSE.
7. Check the EVSE operability and availability status.
8. Check the minimum available power condition.
9. Check the distribution network admissibility.
10. Check the user limits – maximum waiting time, distance and route deviation.
11. Check the data quality and currency.
12. Check the minimum cybersecurity threshold.
13. Build the set of admissible alternatives A_t^{adm}.
14. If $A_t^{adm} = \emptyset$, activate a fallback procedure, for example, expand the search range, relax the user constraints, or return information about the lack of an available alternative.
15. If $A_t^{adm} \neq \emptyset$, compute the operationalised criteria values for each alternative.
16. Apply the AHP-determined criteria weights.
17. Apply the PROMETHEE preference functions and calculate the pairwise preference indices of the alternatives.
18. Calculate the positive, negative and net flows for each alternative.
19. Order the alternatives in descending order of net flow.
20. Determine the main recommendation a_t^*.
21. Save the complete sequence of backup alternatives R_t.
22. Calculate the net flows of the first and second alternatives $\Delta\phi_{1-2}(t)$.
23. If $\Delta\phi_{1-2}(t)$ is very small, indicate the sensitivity of the selection or retain the previous recommendation if it is still admissible.
24. Update the decision after a defined time interval or in the event of a significant occurrence.
25. If the selected point becomes unavailable or no longer matches the filters, use the next alternative from the backup sequence or perform a full recalculation.

This algorithm ensures a clear transition from data to decision. It makes it possible to validate not only the final selection result but the entire logic of the assignment process: how many alternatives are excluded in filtering, how the PROMETHEE ranking changes, how often backup alternatives are available and how dynamic updating affects decision stability.

3.5. Logic of the prototype calculation implementation and result interpretation

The developed AHP–PROMETHEE methodology is linked to the logic of the calculation prototype implementation. The prototype is not interpreted as a commercially ready decision support system or operator platform. Its task is to ensure that the theoretical model and the calculation methodology are reproducibly verifiable with data, scenarios, key performance indicators (KPIs) and visually interpretable results.

The prototype validation cycle can be described as follows:

Input data → Preprocessing → Filtering → AHP weights → PROMETHEE ranking → Assignment → KPIs and interpretation.

The prototype includes a data preparation layer, a geospatial layer, a scenario layer, an MCDM calculation layer, a cybersecurity layer and a result interpretation layer. Such a structure makes it possible to link the physical data of the charging infrastructure with a dynamic decision-making model and ensures the transparency of the calculations.

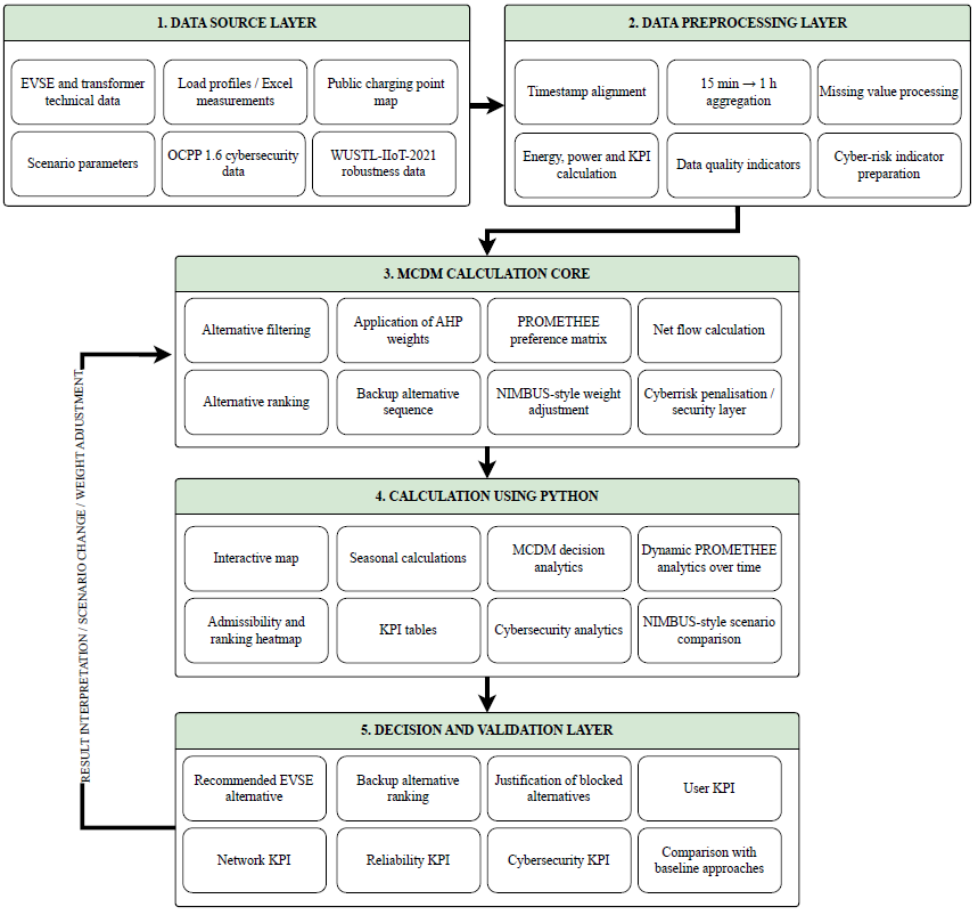

Fig. 3.2. The place of the prototype and result visualisation environment in the decision support system architecture.

Source: Prepared by the author, based on the literature on decision support system development, IoT energy management, EV decision-making systems and cybersecurity risk assessment [12]–[14], [36], [44].

Table 3.3

Functional structure of the prototype

Prototype layer	Content	Role in the Doctoral Thesis
Data preparation layer	Loading of load profiles, timestamp processing, data aggregation, missing-value check	Ensures preparation of the calculation data for the MCDM model

Table 3.3 (continued)

Geospatial layer	Charging point siting, distance interpretation, anonymised validation zones	Provides the spatial context and the interpretation of the reachability criterion
Scenario and period layer	Analysed periods, EV demand parameters, scenario configurations	Makes it possible to test the model's operation under various operating conditions
MCDM calculation layer	Filtering, criteria values, AHP weights, PROMETHEE flows, ranking and assignment	Implements the methodological core of the Doctoral Thesis
Cybersecurity and reliability layer	Data quality, communication status, cyberrisk indicators, security penalisation	Provides the reliability-oriented assignment logic
Result interpretation layer	Rankings, KPIs, MCDM decisions, charts, maps and comparisons	Makes the calculation results reviewable and explainable

Note: The functional structure of the prototype shows that the developed solution is not merely a mathematical calculation but an integrated validation environment of data, scenarios, geospatial information, the MCDM algorithm and security indicators.

One of the most essential elements of the prototype is the MCDM decision snapshot. This means that at a particular time t the complete decision state is recorded: the EV demand, the candidate set, the admissible alternatives, the criteria values, the AHP weights, the PROMETHEE flows, the selected alternative and the backup sequence.

$$S_t^{MCDM} = \{x_{EV}(t), A_t^0, A_t^{adm}, C_t, w, \phi^+(t), \phi^-(t), \phi(t), R_t, a_t^*\} \tag{3.9}$$

In this set, $x_{EV}(t)$ is the EV demand state, A_t^0 is the initial candidate set, A_t^{adm} is the set of admissible alternatives, C_t is the criteria matrix, w is the AHP weight vector, $\phi^+(t), \phi^-(t), \phi(t)$ are the PROMETHEE flows, R_t is the complete ranking, and a_t^* is the recommended alternative.

This structure makes it possible to analyse not only the final result but also the decision-formation process, since in dynamic charging point assignment the final selection may change depending on load, availability, data quality or security risk.

If the cyberrisk indicator is used as a penalisation layer, the risk-adjusted net flow can be described as follows:

$$\phi_{risk}(a,t) = \phi(a,t) - \lambda \rho_{cyb}(a,t), \tag{3.10}$$

where $\phi_{risk}(a,t)$ is the risk-adjusted net flow, $\phi(a,t)$ is the initial PROMETHEE net flow, $\rho_{cyb}(a,t)$ is the cyberrisk indicator, and λ is the cyberrisk penalisation coefficient.

In Chapter 3, the theoretical MCDM model is transferred into a practically executable calculation methodology. The operationalisation of criteria, the use of AHP weights, the PROMETHEE prioritisation procedure, the dynamic filtering algorithm and the logic of the prototype calculation implementation are defined. This chapter prepares the transition to Chapter 4, where the data, scenario and experimental validation environment are created, and to Chapter 5, where the model is validated with calculation results.

4. CREATION OF THE DATA, SCENARIO AND EXPERIMENTAL ENVIRONMENT

Chapter 4 creates the data, scenario and experimental validation environment needed to test the theoretical model developed in Chapter 2 and the algorithmic implementation defined in Chapter 3. The aim of the chapter is to link the AHP–PROMETHEE-based dynamic EV charging point assignment model with practically usable validation data, scenarios, filtering conditions and evaluation indicators. The validation is carried out as a methodological and scenario-based experimental test, rather than as a full-scale field experiment with a direct connection to real-time CPO, CSO, DSO and EV user systems.

4.1. Data structure for validating the MCDM model

The validation environment of the Doctoral Thesis is built using four anonymised EV charging infrastructure sites:

$$V = \{RIGA1, RIGA2, PIERIGA1, PIERIGA2\}, \tag{4.1}$$

where *RIGA*1 and *RIGA*2 represent city-type charging infrastructure sites, while *PIERIGA*1 and *PIERIGA*2 represent peri-urban sites. Each validation object is interpreted as a local cyber-physical charging infrastructure unit that combines territory, transformer, power supply source, electric vehicle charging stations (EVCS), load profile, data quality and cybersecurity layers. In total, the validation model includes seven EVCS alternatives with 25 charging points, of which 20 are AC and 5 are DC charging points. The total installed EVCS power is 598 kW, while the total permitted/design power is 463.32 kW. The dynamic data layer consists of 11 load profile objects: seven EVCS profiles and four power supply source profiles.

Table 4.1

Overall structure of the validation objects

Validation object	Territory type	Power supply structure	Charging infrastructure structure	Dynamic data layer	Validation significance
RIGA1	City territory	Two 630 kVA transformers: $RIGA1_{TR1}$ and $RIGA1_{TR2}$	3 EUS objects, 10 charging points in total: 6 AC and 4 DC	$RIGA1_{BAR1TR1}$, $RIGA1_{BAR1TR2}$, $RIGA1_{EUS1}$, $RIGA1_{EUS2}$, $RIGA1_{EUS3}$	City object with combined AC/DC charging and a separate distribution of transformer loads
RIGA2	City territory	Two 400 kVA transformers: $RIGA2_{TR1}$ and $RIGA2_{TR2}$	2 EUS objects, 10 AC charging points in total	$RIGA2_{BAR1TR1}$, $RIGA2_{BAR1TR2}$, $RIGA2_{EUS1}$, $RIGA2_{EUS2}$	City object with a fully AC charging structure and a different permitted/installed power ratio
PIERIGA1	Urban territory	One 250 kVA transformer $PIERIGA1_{TR2}$	1 EUS object, 2 AC charging points	$PIERIGA1_{EUS1}$	Peri-urban object with a smaller charging infrastructure scale
PIERIGA2	Urban territory	One 160 kVA transformer $PIERIGA2_{TR1}$	1 EUS object, 3 charging points: 1 DC and 2 AC	$PIERIGA2_{EUS1}$	Peri-urban object with a mixed AC/DC structure, a load control device and a smaller transformer power

Note: The names of the validation objects are anonymised. They do not include precise addresses, customer-identifying information or commercial names. The precise coordinates of the objects are not indicated in the public presentation of the Doctoral Thesis.

In total, the validation environment includes seven MCDM alternatives: $RIGA1_{EUS1}$, $RIGA1_{EUS2}$, $RIGA1_{EUS3}$, $RIGA2_{EUS1}$, $RIGA2_{EUS2}$, $PIERIGA1_{EUS1}$ and $PIERIGA2_{EUS1}$. These alternatives are filtered, evaluated and ranked with the PROMETHEE method. In addition, the power supply source profiles are analysed, making it possible to link the EVCS load with the relevant power supply object.

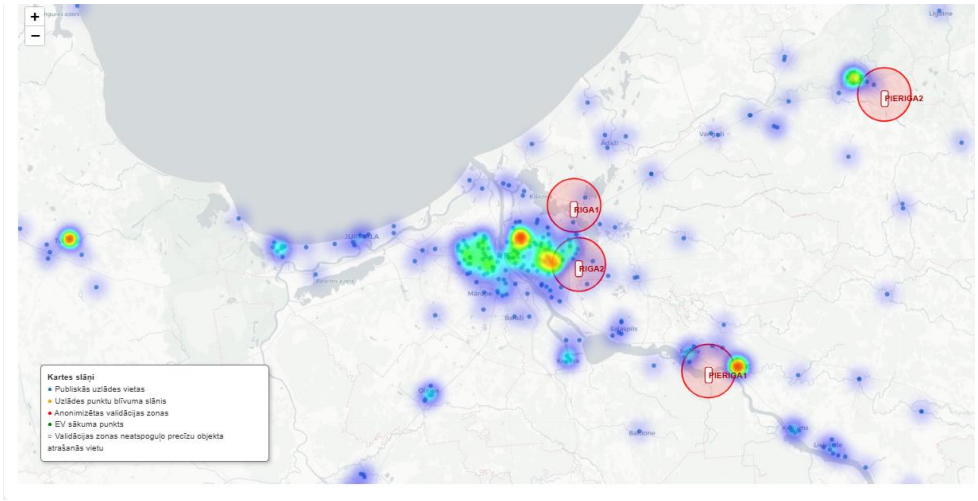

Fig. 4.1. Anonymised validation zones and the EV starting point in the experimental environment.

Source: Prepared by the author. The precise locations of the validation objects are not shown; anonymised zones are used on the map.

To preserve the confidentiality of the infrastructure objects, the precise coordinates of the validation objects are not made public. In the figures, they are replaced by anonymised validation zones. In addition to the geospatial layer, the validation environment uses dynamic load profiles showing changes over time in the loads of power supply sources and the associated EVCS.

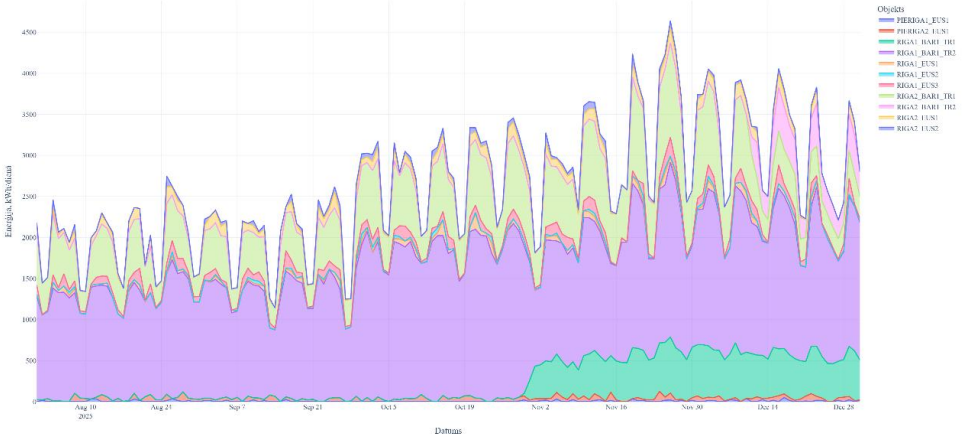

Fig. 4.2. Example of power supply source and EVCS load profiles during the validation period. *Source: Prepared by the author, using the power supply source and EVCS load profile data of the validation objects.*

In the dynamic charging point assignment model, the decision initiator is the EV and its charging need. A charging demand event in the validation model can be described as follows:

$$q_r = [t_r, SOC_r, E_{req,r}, P_{acc,r}, L_{EV,r}, u_{pref,r}], \tag{4.2}$$

where q_r is the r-th charging request, t_r is the request time, SOC_r is the initial battery state of charge, $E_{req,r}$ is the required amount of energy, $P_{acc,r}$ is the EV acceptable charging power, $L_{EV,r}$ is the EV location or starting point, and $u_{pref,r}$ are the user constraints.

If actual BMS data are not available, the SOC, the required energy, the battery capacity and the EV acceptable charging power are defined in scenario form. This makes it possible to control the experimental conditions and to test the MCDM model's response in various charging-need situations [7], [12], [34], [35].

The distribution network data layer ensures that the model is not limited to comparing user convenience and the technical parameters of the charging point. The EV charging load can affect transformer and line loading, the voltage regime, the power reserve and the admissibility of local network operation [10], [11], [33], [37]. Therefore, in the validation model, each charging alternative is linked to the relevant power supply object, transformer or power supply source load profile.

Several network criteria can be calculated from the available load profiles. The connection load coefficient can be defined as

$$k_{load}(a,t) = \frac{P_{feed}(a,t)}{P_{allow}(a)}. \tag{4.3}$$

The free power reserve is calculated as follows:

$$P_{res}(a,t) = P_{allow}(a) - P_{feed}(a,t). \tag{4.4}$$

If the impact of a potential new charging session is analysed, the overload risk indicator can be defined as follows:

$$r_{over}(a,t) = \max(0, \frac{P_{feed}(a,t)+P_{req}(a,t)-P_{allow}(a)}{P_{allow}(a)}), \tag{4.5}$$

If $r_{over}(a,t) > 0$, adding a new charging session at the particular node would exceed the permitted power limit. Such an indicator can act as a filtering condition or as a network risk criterion, depending on the scenario.

A significant limitation of the validation data is the lack of sufficient voltage and phase-current information for fully calculating voltage deviation and phase unbalance indicators. Therefore, these indicators are retained as methodologically envisaged network criteria, while the practical validation focuses on load, permitted power, power reserve and overload risk indicators.

The reliability and cybersecurity layer reflects the cyber-physical nature of EV charging infrastructure, where electricity transfer is linked with digital communication, operator platforms, authentication, payment systems, data integrity and service availability [9], [13], [14], [40], [41]. The cyberrisk indicators include authentication, data integrity, communication security, service availability risk, incident detection capability and third-party or cloud-service dependencies.

4.2. Data preprocessing and architecture of the experimental environment

After defining the validation data structure, heterogeneous EV, EVCS, power supply source, distribution network, data quality and cybersecurity data are prepared for use in the MCDM calculation model [45]. Data preprocessing includes cleaning and synchronisation, criteria normalisation, and the definition of thresholds and limit values. Each load profile is transformed into a standardised form:

$$D_{raw} \rightarrow D_{clean} \rightarrow D_{\Delta t}, \tag{4.6}$$

where D_{raw} are the original raw data, D_{clean} are the cleaned and structured data, and $D_{\Delta t}$ are the data at the selected time step.

The original load data are prepared at a 15-minute time step, which is sufficient for representing EVCS and power supply source load dynamics while keeping the calculation volume manageable. For summaries and visualisations, the data may be aggregated at a 1-hour step.

Normalisation transforms criteria with different units onto a common interpretation scale and ensures that benefit- and cost-type criteria are compared in the correct direction. The experimental environment is implemented as a layered calculation environment: the data layer imports and prepares the input data, the criteria layer transforms them into computable indicators, the MCDM layer applies AHP weights and PROMETHEE ranking, and the result layer stores the selected alternative, backup alternatives, net flows, KPIs and scenario comparisons.

The model execution chain can be written as follows:

$$D_{exp} \rightarrow D_{prep} \rightarrow C_t \rightarrow A_t^0 \rightarrow A_t^{adm} \rightarrow w \rightarrow \phi(a,t) \rightarrow R_t \rightarrow a_t^* \rightarrow KPI. \tag{4.7}$$

This sequence separates filtering from prioritisation: filtering excludes inadmissible alternatives, while PROMETHEE compares only alternatives that meet the minimum requirements at the particular moment. For each scenario, both intermediate and final results are stored, enabling Chapter 5 to analyse not only the selected charging point but also the full decision-formation process.

4.3. Scenario system

The scenario system is necessary so that the developed MCDM model can be tested under various operating conditions. A single static validation episode is not sufficient, because the dynamic EV charging point assignment problem depends on time-varying data. Therefore, the analysis examines how the model responds to seasonal load changes, differences between city and peri-urban infrastructure, increased network load, deterioration of data quality and cybersecurity risk scenarios.

Each scenario can be characterised as follows:

$$S_s = [T_s, Q_s, W_s, G_s, D_s, SEC_s, \Theta_s], \tag{4.8}$$

where T_s is the analysed period, Q_s are the EV demand parameters, W_s is the criteria weight configuration, G_s is the network load or power reserve conditions, D_s is the data quality conditions, SEC_s is the cybersecurity risk conditions, and Θ_s is the filtering and PROMETHEE threshold configuration.

In the initial data quality layer, each of the 11 profiles has 10 300 records, in total 113 300 measurement rows. In the preprocessing stage, 113 289 rows, i.e. 10 299 records per data object, were retained in the final calculation set. In the final calculations, the data period

runs from 01:00 on 1 August 2025 to 23:45 on 31 December 2025 at a 15-minute step. In the processed validation set, the total amount of electricity is 403 104.55 kWh.

Table 4.2

Coverage of the scenario validation data

Indicator	Value	Significance in validation
Validation sites	4	Comparison of city and peri-urban objects
EVCS alternatives	7	Set of alternatives for PROMETHEE ranking
Total number of charging points	25 (20 AC, 5 DC)	Characterisation of the charging infrastructure scale
Load profile data objects	11 (7 EVCS and 4 power supply sources)	Dynamic data layer of the EVCS and power supply sources
Raw measurement rows	113 300	Initial time-series coverage before final preprocessing
Processed measurement rows	113 289	Final calculation dataset for dynamic validation
Raw validation period	01.08.2025, 01:00–01.01.2026, 00:00	Time bounds of the original files
Processed validation period	01.08.2025, 01:00–31.12.2025, 23:45	Time axis used in the final calculations
Time step	15 min	Step of the real-time dynamic validation
Duplicate timestamp records	88	Identified in the data quality check
Data completeness	100 %	For all main profiles after validation
Total energy in the processed set	403 104.55 kWh	Used in linking the Chapter 5 calculation results
Total energy in the raw/site KPI layer	403 129.67 kWh	Sum of energy of the initial data quality and object KPI layer
Total installed/permitted EVCS power	598.00/463.32 kW	Characterisation of the technical capacity of the alternatives
Main data and calculation fields	76 unique fields in the main validation sheets	Technical data, EVCS statistics, distance/price, data quality, load KPIs and scenario KPIs

The base scenario characterises a normal operating regime in which there is no particularly elevated network, reliability or cybersecurity risk. This scenario uses the base AHP weights, standard filtering thresholds and the available load profiles.

The seasonal scenarios make it possible to analyse how the MCDM model operates in different periods of the year. The validation data period from August to December makes it possible to define a summer, autumn and winter regime:

$$S_{season} = \{S_{summer}, S_{autumn}, S_{winter}\}. \tag{4.9}$$

Table 4.3

Structure of the seasonal scenarios

Scenario	Decision moment/key	Variable factor	Impact on the admissible set	Validation question
Summer scenario	15.08.2025 10:00	Summer load and demand regime	72 h window, 288 steps	Tests the model in the summer regime
Autumn scenario	15.10.2025 16:00	Transitional-period load regime	72 h window, 288 steps	Tests the model in the autumn regime
Winter scenario	15.12.2025 13:00	Winter load regime	72 h window, 288 steps	Tests the model in the winter regime
Normal regime	normal	Actual data without additional degradation	7/7 alternatives	Base comparison regime

Table 4.3 (continued)

Data quality degradation	data_degradation	Strict data quality filter	0/7 alternatives	Tests the fallback/no-assignment situation
Cybersecurity risk regime	cyber_risk	Elevated cyberrisk for some alternatives	2/7 alternatives; admissible ratio 28.57 %	Tests security-aware filtering and penalisation
Network load regime	grid_stress	Strengthened network load criterion	7/7 alternatives; the net flow intensity changes	Tests network state prioritisation
Combined stress	combined_stress	Combination of cybersecurity and network/data risk	2/7 alternatives; admissible ratio 28.57 %	Tests the model's resilience under multiple risks

The distinction between city and peri-urban scenarios is methodologically important, because charging infrastructure suitability depends on local technical and operating conditions. In city objects, infrastructure concentration and a potentially larger simultaneity effect are more significant, whereas in peri-urban objects network capacity constraints, a smaller number of backup alternatives and uncertainty in communication or data availability may be more important [45], [46].

Data quality and cybersecurity scenarios are needed to test whether the integration of reliability, data quality and digital security criteria affects the result of dynamic charging point assignment. These scenarios analyse how charging point selection is influenced by a decrease in data completeness, an increase in data age, communication disruptions, elevated cyberrisk or security penalisation [13], [14], [40], [41].

In addition, a reliability-criteria-oriented weight sensitivity scenario is defined. Its aim is to test how the PROMETHEE ranking changes if greater importance is assigned to reliability, data quality, distribution network admissibility and cybersecurity.

4.4. Evaluation indicators

In order to validate the developed AHP–PROMETHEE model in Chapter 5, it is necessary to define evaluation indicators, i.e. KPIs. These indicators make it possible to analyse not only which alternative is selected but also how the model affects the user experience, infrastructure utilisation, distribution network load, decision stability, data quality and cybersecurity risk.

The KPIs are structured into five groups:

$$KPI = [KPI_U, KPI_I, KPI_G, KPI_R, KPI_{SEC}], \tag{4.10}$$

where KPI_U are the user-level indicators, KPI_I – the infrastructure-level indicators, KPI_G – the distribution network-level indicators, KPI_R – the reliability indicators, and KPI_{SEC} – the cybersecurity and data quality indicators.

Table 4.4

KPI structure

KPI group	Main indicators	Desired direction	Significance in validation
User KPIs	Average waiting time, average distance, assignment success rate, required charge satisfaction	Waiting and distance minimal; ASR and RCS maximal	Show the satisfaction of user needs
Infrastructure KPIs	Utilisation against installed power, utilisation against permitted power, distribution of selections, use of backup alternatives	Do not exceed limits; preserve backup options	Show the infrastructure load and the distribution of selections

Table 4.4 (continued)

Distribution network KPIs	Grid violation ratio, average power reserve, load deviation, overload risk	Violations minimal; reserve maximal	Show the impact of the network criteria
Reliability KPIs	Ranking stability, reassignment frequency, admissible alternatives loss, reserve availability	Stability and reserve availability high; reassignment justified	Show the resilience of the dynamic decision
Cybersecurity and data quality KPIs	Security penalty impact, data quality impact, cyberrisk impact, communication risk impact	Depends on the scenario	Show the contribution of the security and data quality layer

The assignment success rate indicator characterises how often the model is able to find at least one admissible alternative:

$$ASR = \frac{N_{success}}{N} \times 100\ \%. \tag{4.11}$$

The grid violation ratio can be defined as follows:

$$GVR = \frac{N_{viol}}{N} \times 100\ \%. \tag{4.12}$$

Ranking stability can be defined as the proportion of cases in which the first alternative does not change between two successive calculation steps.

$$RS = \frac{N_{stable}}{N-1} \times 100\ \% \tag{4.13}$$

The loss of admissible alternatives can be calculated as follows:

$$AAL = \frac{|A_t^0| - |A_t^{adm}|}{|A_t^0|}. \tag{4.14}$$

Reserve availability can be defined as the proportion of cases in which at least two alternatives are available after filtering:

$$RA = \frac{N_{|A_t^{adm}|\geq 2}}{N} \times 100\ \%. \tag{4.15}$$

In Chapter 5, these KPIs are used to show that the cybersecurity and data quality layer is not a decorative addition but directly affects the admissibility of alternatives, the ranking, the net flow and the robustness of the backup selection [43], [47].

4.5. Data and scenario limitations

The validation approach has several limitations. First, the data used include the technical parameters and load profiles of the EV charging infrastructure but do not include full real-time information on EV SOC, user routes, charging session durations, reservations or actual queues. Therefore, EV demand data, user preferences and waiting time indicators are partly defined in scenario form. Second, the validation dataset does not contain complete voltage and phase-current data for all objects; therefore, the practical network analysis is based on load, permitted power, power reserve and overload risk indicators. Third, the 15-minute time step is suitable for load profile analysis but is not intended for modelling second- or minute-level EVSE errors, communication delays or transient processes. Fourth, the cybersecurity scenarios are based on cyberrisk indicators defined in the literature and in the author's co-authored research, because full SOC/SIEM, Open Charge Point Protocol (OCPP) or authentication event logs are not available for the validation objects [13], [14], [40], [41]. Fifth, the geospatial layer uses anonymised validation zones instead of precise object coordinates.

5. MODEL VALIDATION AND ANALYSIS OF RESULTS

Chapter 5 validates the AHP–PROMETHEE-based dynamic EV charging point assignment model developed in Chapters 2 and 3. Whereas Chapter 4 defined the structure of the data, scenario and experimental environment, the task of this chapter is to test whether the developed model is practically able to calculate an interpretable charging point ranking, provide a dynamic assignment decision and yield a more justified result than simplified selection approaches.

The validation is based on the calculation results of the experimental environment, which used four anonymised validation sites, seven EVCS alternatives, eleven load profile data objects and 113 289 processed measurement rows. In the full load KPI data layer, the total amount of electricity analysed is 403 104.55 kWh. In addition to the overall data period, seasonal validation periods and representative decision moments were analysed.

The aim of the validation is not to determine a single universally optimal charging station but to assess the model's ability to rank alternatives repeatedly and interpretably under changing conditions, taking into account EV demand, available power, waiting time, distribution network load, power reserve, data quality, reliability and cybersecurity risk.

5.1. Validation approach and the comparative assignment strategies

Three main aspects are tested in the validation. First, it is assessed whether the AHP–PROMETHEE model can calculate a complete and interpretable charging point ranking, in which a positive flow, a negative flow, a net flow and a place in the ranking are determined for each alternative. Second, it is analysed whether the selected alternative and the sequence of backup alternatives change depending on the season, the distribution network load, the data quality, and the cybersecurity scenarios. Third, it is compared whether the full reliability-oriented model yields a more justified result than simplified selection strategies.

The full model is interpreted as a reliability-oriented AHP–PROMETHEE approach. AHP is used to determine the criteria weights, whereas PROMETHEE is used for the pairwise comparison of alternatives and for calculating the final ranking [25], [27]. The criteria system used in the validation of the full model includes nine criteria: reliability, power reserve, cyberrisk, data quality, network load, available charging power, distance, waiting time, and price.

The final selection is determined by the PROMETHEE net flow.

Table 5.1

Comparative charging point assignment strategies

Approach	Selection logic	Mathematical interpretation	Limitation
Nearest station	Selects the alternative with the smallest distance to the EV	$a_t^d = \arg\min_{a \in A_t^{adm}} d(a,t)$	Ignores power, waiting, network state, data quality and cyberrisk
Shortest waiting time	Selects the alternative with the smallest waiting time	$a_t^W = \arg\min_{a \in A_t^{adm}} W(a,t)$	May select an alternative that is less suitable technically or in network terms
Largest available power	Selects the alternative with the largest available charging power	$a_t^P = \arg\max_{a \in A_t^{adm}} P_{ch}^{avail}(a,t)$	Ignores whether higher power is needed, reachable or admissible in network terms
Approach without network criteria	PROMETHEE ranking without network load and power reserve criteria	$\phi_{noG}(a,t)$, where the network criteria weights are 0, and the remaining weights are normalised	Does not take into account the local distribution network impact

Table 5.1 (continued)

Approach without the cybersecurity criterion	PROMETHEE ranking without the cyberrisk criterion and security penalisation	$\phi_{noSEC}(a,t)$, where the cyberrisk criterion weight is 0	Does not take into account the cybersecurity and data integrity risk
Full reliability-oriented AHP–PROMETHEE model	Uses all user, infrastructure, network, data quality, reliability and cybersecurity criteria	$a_t^* = \arg\max_{a \in A_t^{adm}} \phi(a,t)$	A more complex but interpretable multi-criteria model

5.2. Results of the AHP weight and PROMETHEE rank calculations

Seven EVCS alternatives are used in the validation environment:

$$A = \begin{Bmatrix} RIGA1_{EUS1}, RIGA1_{EUS2}, RIGA1_{EUS3}, \\ RIGA2_{EUS1}, RIGA2_{EUS2}, \\ PIERIGA1_{EUS1}, PIERIGA2_{EUS1}. \end{Bmatrix}. \quad (5.1)$$

The AHP weight results are used as the relative-importance structure of the criteria, whereas the PROMETHEE calculation shows how these weights, together with the current criteria values, are transformed into a ranking of alternatives.

Table 5.2

Comparison of the base and reliability-oriented criteria weights

Criterion	Symbol	Type	Base weight	Reliability-oriented weight	Change, %
Reliability	R_{rel}	Maximised	0.19466	0.21755	11.76 %
Power reserve	P_{res}	Maximised	0.17775	0.18277	2.82 %
Cyberrisk	ρ_{cyb}	Minimised	0.15564	0.17395	11.76 %
Data quality	D_{qual}	Maximised	0.10629	0.10929	2.82 %
Network load	k_{load}	Minimised	0.10276	0.10107	–1.65 %
Available charging power	P_{ch}^{avail}	Maximised	0.09784	0.08748	–10.59 %
Distance	d	Minimised	0.06461	0.0491	–24.00 %
Waiting time	W	Minimised	0.05511	0.04435	–19.53 %
Price	p	Minimised	0.04534	0.03446	–24.00 %
Total			**1**	**1**	

In the base model, the largest weights are assigned to reliability, power reserve and cyberrisk. Together, these three criteria make up 52.805 % of the total weight. If data quality and network load are added to this group, the reliability-oriented criteria block makes up 73.710 % of the total weight. In the reliability-oriented configuration, this block increases to 78.463 %, while the total weight of distance, waiting time, and price decreases to 12.791%. This shows that the model is not merely a user-convenience model, but prioritises infrastructure operability, data reliability, network admissibility and cybersecurity risk control.

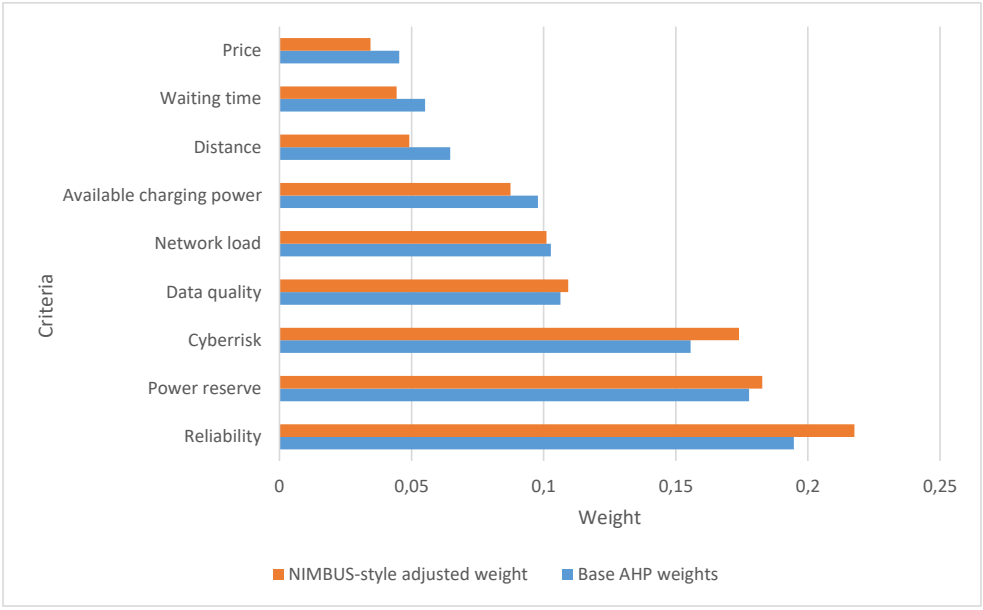

Fig. 5.1. Comparison of the base and reliability-oriented adjusted criteria weights.
Source: Prepared by the author, based on the base and adjusted weight configurations.

To assess the model's operation under various operating conditions, the PROMETHEE calculations were performed at three representative seasonal decision moments – in summer, autumn and winter.

Table 5.3

Summary of the PROMETHEE II decision results in the seasonal scenarios

Season	Weight configuration	Best alternative	ϕ_1	Second alternative	ϕ_2	$\Delta\phi_{12}$	Admissible alternatives
Summer	Base	$PIERIGA2_{EUS1}$	0.259391	$RIGA1_{EUS1}$	0.181426	0.077964	7/7
Summer	Reliability-oriented	$PIERIGA2_{EUS1}$	0.268799	$RIGA1_{EUS1}$	0.215763	0.053036	7/7
Autumn	Base	$PIERIGA2_{EUS1}$	0.263437	$RIGA1_{EUS1}$	0.126437	0.137	7/7
Autumn	Reliability-oriented	$PIERIGA2_{EUS1}$	0.27346	$RIGA1_{EUS1}$	0.159237	0.114222	7/7
Winter	Base	$PIERIGA2_{EUS1}$	0.246861	$RIGA1_{EUS1}$	0.139898	0.106963	7/7
Winter	Reliability-oriented	$PIERIGA2_{EUS1}$	0.256556	$RIGA1_{EUS1}$	0.172286	0.08427	7/7

The PROMETHEE II results show that $PIERIGA2_{EUS1}$ takes first place at all three seasonal decision moments in both the base and the reliability-oriented configuration. In all the analysed cases, $RIGA1_{EUS1}$ is in second place and can be interpreted as the main backup alternative. In the reliability-oriented configuration, the net flow of $PIERIGA2_{EUS1}$ increases slightly, but at the same time the difference between the net flows of the first and second alternatives decreases. This means that strengthening the reliability and security criteria does not change the main recommendation but increases the relative competitiveness of the backup alternative. $PIERIGA2_{EUS1}$ takes first place at all three seasonal decision moments in both the base and the reliability-oriented configuration. Second place in all analysed cases is held by $RIGA1_{EUS1}$, which can be interpreted as the main backup alternative. In the reliability-oriented configuration, the $PIERIGA2_{EUS1}$ net flow increases slightly, but at the same time the difference between the net flows of the first and second alternatives decreases. This means that

strengthening the reliability and security criteria does not change the main recommendation but increases the relative competitiveness of the backup alternative.

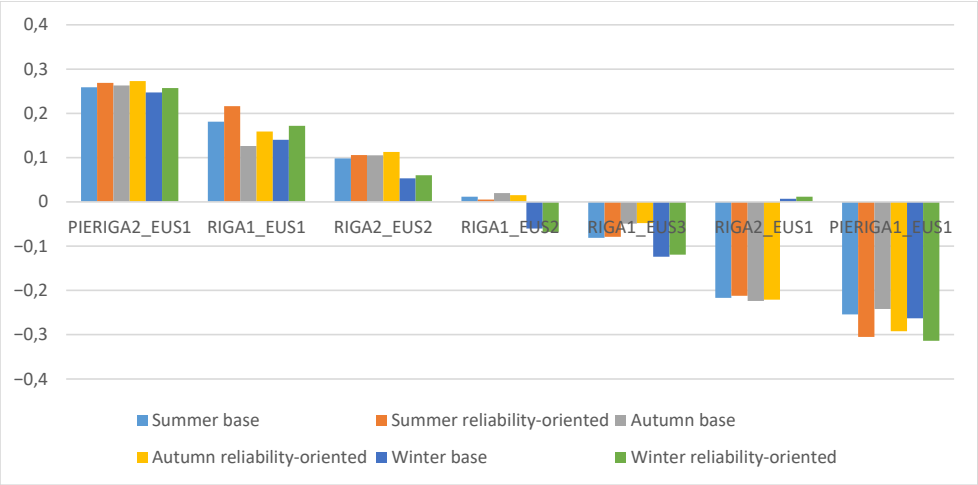

Fig. 5.2. PROMETHEE II net flows at the decision moment for both the base configuration and the reliability-oriented configuration.

Source: Prepared by the author, based on the PROMETHEE II decision-moment calculations.

5.3. Base scenario validation results

The aim of the base scenario validation is to test whether the developed AHP–PROMETHEE model can, under normal operating conditions, provide a stable, interpretable and technically justified EV charging point assignment. In the base scenario, no additional network peak load, data quality degradation or elevated cybersecurity risk correction is applied.

The dynamic validation of the base scenario was performed over three seasonal 72-hour periods: summer, autumn and winter. The calculation was performed at a 15-minute step, so 288 dynamic charging point assignment results were obtained in each seasonal period, and 864 decision moments in total across the three seasons.

Table 5.4

Comparison of the base scenario KPIs by season

Indicator	Summer	Autumn	Winter
72 h window energy, kWh	580.18	1187.15	1004.30
Assignment success rate	100.00 %	100.00 %	100.00 %
Average number of admissible EVCS	6.98	6.98	6.94
Minimum number of admissible EVCS	6	6	6
Admissible alternatives ratio	99.70 %	99.65 %	99.21 %
Loss of admissible alternatives	0.30 %	0.35 %	0.79 %
Reserve availability	100.00 %	100.00 %	100.00 %
Ranking stability	85.42 %	90.28 %	86.46 %
Reassignment frequency	14.58 %	9.72 %	13.54 %
Average $\Delta\phi_{12}$	0.06211	0.08461	0.08440

In all three seasonal periods, the assignment success rate reaches 100 %. This means that in each of the 864 analysed decision moments, the model can identify at least one admissible charging alternative. The average number of admissible EVCS remains close to seven alternatives, while reserve availability is 100 % in all seasons. This is essential in the

context of dynamic EV charging point assignment because the selected alternative may become occupied, technically unavailable, undesirable in network terms or risky in security terms.

Ranking stability in the base scenario is 85.42 % in summer, 90.28 % in autumn and 86.46 % in winter. Correspondingly, the reassignment frequency is 14.58 % in summer, 9.72 % in autumn and 13.54 % in winter. These results show that the model is dynamic but does not make chaotic changes in recommendations.

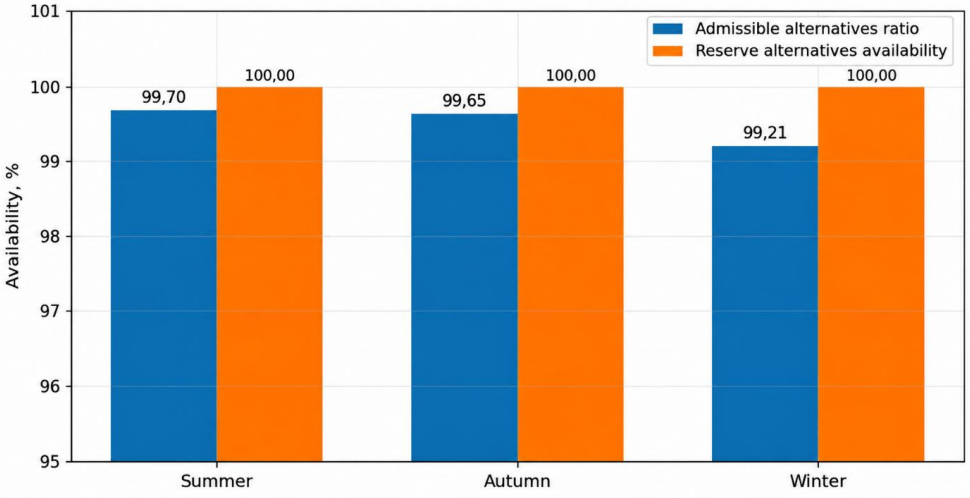

Fig. 5.3. Changes in the number of admissible alternatives over time during the seasonal validation periods of the base scenario.

Source: Prepared by the author, based on the seasonal validation results of the base scenario.

5.4. Comparative analysis with simplified assignment approaches

The aim of the comparative analysis is to test the practical aspect of the Doctoral Thesis hypothesis – whether a multi-criteria, reliability-oriented dynamic assignment approach provides a more justified selection than approaches based on a single dominant criterion.

The comparison uses four assignment approaches: the full AHP–PROMETHEE model, selection of the nearest alternative, selection by the shortest waiting time, and selection of the largest effective charging power.

Table 5.5

Comparison of the selected alternatives and risk profile of the assignment methods

Assignment method	**Full AHP–PROMETHEE model**	**Nearest alternative**	**Shortest waiting time**	**Largest effective charging power**
Selection at the seasonal moments	$PIERIGA2_{EUS1}$	$PIERIGA1_{EUS1}$	$RIGA2_{EUS2}$	$PIERIGA1_{EUS1}$
Avg. network load	0.000272	0.000159	0.010918	0.000272
Avg. cyberrisk	0.16	0.39	0.22	0.16
Avg. data quality	0.9	0.6	0.8	0.9
Avg. reliability	0.94279	0.83985	0.90829	0.94279
Avg. effective power, kW	50	22	22	50
Avg. distance, km	23.14	17.49	25.72	23.14

At all three seasonal decision moments, the full AHP–PROMETHEE model selects $PIERIGA2_{EUS1}$. The largest-effective-charging-power approach gives the same selection at the particular decision moments. However, these approaches are not methodologically equivalent because the single-criterion approach does not explain the suitability of the alternative by reliability, data quality, network and cybersecurity criteria. The same choice at the specific decision moments is also given by the largest effective charging power approach. However, these approaches are not methodologically equivalent, since the single-criterion approach does not explain the suitability of an alternative in terms of the reliability, data quality, network and cybersecurity criteria.

The nearest-alternative approach selects $PIERIGA1_{EUS1}$, because it has the smallest distance – 17.49 km. However, this alternative has a higher cyberrisk – 0.39, lower data quality – 0.60 and a lower reliability indicator – 0.840. The shortest-waiting-time approach selects $RIGA2_{EUS2}$, but the full model does not assign it first place, because its overall multi-criteria profile is weaker than that of $PIERIGA2_{EUS1}$.

The comparative analysis confirms that dynamic EV charging point assignment cannot be reduced to selecting the nearest, fastest or most powerful alternative. In reliability-oriented assignment, the most suitable alternative is the one that has the best overall multi-criteria profile at the particular decision moment.

5.5. Scenario and stress condition analysis

The aim of the scenario analysis is to test whether the model retains its assignment capability even when some alternatives become less suitable due to network, data quality or cybersecurity considerations. Each scenario changes one or more factors that influence the decision environment: the network load, the data quality, the cyberrisk level or a combination of these factors.

Table 5.6

Comparison of the average KPIs of the stress scenarios

Scenario	Assignment success rate	Avg. number of admissible alternatives	Admissible alternatives ratio	Avg. TOP 1 ϕ	Interpretation
Normal regime	100.00 %	7.00	100.00 %	0.256563	Reference regime; all alternatives admissible
Network load regime	100.00 %	7.00	100.00 %	0.261456	The network load correction does not change the admissible set at the decision level
Data quality degradation	0.00 %	0.00	0.00 %	—	The strict data quality filter excludes all alternatives
Cybersecurity risk regime	100.00 %	2.00	28.57 %	0.309073	The security filter narrows the choice space to 2/7 alternatives
Combined stress	100.00 %	2.00	28.57 %	0.309073	The result coincides with the cybersecurity stress regime; 2/7 alternatives admissible

In the network load regime, the assignment success rate remains 100 %, and all seven alternatives remain admissible. However, the average TOP-1 net flow increases to 0.261456, which indicates that the network criteria correction affects the prioritisation of alternatives.

In the data quality degradation scenario, under the influence of the strict data quality filter, the number of admissible alternatives decreases to 0 out of 7, and the assignment success rate is 0 %. In this case, the PROMETHEE ranking is not calculated because there is not a single admissible alternative. This can be interpreted as a feature of the reliability-oriented

approach: if the data are not sufficiently reliable, the model does not need to issue an automatic recommendation.

In the cybersecurity risk and combined stress scenarios, only 2 out of 7 alternatives, i.e., 28.57 %, are admissible. Nevertheless, the model still maintains a 100 % assignment success rate and can select $PIERIGA2_{EUS1}$ as the best admissible alternative.

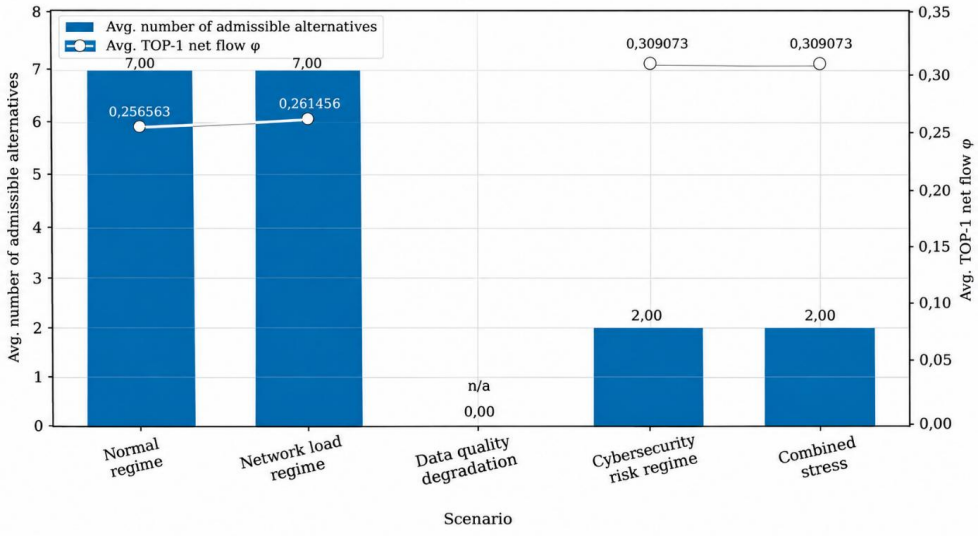

Fig. 5.4. Comparison of the stress scenario KPIs.

Source: Prepared by the author, based on the calculation results of the experimental validation environment.

5.6. Sensitivity analysis

The aim of the sensitivity analysis is to test how stable the developed AHP–PROMETHEE model is against changes in the criteria weights, in the cyberrisk impact and in the importance of the network criteria. In the full August–December period, 3 672 decision moments were analysed.

Table 5.7

Number of selected alternatives in the full August–December period

Weight configuration	Base	Reliability-oriented
Main selected alternative	$PIERIGA2_{EUS1}$	$PIERIGA2_{EUS1}$
Selection ratio	77.12 %	60.92 %
Second alternative	$RIGA1_{EUS1}$	$RIGA1_{EUS1}$
Selection ratio	22.79 %	39.03 %
Assignment success	100.00 %	100.00 %
Ranking stability	85.81 %	80.53 %
Reassignment frequency	14.19 %	19.47 %
Avg. $\Delta\phi_{12}$	0.07012	0.06162

In the base configuration, the most frequently selected alternative is $PIERIGA2_{EUS1}$, which is selected in 2 832 time steps, i.e., 77.12 % of cases. $RIGA1_{EUS1}$ is selected in 837 time steps, i.e., 22.79 % of cases. In the reliability-oriented configuration, $PIERIGA2_{EUS1}$ retains the

largest share, but the number of its selections decreases to 60.92 %, while the share of $RIGA1_{EUS1}$ increases to 39.03 %.

In both weight configurations, the assignment success is 100 %. This means that changing the weight configuration does not reduce the model's ability to provide a valid assignment result. At the same time, in the reliability-oriented configuration, the ranking stability decreases from 85.81 % to 80.53 %, while the reassignment frequency increases from 14.19 % to 19.47 %. This indicates that the model becomes more sensitive to changes in the reliability, network and cybersecurity profile but does not lose its ability to assign an admissible charging alternative.

In addition, the impact of the cyberrisk criterion weight and of direct cyberrisk penalisation was analysed. As the importance of cyberrisk increases, the competitiveness of alternatives with a better reliability, data quality and cybersecurity profile increases. The network criteria sensitivity analysis shows that strengthening the network load and power reserve criteria can, in certain cases, rearrange the first place in favour of alternatives with a better network profile. This means that the model is not mechanically tied to a single alternative but can adapt to situations in which the distribution network state becomes a dominant constraint.

5.7. Assessment of the contribution of the reliability and cybersecurity layer

The contribution of the reliability, data quality and cybersecurity layer is assessed by how these indicators affect the filtering of alternatives, the PROMETHEE ranking, the net flow, the backup sequence and decision stability. In the context of the Doctoral Thesis, reliability is not interpreted only as the physical operability of the charging equipment.

The data quality and cybersecurity stress scenarios show that these layers affect not only the net flow of the alternatives but also the set of admissible alternatives itself. In the data quality degradation scenario, the strict data quality filter excludes all alternatives, so the assignment success decreases to 0 %. In the cybersecurity risk regime and the combined stress scenario, only 2 out of 7 alternatives are admissible, yet the model still retains the ability to select an admissible alternative.

The cybersecurity layer is used in the model in three ways: as a filter, as a PROMETHEE criterion, and as a net flow penalisation mechanism. Such a three-level integration ensures that cybersecurity risk can affect both the admissibility of an alternative and its relative priority among other alternatives.

In addition to the MCDM scenario analysis, a cybersecurity data layer was used in the experimental environment, based on the processing of OCPP application-level, OCPP TCP/IP-level and WUSTL-IIoT datasets. The aim of this layer is not to replace an EVSE technical security audit, but to justify the use of the cyberrisk indicator as an MCDM criterion that influences the decision [48], [49].

Table 5.8

Summary of the cybersecurity data layers

Data layer	OCPP application level, training data	OCPP TCP/IP level, training data	WUSTL-IIoT 2021
Rows	3020	3090	1 194 464
Attack ratio	80.00 %	80.00 %	7.28 %
Avg. risk score	0.234	0.456	0.582
P95 risk score	0.339	0.645	0.614
AUC	0.723	0.911	0.034
Recall	0.532	0.528	0.009
F1	0.688	0.685	0.01

Table 5.8 (continued)

Interpretation	Moderate application-level anomaly separability; usable for protocol-level indication	Better communication-level anomaly separability; suitable for a communication risk indicator	Additional industrial IIoT domain layer; results must be interpreted with a domain-transferability limitation

Source: Author's calculations, based on the processing of the OCPP APP, OCPP TCP/IP and WUSTL-IIoT data layers; the OCPP data layers are based on the Federated OCPP 1.6 Intrusion Detection Dataset [59], while WUSTL-IIoT 2021 is used as an additional IIoT cybersecurity dataset [60].

The cybersecurity data layer results show that distinguishing attack traffic from normal traffic depends on the data domain and the feature structure. The AUC obtained in the OCPP TCP/IP data layer is 0.911, which indicates good separability between normal and anomalous communication behaviour. In the OCPP application-level data layer, the AUC is 0.723, which indicates a moderate classification capability. The WUSTL-IIoT data layer, by contrast, must be interpreted with caution, because it reflects a broader industrial IoT domain and is not directly identical to the EV charging infrastructure communication environment.

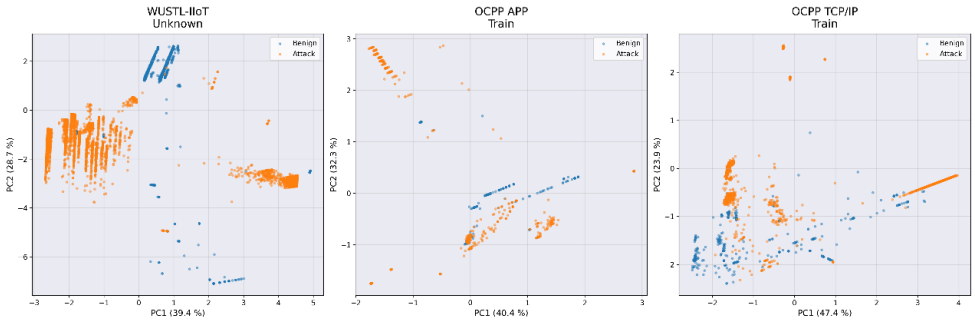

Fig. 5.5. PCA projection of the cybersecurity data layers: comparison of normal and attack traffic.

Source: Prepared by the author, based on the calculation results of the OCPP APP, OCPP TCP/IP and WUSTL-IIoT data layers.

The practical contribution of the reliability and cybersecurity layer is expressed at several levels. First, it improves the interpretability of the decision. Second, it reduces the risk of recommending an alternative for which there are insufficiently reliable data. Third, the cybersecurity layer makes it possible to avoid recommending high-risk alternatives. Fourth, the use of the full ranking ensures the availability of backup alternatives. Fifth, this layer links EV charging point assignment with the reality of the cyber-physical infrastructure.

5.8. Summary of Chapter 5

In Chapter 5, the developed AHP–PROMETHEE-based dynamic EV charging point assignment model was validated. The results confirm that the model can calculate a complete and interpretable ranking of charging points, identify the most suitable alternative and maintain a sequence of backup alternatives.

The AHP weight analysis shows that the model is reliability-oriented, as the criteria of reliability, power reserve, cyberrisk, data quality and network load account for 73.710 % of the total weight in the base configuration and 78.463 % in the reliability-oriented configuration. The seasonal PROMETHEE II results show that $PIERIGA2_{EUS1}$ retains first place in all analysed seasonal scenarios, while $RIGA1_{EUS1}$ forms the main backup alternative.

In the base scenario, the assignment success rate reaches 100 % in all seasons, while ranking stability remains within the range of 85.42–90.28 %. The comparison with simplified assignment approaches confirms that the nearest, fastest available or most powerful alternative is not always the most suitable when reliability, data quality, distribution network admissibility and cybersecurity are evaluated simultaneously.

The stress scenarios show that data quality degradation may completely prevent assignment, whereas under cybersecurity risk and combined stress conditions the number of admissible alternatives decreases to 2 out of 7; nevertheless, the model retains the ability to select an admissible alternative. The sensitivity analysis confirms that the model maintains its assignment capability under changes in weight configuration and can adjust the priority of alternatives when the importance of reliability, cybersecurity or network criteria increases.

6. DISCUSSION OF RESULTS, IMPLEMENTATION POSSIBILITIES AND RESEARCH LIMITATIONS

Chapter 6 interprets the validation results of the Doctoral Thesis, evaluates the hypothesis, characterises the scientific and practical contribution, and identifies the implementation possibilities, research limitations and directions for further development. The chapter summarises how the developed AHP–PROMETHEE model provides reliability-oriented dynamic EV charging point assignment by integrating user, charging infrastructure, distribution network, data quality, reliability and cybersecurity criteria into a unified decision-making model.

6.1. Interpretation of results and evaluation of the hypothesis

The Doctoral Thesis substantiates that the selection of an electric vehicle charging point cannot be reduced solely to choosing the nearest, fastest or most powerful station. Such simplified approaches can be useful as initial guidelines, yet they do not take into account the actual availability of the charging point, distribution network load, power reserve, data timeliness, communication reliability and cybersecurity risks. Therefore, the Thesis interprets charging point assignment as a dynamic multi-criteria decision-making problem.

The developed AHP–PROMETHEE model achieves the objective of the Doctoral Thesis at the level of methodological and scenario validation. The AHP method provides hierarchical structuring of criteria and determination of their relative importance, whereas the PROMETHEE method makes it possible to compute the priorities of alternatives using the positive, negative and net flows [25], [27], [29]. Such an approach provides not only the final recommendation but also its explanation.

An essential result of the study is the obtaining of a complete ranking of charging points rather than the determination of only a single selected alternative. The PROMETHEE II net flow serves as the final priority indicator, while the full ranking makes it possible to determine the main and backup alternatives. This is significant in the context of dynamic charging point assignment, because in real operation the selected charging point may become occupied, inoperable, less admissible in network terms, or riskier in cybersecurity terms.

The validation results show that at the seasonal PROMETHEE II decision moments $PIERIGA2_{EUS_1}$ retains first place in the summer, autumn and winter scenarios in both the base and the reliability-oriented weight configurations. $RIGA1_{EUS_1}$ retains second place at all seasonal decision moments and can be interpreted as the main backup alternative.

The analysis of the AHP weights shows that the model is essentially reliability-oriented. In the base configuration, the combined weight of the reliability, power reserve, cyberrisk, data quality and network load criteria is 73.710 % of the total weight. In the reliability-oriented configuration, this block of criteria increases to 78.463 %, whereas the combined weight of distance, waiting time, and price decreases to 12.791 %. This means that the model is not merely a user-comfort model, but rather an approach in which user needs are balanced against infrastructure operability, distribution network admissibility, data trustworthiness and cybersecurity risk.

In the data quality degradation scenario, the number of admissible alternatives decreases to 0 out of 7, and the assignment success rate is 0 %. This result should not be interpreted as a failure of the model, but rather as a feature of a reliability-oriented approach: if the data quality does not meet the minimum requirements, the model should not issue an automatic recommendation. In the cyberrisk and the combined stress scenario, the set of admissible alternatives narrows to 2 out of 7 alternatives, i.e., 28.57 %, yet the assignment success rate remains 100 %.

Table 6.1

Evaluation of the hypothesis elements based on the validation results of Chapter 5

Hypothesis element	Validation interpretation	Evaluation
A multi-criteria approach provides a more substantiated choice than single-criterion approaches	The full model balances distance, waiting time, available power, network criteria, reliability, data quality and cybersecurity	Supported
Dynamic assignment improves adaptation to the situation	The seasonal scenarios and the weight sensitivity analysis show that the ranking and the net-flow differences can change according to operating conditions	Supported
The inclusion of network criteria reduces the likelihood of technically risky choices	The network criteria make it possible to downgrade or exclude alternatives with an unfavourable network profile	Supported at the methodological and scenario level
The reliability, cybersecurity and data quality layer affects the quality of the decision	Riskier or less data-reliable alternatives are penalised, downgraded in the ranking or excluded	Supported
The model has been proven in full real-world field operation	Validation was carried out using anonymised objects, a scenario and prototype computation environment, rather than a full-scale CPO–DSO–EV field experiment.	Not fully proven at this stage of the research

It follows from the table that the hypothesis is supported within the limits of methodological and scenario validation. Full practical effectiveness in a real operating environment still needs to be confirmed through broader data integration, real-time CPO/CSO and DSO data, as well as a more complete cybersecurity monitoring layer.

6.2. Comparison with the literature and scientific contribution

The results of the Doctoral Thesis should be interpreted in the context of the literature on EV charging infrastructure, MCDM, smart charging, distribution networks and cybersecurity. The contribution of the Thesis is not associated solely with the application of the AHP or PROMETHEE methods, since both methods are widely known in multi-criteria decision-making [25], [27], [28]. The specific aspect of the Thesis is the adaptation of these methods to reliability-oriented dynamic assignment of an EV charging point for a specific vehicle at a specific time.

The existing literature in the field of EV charging infrastructure largely focuses on the issues of station siting, capacity, infrastructure coverage and sustainable planning [10], [16]–[19]. These studies are essential for long-term infrastructure development, yet they do not answer an operational question: which of the already available charging points to assign to a specific EV at a given moment.

In this Doctoral Thesis, the emphasis is shifted from infrastructure planning to a dynamic operational-level decision. The charging point is interpreted as a time-varying MCDM alternative whose suitability depends on EV demand, waiting time, available power, network load, data quality, reliability and cybersecurity status.

In the MCDM literature, AHP, PROMETHEE, TOPSIS, ELECTRE and other methods are widely used for infrastructure evaluation, sustainability analysis, energy system decisions and the selection of charging station locations [16], [19], [24]–[28]. However, in many EV charging infrastructure studies, MCDM is used for strategic or tactical planning, rather than for operational dynamic prioritisation of alternatives. In this study, AHP serves to structure the importance of criteria, while PROMETHEE serves to rank the admissible alternatives at a specific moment in time.

The context of the cybersecurity literature should be highlighted separately. Studies of EV charging infrastructure cybersecurity emphasise the importance of authentication, communication, data integrity, service availability and third-party risk [9], [13], [14], [40], [41]. However, these risks are often analysed as a separate cybersecurity or risk assessment task, rather than as a direct part of the charging point selection mechanism. In this work, the cybersecurity risk is integrated into the MCDM model itself – as a filtering condition, as a criterion to be minimised in the PROMETHEE procedure, and as a correction factor for the final net flow.

The scientific contribution of the Doctoral Thesis can be structured at three levels. The theoretical contribution is the formalisation of dynamic EV charging point assignment as an MCDM problem and the interpretation of the charging point as a cyber-physical alternative. The methodological contribution is a model for the sequential use of AHP–PROMETHEE for the dynamic ranking of admissible charging points, integrating filtering, reliability criteria and cyberrisk penalisation. The practical contribution is a reproducible computation core of a decision support system for the management of EV charging infrastructure.

6.3. Practical implementation possibilities

The developed model is a methodologically validated computation core that can be further developed for practical use at several levels. The main potential user groups are charging infrastructure operators, distribution system operators, municipalities and regional mobility planners, as well as cybersecurity and data management specialists.

For charging infrastructure operators, i.e., CPO/CSO, the model can serve as a decision support instrument for recommending charging points. In practical implementation, it could be integrated into the operator platform or the user application, where the user is offered not merely the nearest or available station, but the most suitable alternative, taking into account available power, waiting time, price, data quality, reliability and cybersecurity risk.

For distribution system operators, the model offers the possibility of incorporating network status information into the operational selection of a charging point. This does not mean that the CPO/CSO system would replace the distribution system operator (DSO) network control system, but rather that local load, power reserve or network admissibility indicators could be used in the decision support layer.

For municipalities and regional mobility planners, the model could help to analyse how the existing charging infrastructure performs under various scenarios. Since the model includes a geospatial layer, charging point availability and network criteria, it can also be used for analysing infrastructure development priorities.

In the context of cybersecurity management, the model offers a way to link security indicators with a practical decision. In practical implementation, this would make it possible to downgrade in the ranking those alternatives with elevated authentication, communication or data integrity risk, rather than recommending them merely because they are close to the user or provide high charging power.

The model can be implemented gradually. In the first stage, it can operate as an analytical recommendation tool using the available operator and load data. In the second stage, it can be supplemented with DSO network indicators and a data quality layer. In the third stage, integration of cybersecurity monitoring and event-driven recomputation logic is possible. At a more complete implementation stage, the model can become the analytical module of a digital twin of EV charging infrastructure or of a smart mobility platform.

6.4. Research limitations

The results of the Doctoral Thesis should be interpreted in the light of several limitations.

1. The validation was carried out as a methodological and scenario-based test, rather than as a full-scale field experiment with direct connection to real-time CPO/CSO, DSO, EV and user systems. The validation used anonymised objects, load profiles, technical data, scenario assumptions and prototype calculation logic.

2. The validation dataset does not contain complete real-time data on EV SOC, routes, user behaviour, reservations, actual queues or charging sessions. These parameters were defined in scenario form or derived from the available data. In addition, the dataset does not contain complete voltage and phase-unbalance data for all objects; therefore, the practical network analysis is based on load, permitted power, power reserve and overload risk indicators.

3. The cybersecurity layer is not a full cybersecurity audit of the specific validation objects. The OCPP APP, OCPP TCP/IP and WUSTL-IIoT datasets are used to justify the operationalisation of the cyberrisk indicator, but they do not replace vulnerability analysis, penetration testing, security architecture review or the assessment of the operator's security controls.

4. Limitations are also related to the selected MCDM methodology. The AHP weights reflect an expert-defined or scenario-defined priority structure; therefore, they are not absolute or universal for all countries, operators or user groups. This approach is transparent and auditable, but it retains subjectivity. In practical implementation, the AHP weights could be revised through a broader expert survey, user segmentation or historical data analysis.

5. The PROMETHEE method is based on pairwise comparisons of alternatives for each criterion; therefore, as the number of charging points increases, the computational volume grows substantially. For a small or medium-sized set of alternatives, this is acceptable, but in a large public charging network with hundreds or thousands of points, practical implementation would require candidate pre-filtering, geographical narrowing, clustering, parallelisation or the use of faster MCDA methods.

6. The AHP–PROMETHEE combination is not the only possible approach. It was selected because of its interpretability, structured criteria weighting and ability to produce a complete ranking. For larger sets of alternatives, the TOPSIS method could be evaluated, as it is based on the distance to the ideal and negative-ideal solutions and is usually computationally simpler. At the same time, TOPSIS does not provide the same pairwise comparison and positive/negative flow interpretation as PROMETHEE; therefore, the choice of method is a trade-off between computational speed, interpretability and explainability of the decision.

7. The weighting system used in this work is not a data-driven or machine-learning model. The AHP weights are based on expert judgement rather than on a historically trained model. An alternative approach would be a machine-learning model that, using historical charging-session data, user choices, network states, failures, security events and operator decisions, learns the importance of the criteria or directly predicts the most suitable charging point. Such an approach could complement AHP-based weight determination, but it would require a large, high-quality and representative training dataset, as well as control over explainability, model drift and auditability.

8. The Thesis does not model full transport flows at city or national scale, electricity market dynamics or a full digital twin of the EV–CPO–DSO–user system with real-time bidirectional data flows and control commands. The developed model is a decision-support calculation core that can be further extended for practical implementation.

6.5. Directions for further development

The model developed in the Doctoral Thesis forms the basis for several directions of further development.

The first direction is validation of the model with a broader and real-time dataset. In future research it would be necessary to integrate real CPO/CSO, DSO and EV user data,

including charging-session status, queues, reservations, actual waiting times, EV SOC, the user's route and local network measurements.

The second direction is the integration of a digital twin approach. A digital twin of the distribution network and the charging infrastructure would make it possible to link the physical infrastructure, geospatial data, load profiles, network events, EVSE statuses and decision algorithms in a unified modelling environment [51]. In this case, the developed AHP–PROMETHEE model could operate as the decision-making layer of the digital twin.

The third direction is the development of a predictive assignment model. In the future, the model could be supplemented with forecasts of waiting time, charging point load, EV demand, network load and data quality degradation.

The fourth direction is the comparative development of MCDM methods. In the future, it is possible to examine how the developed AHP–PROMETHEE approach compares with TOPSIS, ELECTRE, VIKOR, fuzzy AHP, ANP or other MCDA methods. A comparison with TOPSIS in larger sets of alternatives would be particularly significant, since TOPSIS could provide faster computation in cases where a very large number of charging points must be evaluated.

The fifth direction is the automation of AHP weight determination or its supplementation with machine-learning approaches. In a practical environment where extensive historical data on EV user choices, charging sessions, network status, failures, security events and operator decisions accumulate, a machine-learning model could be developed that learns the importance of criteria from the data. The AHP expert assessment could serve as the initial weight structure, while the machine-learning model could serve as an adaptive weight-correction or recommendation layer.

The sixth direction is the deepening of the cybersecurity layer. In the future, it would be necessary to build a closer linkage with OCPP, ISO 15118, Plug & Charge, certificate management, authentication, authorisation and secure data exchange mechanisms.

The seventh direction is the integration of RES, BESS and V2G. The model could be supplemented with indicators of local PV generation, BESS SOC, charging/discharging power, network flexibility and V2G potential. This would make it possible to link charging point selection not only with the current network load but also with local energy flexibility and the use of renewable energy resources.

6.6. Conclusions of Chapter 6

Chapter 6 interprets the validation results, evaluates the hypothesis, and summarises the scientific contribution, implementation possibilities, research limitations and directions for further development.

The developed AHP–PROMETHEE model achieves the objective of the Doctoral Thesis at the level of methodological and scenario validation by integrating EV, charging point, distribution network, user, data quality, reliability and cybersecurity criteria into a unified dynamic assignment process.

The hypothesis is supported within the limits of methodological and scenario validation. The results show that a reliability-oriented, dynamic and multi-criteria approach provides a more substantiated and interpretable charging point assignment than static or limited-criteria approaches, although full-scale field validation is still required.

The main limitations are related to scenario-based validation, data availability, distribution network data detail, cybersecurity-layer interpretation, AHP weight subjectivity and PROMETHEE scalability. Future research should therefore include broader real-time data integration, faster MCDA methods such as TOPSIS, hybrid AHP–machine-learning approaches and further cybersecurity-layer development.

CONCLUSIONS AND PROPOSALS

Conclusions

1. The Doctoral Thesis develops and validates a reliability-oriented multi-criteria model for dynamic electric vehicle charging point assignment, integrating technical, user-related, distribution network, data quality, reliability and cybersecurity criteria into a unified decision-making process.
2. It is demonstrated that EV charging point assignment is a dynamic multi-criteria decision-making problem that cannot be reasonably solved using only a single criterion, such as distance, price, waiting time or available charging power.
3. The developed AHP–PROMETHEE methodology provides a structured, explainable and practically applicable decision-making process. AHP makes it possible to determine the relative importance of the criteria, while PROMETHEE enables the ranking of admissible alternatives and the determination of backup choices.
4. The developed dynamic filtering mechanism ensures that technically, operationally, network-wise, data-wise or cybersecurity-wise inadmissible alternatives are excluded before the ranking stage. This strengthens the reliability of the final recommendation and reduces the risk of technically or operationally unsuitable assignments.
5. The validation results confirm that the model is primarily oriented towards reliability, distribution network admissibility, data quality and cybersecurity. In the base configuration, the combined weight of these criteria exceeds 73 % of the total criterion weight, confirming that the model is not limited to user convenience but balances user needs with infrastructure and network constraints.
6. The seasonal validation results show that the model can maintain a stable ranking of charging alternatives under different seasonal conditions. The results also confirm the importance of maintaining a complete ranking and backup sequence, since the suitability of alternatives may change over time.
7. The stress scenario analysis confirms the substantial influence of data quality and cybersecurity criteria on the admissibility of alternatives and the final decision. In particular, data quality degradation may prevent automatic assignment, which should be interpreted as a reliability-oriented feature rather than a failure of the model.
8. The comparison with simplified assignment strategies shows that the nearest, fastest available or most powerful charging point is not always the most suitable alternative when distribution network load, power reserve, reliability, data quality and cybersecurity risk are considered simultaneously.
9. The hypothesis of the Doctoral Thesis is supported within the limits of methodological and scenario-based validation. The developed model provides a more substantiated and more interpretable charging point assignment than static or limited-criteria approaches, although full-scale field validation with real-time CPO/CSO, DSO, EV and user data is still required.
10. The scientific contribution of the Doctoral Thesis is the formalisation of dynamic EV charging point assignment as a reliability-oriented multi-criteria cyber-physical decision-making problem. The methodological contribution is the sequential AHP–PROMETHEE approach with dynamic filtering, ranking and backup alternatives. The practical contribution is a reproducible computation core of a decision support system prototype for EV charging infrastructure management.

Proposals

1. EV charging infrastructure operators should use a multi-criteria approach in charging point recommendation systems instead of relying only on distance, price, waiting time or nominal charging power.
2. Before providing a charging point recommendation, dynamic filtering of alternatives should be carried out in order to exclude alternatives that are technically, operationally, network-wise, data-wise or cybersecurity-wise inadmissible.
3. Charging infrastructure operators and distribution system operators should develop data exchange mechanisms that allow local network load, available power reserve and network admissibility indicators to be taken into account in charging point assignment.
4. Data quality should be treated as a mandatory element of charging point assignment. If data are outdated, incomplete or unreliable, the system should either downgrade the respective alternative or exclude it from automatic recommendation.
5. Cybersecurity indicators should be integrated into EV charging infrastructure decision support systems. Authentication, communication security, data integrity, service availability and third-party risk should influence the ranking of charging alternatives.
6. The developed AHP–PROMETHEE model should be further validated using broader real-time datasets, including charging session status, actual queues, reservations, EV SOC, user routes, local network measurements and operator event logs.
7. For large public charging networks with hundreds or thousands of charging points, faster MCDA methods, such as TOPSIS, should be evaluated alongside PROMETHEE. Practical implementation should also include pre-filtering, geographical narrowing, clustering or parallel computation.
8. In future developments, AHP-based expert weights should be supplemented with data-driven or machine-learning-based weight correction, using historical charging sessions, user choices, network states, failures, cybersecurity events and operator decisions.
9. The developed model should be further extended towards a digital twin of EV charging infrastructure, where physical infrastructure, geospatial data, load profiles, EVSE statuses, distribution network events and decision algorithms are linked in a unified modelling environment.
10. Future research should also integrate RES, BESS and V2G indicators into the assignment model, enabling charging point selection to consider not only current network constraints, but also local energy flexibility, renewable energy availability and the potential contribution of electric vehicles to distribution network management.

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