Publizierbarer Endbericht

Gilt für Studien aus der Programmlinie Forschung

A) Projektdaten

Allgemeines zum Projekt	
Kurztitel:	DIVERGENT
Langtitel:	Decision-making and data-processing methods for Vehicle-to-Home power flow management
Zitiervorschlag:	DIVERGENT: Decision-making and data-processing methods for Vehicle-to-Home power flow management
Programm inkl. Jahr:	Zero Emission Mobility 2022/01
Dauer:	01.10.2023 bis 30.09.2025
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Projekt- und KooperationspartnerIn (inkl. Bundesland):	Silicon Austria Labs GmbH, Graz (Steiermark) Easelink GmbH, Graz (Steiermark) Virtual Vehicle Research GmbH, Graz (Steiermark) CISC Semiconductor GmbH, Klagenfurt (Kärnten) Energie Steiermark AG, Graz (Steiermark)
Schlagwörter:	vehicle-to-home; smart bidirectional charging; multi-criteria decision making; ac-charging; battery lifetime estimation
Projektgesamtkosten:	1.219.114 €
Fördersumme:	999.713 €
Klimafonds-Nr:	
Erstellt am:	08.04.2026

B) Projektübersicht

1 Kurzfassung

Das Projekt DIVERGENT untersuchte dezentrale Entscheidungsmethoden und Algorithmen zur Unterstützung des intelligenten bidirektionalen Ladens (SBC) von Elektrofahrzeugen (EVs). Das Projektkonsortium, bestehend aus Silicon Austria Labs (SAL), Virtual Vehicle (VIF), Easelink, CISC und Energie Steiermark, entwickelte und evaluierte Methoden, die sowohl klassische Entscheidungsalgorithmen als auch Ansätze auf Basis von Reinforcement Learning und maschinellem Lernen umfassen.

Im Rahmen des Projekts wurden drei Hauptziele erreicht:

- Entwicklung von Entscheidungsmethoden zur Unterstützung der bidirektionalen Aushandlung von Leistungsprofilen (Power Profile, PoP) für EVs. Es wurde eine modulare Simulationsumgebung entwickelt, die Interaktionen zwischen dem Energienetz, PV-Erzeugung, stationären Batterien, Haushaltverbrauch und EVs mit bidirektionaler Ladefähigkeit modelliert. Ein auf Soft Actor-Critic (SAC) basierender Deep Reinforcement Learning (DRL) Agent wurde implementiert und evaluiert. Die Ergebnisse zeigen, dass der SAC-basierte Ansatz die regelbasierten Strategien übertrifft und im Median eine Kostenersparnis von 3,35 EUR pro Episode (3 Tage) erzielt.
- Untersuchung des Einflusses des bidirektionalen Ladens auf den Batteriezustand (State of Health, SoH) und die Lebensdauer. Simulative Untersuchungen zeigten, dass Vehicle-to-Home (V2H) in Kombination mit überschüssigem PV-Laden im Vergleich zu unidirektionalen Ladestrategien profitabel sein kann. Die Rentabilität hängt dabei stark vom Nutzerprofil ab.
- Implementierung eines Demonstrators für ein intelligentes bidirektionales automatisiertes AC-Ladesystem. Ein ISO 15118-20-konformes bidirektionales Ladesoftwaresystem wurde als Prototyp implementiert, das Vehicle-to-Home-Funktionalität ermöglicht. Das System wurde mit einem Hardware-in-the-Loop-Laboraufbau einschließlich der Matrix-Charging-Technologie von Easelink integriert und validiert.

Darüber hinaus wurde ein cloud-basierter Energieverteilungsalgorithmus für DC-Mikronetze entwickelt und evaluiert, der erneuerbare Energiequellen und die Verfügbarkeit von EVs als Energiespeicher berücksichtigt. Die optimierte Variante erzielte einen um 6 % (484 EUR) höheren Jahresgewinn im Vergleich zum nicht-optimierten Ansatz.

Die Projektergebnisse wurden in 3 Konferenzpublikationen veröffentlicht, ein Journalartikel wurde eingereicht, und der gesamte Quellcode wurde als Open Source bereitgestellt.

2 Executive Summary

The DIVERGENT project investigated decentralized decision-making (DM) methods and algorithms for supporting smart bidirectional charging (SBC) of electric vehicles (EVs). The project consortium, consisting of Silicon Austria Labs (SAL), Virtual Vehicle (VIF), Easelink, CISC, and Energie Steiermark, developed and evaluated methods that encompass both classical decision-making algorithms and approaches based on reinforcement learning and machine learning.

Three main goals were achieved within the project:

- Development of decision-making methods supporting bidirectional EV power profile (PoP) negotiation. A modular simulation environment was developed that models interactions between the energy grid, PV generation, stationary batteries, household consumption, and EVs with bidirectional charging capability. A Soft Actor-Critic (SAC) based deep reinforcement learning (DRL) agent was implemented and evaluated. The results show that the SAC-based approach outperforms rule-based strategies, achieving a median cost saving of EUR 3.35 per episode (3 days).
- Investigation of the influence of bidirectional charging on the battery state of health (SoH) and lifetime. Simulative investigations showed that Vehicle-to-Home (V2H) combined with excess PV charging can be profitable compared to unidirectional charging strategies. The profitability strongly depends on the user profile.
- Implementation of a smart bidirectional automated AC charging system demonstrator. An ISO 15118-20 compliant bidirectional charging software system prototype was implemented, supporting Vehicle-to-Home functionality. The system was integrated and validated with a hardware-in-the-loop laboratory setup including Easelink's Matrix Charging technology.

A cloud-based energy distribution algorithm for DC microgrids was also developed and evaluated, accounting for renewable energy sources and EV availability as energy storage. The optimized variant achieved a 6% (EUR 484) higher annual profit compared to the non-optimized approach.

The project results were published in 3 conference papers, one journal article was submitted, and the complete codebase was released as open source.

3 Hintergrund und Zielsetzung

The transition towards a climate-neutral energy system, characterized by extensive electrification of transport alongside mass deployment of renewable energy sources such as solar (PV) and wind, places significant stress on existing electrical distribution grids. Bidirectional charging (also known as Vehicle-to-Grid, V2G, or Vehicle-to-Home, V2H) is a powerful approach for utilizing the flexibility inherent in EV batteries. Current standards (such as ISO 15118-20) define the framework for bidirectional charging while leaving aside key aspects of decision-making and negotiation strategy implementation.

In DIVERGENT, the consortium investigated decentralized decision-making (DM) methods and algorithms for supporting smart bidirectional charging (SBC) of electrical vehicles (EVs). The proposed methods were implemented in an integrated demonstrator of the onboard charger and automated AC power supply equipment that also serves as an evaluation platform. For developing the DM methods, both classic decision-making algorithms and algorithms based on reinforcement learning and machine learning were considered. The project expanded the knowledge in vehicle usage simulation, including modelling techniques of EV owner's behaviour, as well as in the field of energy management. In the AC SBC laboratory demonstrator, the bidirectional energy and data flow from the EV battery and on-board-charger through automated AC power-supply equipment to the local household/grid was simulated.

Project Goals

The following goals were defined for DIVERGENT:

- Develop DM methods supporting a bidirectional EV PoP negotiation.
- Investigate bidirectional charging influence on the battery state of health (SoH) and lifetime.
- Implement a smart bidirectional automated AC charging system demonstrator.

4 Projektinhalt und Ergebnis(se)

This section presents the work carried out within the six work packages of the DIVERGENT project and their key results.

4.1 Concept and Specifications (WP2)

WP2 covered the definition of use-cases and target performance of the SBC system, definition of technical requirements for SBC hardware and software, an extended study of corresponding standards and best practices, an extended literature study and patent search, and the design of the general SBC system architecture with specification of key hardware and software interfaces.

Extended study of corresponding standards and best practices

We examined in depth the ISO 15118 standards, which govern communication protocols between electric vehicles (EVs) and charging infrastructure. This structure includes several essential components that ensure smooth information exchange and power transfer.

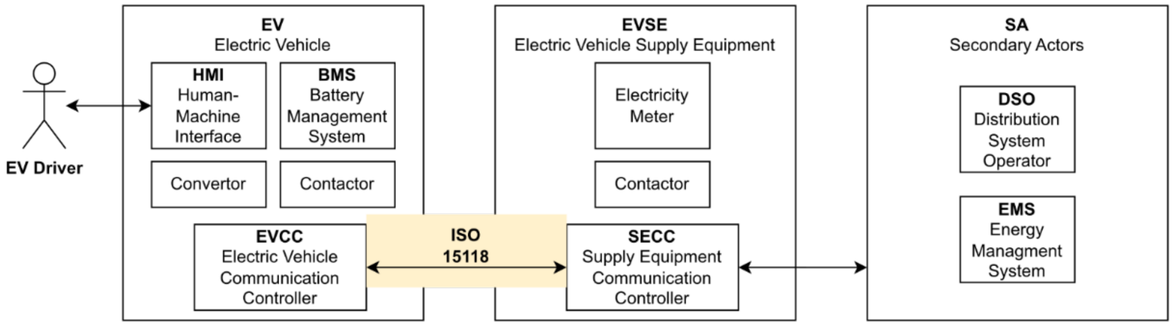

Figure 1: Role of ISO 15118 in charging process.

ISO 15118-1 outlines the framework for high-level communication (HLC) between electric vehicles (EVs) and charging stations, covering both conductive and wireless charging. It defines general requirements and use cases for EV charging, including bidirectional energy transfer, and ensures systems' safety, efficiency, and interoperability. Key components include the energy transfer schedule, smart grid energy limits, and reverse power transfer (RPT), allowing vehicles to send power back to the grid.

Subsequent iterations, including ISO 15118-2 and the more advanced ISO 15118-20, further refine these protocols by introducing enhanced capabilities. ISO 15118-2 established the initial network and application protocol requirements for communication between electric vehicles (EVs) and charging infrastructure, forming the basis for high-level communication (HLC) during charging sessions. This standard has since evolved into ISO 15118-20, which introduces several advancements to accommodate new technologies and improve EV charging capabilities. Key updates include support for bidirectional power transfer (BPT), enabling Vehicle-to-Grid (V2G) and Vehicle-to-Home (V2H) scenarios, where EVs can return energy to the grid or a home system. Wireless Power Transfer (WPT) has also been enhanced, improving efficiency and communication during wireless charging processes. ISO 15118-20 further addresses the integration of Automated Connection Devices (ACD), such as pantographs, allowing for automated charging of commercial vehicles like buses. Additionally, a new dynamic mode has been introduced, where the energy transfer adapts in real-time to grid conditions without the need for pre-defined charging schedules or user intervention. Finally, the standard strengthens security protocols, incorporating longer encryption keys and newer versions of the Transport Layer Security (TLS) protocol to ensure data protection and system integrity.

Design of general SBC system architecture

The deployment diagram of the key DIVERGENT demonstrator components is presented in the figure below. A series of workshops was carried out to define and refine the overall architecture, ensuring that the selected components and their interactions are aligned with the project requirements, technical constraints, and integration needs of the demonstrator.

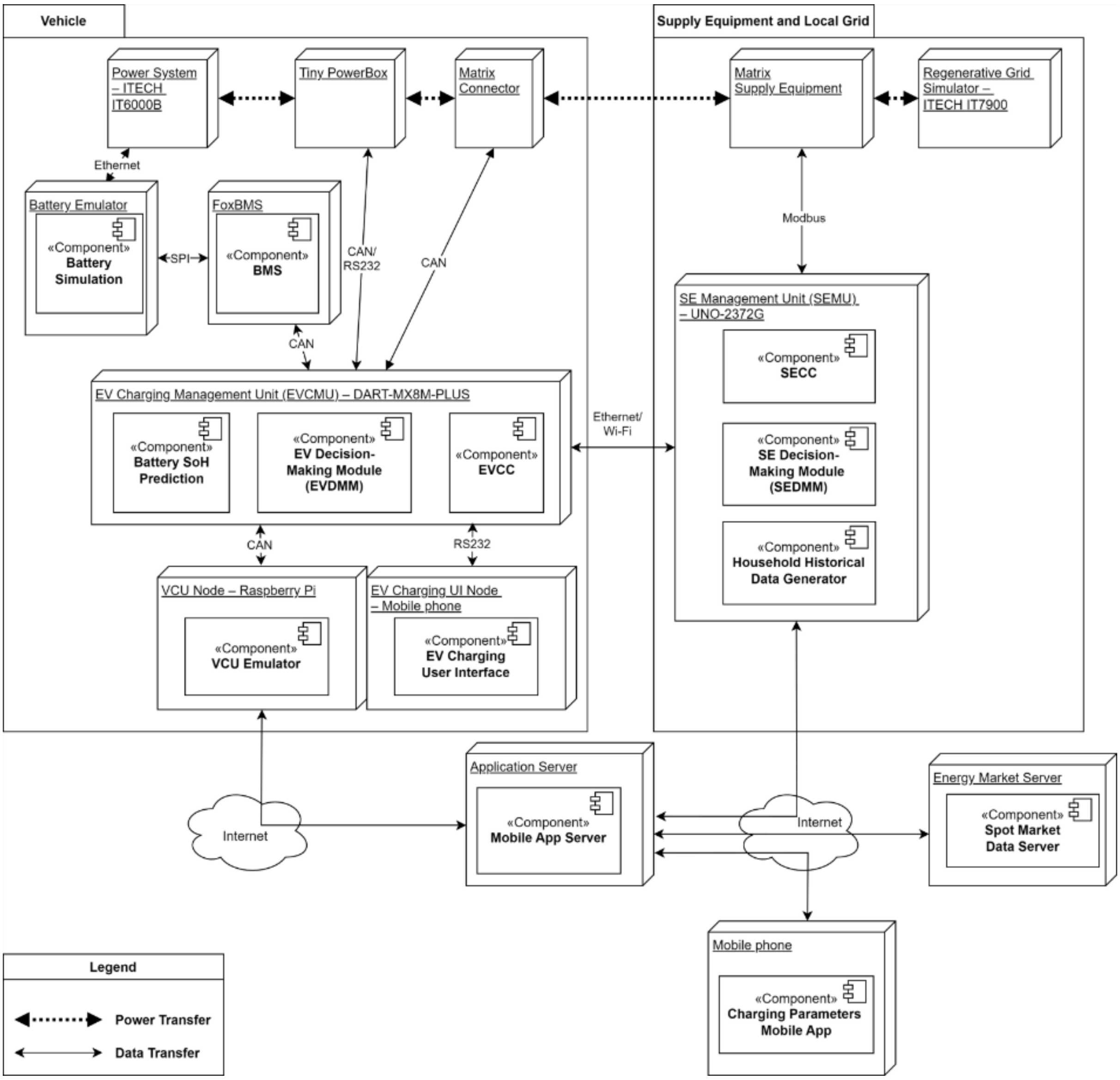

Figure 2: DIVERGNET Demonstrator system architecture.

4.2 Decision-Making Methods Development (WP3)

Vehicle Usage Simulation and User Behaviour

Simulative investigations demonstrated that V2H in combination with excess PV charging can be profitable compared to unidirectional charging strategies. The profitability strongly depends on the user profile. For the assessment of V2H use cases, the consideration of charging and discharging losses is important. When discharging predominantly occurs at night, as is primarily the case for the investigated commuter profile, the efficiency of the discharging process is low because the typical constant discharging losses are comparable in magnitude to the nighttime base load of a household.

Taking advantage of variable tariffs, the potential benefits of optimizing the charging strategy by only charging during the cheapest time periods also strongly depend on the user profile. For the commuter, the benefits are more pronounced, primarily due to the higher overall energy demand resulting from greater annual mileage. The additional benefit for the secondary car user remains relatively limited, since most of the time the EV can cover the energy demand with self-generated PV surplus energy.

A workshop was held with users of electric vehicles on V2H applications. The results showed that acceptance of smart charging and V2X technologies is generally given, especially when monetary benefits, intelligent functions, and ease of use are offered. A key issue remains the need for control and transparency. There is a willingness to postpone charging times, especially if users can ensure the charging status at the desired departure time.

Battery State-of-Health Estimation and Prediction

The project investigated Li-ion battery degradation mechanisms that reduce capacity and increase internal resistance, including solid electrolyte interphase (SEI) growth, lithium plating, cathode degradation, loss of active lithium and electrode active material, electrolyte oxidation and gas generation, binder and current-collector degradation, and thermal degradation. A simplified cause-and-effect representation was developed for DIVERGENT with especially relevant parameters for V2H/V2G applications such as temperature, SoC, C-Rate, and time, which affect capacity fade and power fade.

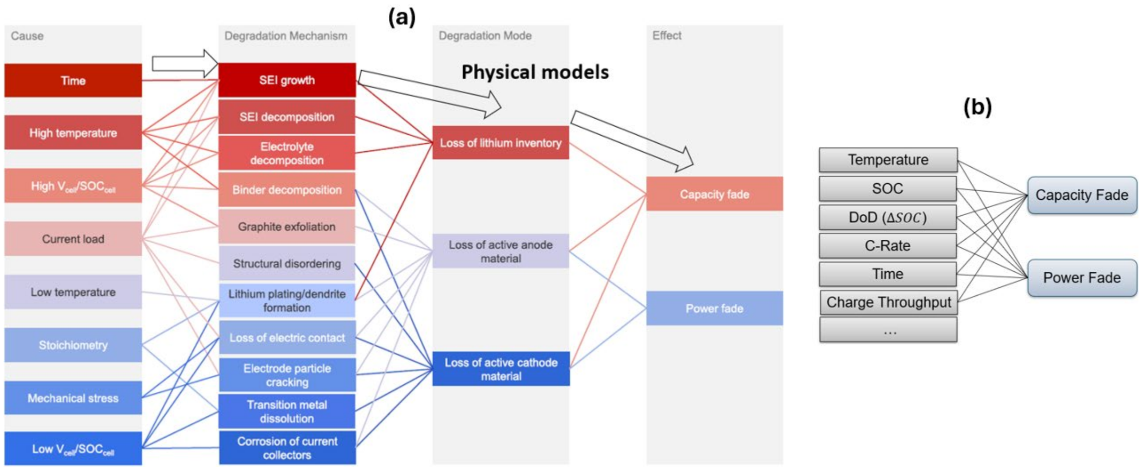

Figure 3: Cause and effect of degradation mechanisms and simplified representation used in DIVERGENT.

Decision-Making and Negotiation Methods

A comprehensive, modular simulation environment was developed to serve as the training and testing platform for the DRL-based decision-making algorithms. The simulator models the interactions between the energy grid with dynamic pricing, the photovoltaic (PV) generation system, a stationary battery (SB) for local energy storage, the electric vehicle battery with bidirectional charging capability, and household consumption patterns. The simulator architecture allows for various scenario configurations ranging from simple setups (EV battery and household only) to complex environments including all components.

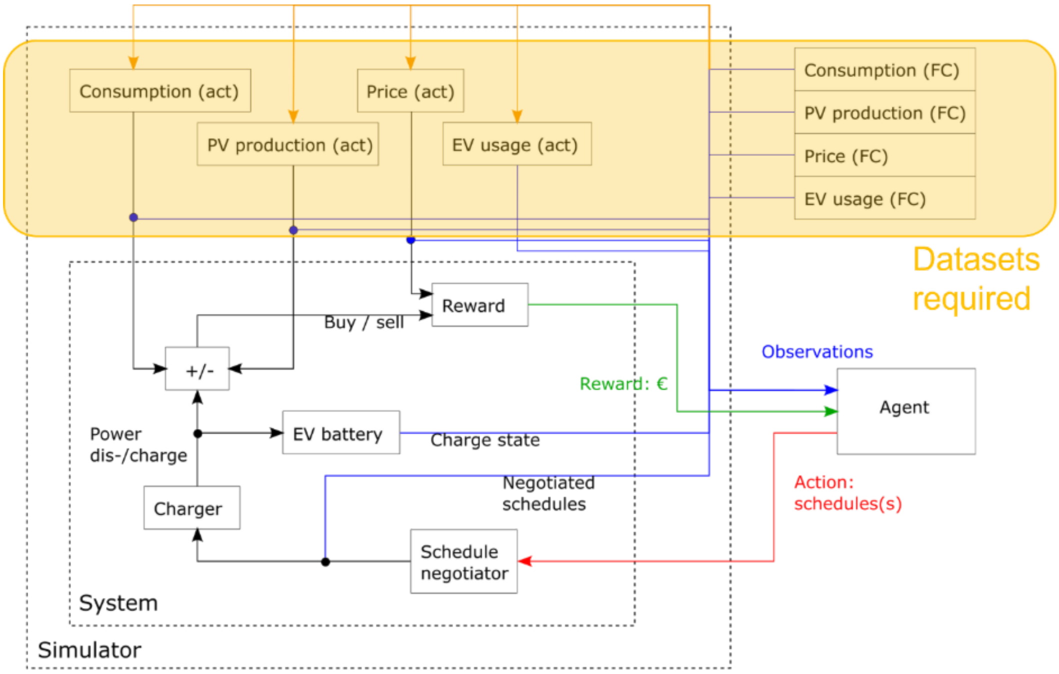

Figure 4: RL Simulator architecture. "act": actual real-time data; "FC": forecast data.

The reward function was developed to balance multiple competing objectives: an energy cost component that minimizes electricity costs considering dynamic pricing; a battery degradation component that models cycle-based degradation applying higher costs to V2G discharge operations; and a range anxiety component that penalizes scenarios where the EV battery has insufficient charge for planned trips.

Soft Actor-Critic (SAC) was selected as the primary DRL method for the final integration in the demonstrator. The SAC-based approach outperformed rule-based strategies, with SAC achieving a median return of -1.13 compared to -2.46 for DDPG, -1.97 for PPO, and -3.3 for the best rule-based method. On average, SAC achieved a median monetary gain of EUR 3.35 per episode compared to the best rule-based approach.

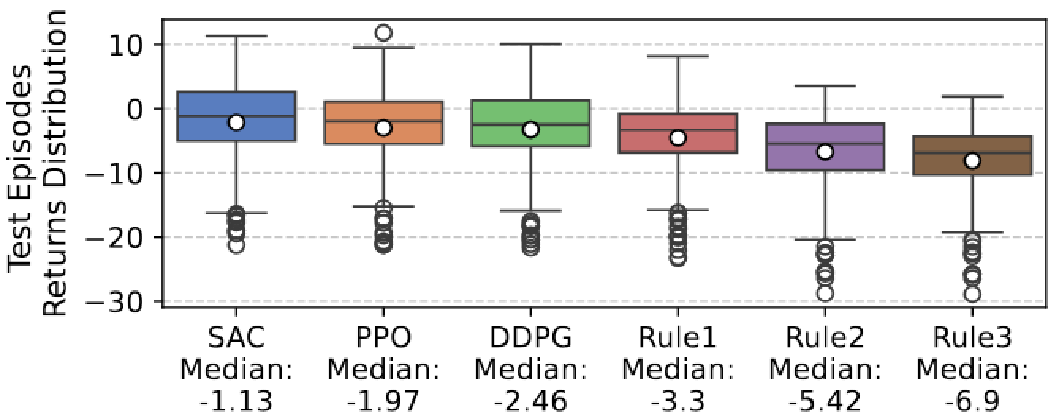

Figure 5: Test episodes return distributions for SAC, PPO, DDPG, and rule-based methods.

The analysis of EV battery capacity impact showed a trade-off: small batteries provide insufficient energy buffer to capitalize on price fluctuations, while larger batteries face limitations from range anxiety concerns and extended charging requirements. The range anxiety weighting factor analysis demonstrated that when it exceeds 0.5, the vehicle departs with sufficient SoC, eliminating the need for additional charging afterward.

Cloud-Based Energy Distribution Algorithm

A cloud-based energy distribution mixed-integer non-linear rolling horizon control algorithm was developed for optimizing energy distribution within a DC-microgrid incorporating renewable energy sources and EVs. The algorithm uses a two-phase methodology: a secondary control algorithm (online phase) operating on a 15-minute time scale that adapts to real-time events, and a tertiary control algorithm (offline phase) operating on a one-hour time scale responsible for long-term planning and economic optimization. The evaluation was performed for a simulated community of ten households, each equipped with a PV system (4.1 kWp), three wind turbines (5.5 kWp), and nine EVs with a battery capacity of 64.8 kWh each. The optimized algorithm achieved a total net profit of EUR 8,655 compared to EUR 8,171 for the non-optimized approach, representing a 6% increase in profit (EUR 484).

Mobile Application Prototype

An OCPP-enabled cloud-based monitoring platform was developed for monitoring electric vehicle charging infrastructure. The platform collects data from multiple charging stations via the OCPP protocol, providing operators with a comprehensive overview of performance and status. The user interface includes input fields for the amount of energy to charge and the desired completion time. The system calculates the optimal charging schedule based on current energy prices.

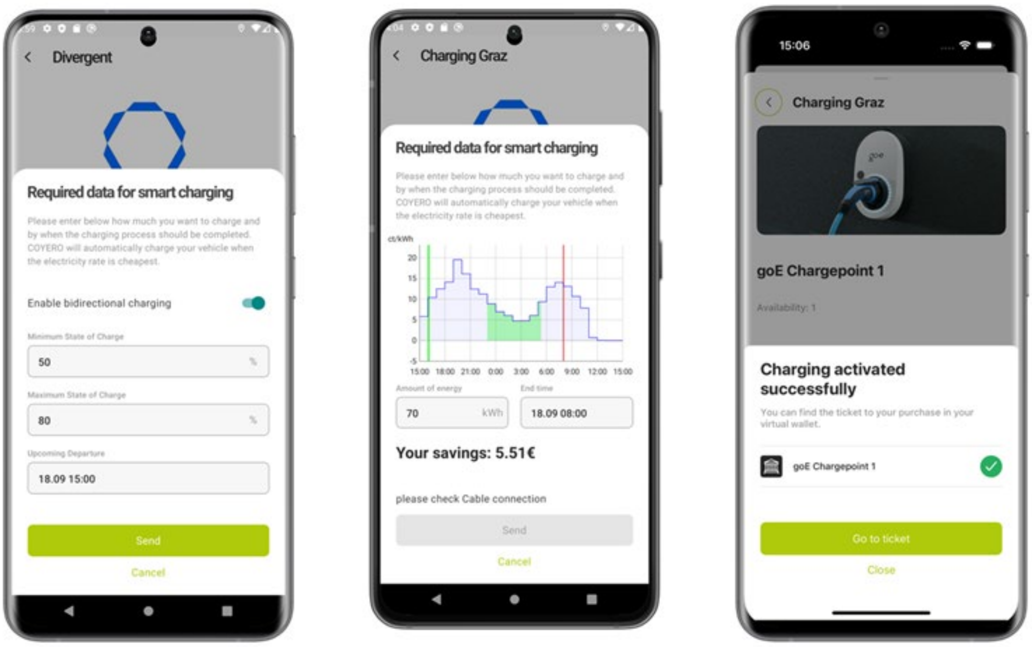

Figure 6: Mobile application UI

4.3 Communication Controllers Development (WP4)

A software implementation of an ISO 15118-20 compliant bidirectional charging software system prototype was developed. The system supports Vehicle-to-Home functionality, enabling bidirectional power flow between vehicles and charging infrastructure in both scheduled and dynamic charging modes.

The implementation includes software prototypes of the Supply Equipment Communication Controller (SECC) and Electric Vehicle Communication Controller (EVCC), along with vehicle-side and decision-making modules. These components run in a distributed architecture built with Python 3.11 and gRPC. The demonstrator supports AC charging (ServiceID 1) and AC bidirectional power transfer (ServiceID 5) as specified in ISO 15118-20. It implements the full nine-phase protocol flow from session setup through charging loops to session termination.

The DIVERGENT-Core system implements a distributed component architecture where each component operates as an independent process communicating via gRPC. The components are deployed on three key nodes: the VCU Node (EV-side logic), the EVCC Node (ISO 15118-20 protocol mediation), and the Supply Equipment Node (charging station logic).

The following key software components have been developed and available in the repository

Core Communication Components

Component	Role	Responsibilities	Key Features
SECC: Supply Equipment Communication Controller	Charging station server implementing ISO 15118-20 protocol	Session management, service discovery, charging parameter negotiation, power delivery control	• Server-side ISO 15118-20 messages • Charging station state management • Scheduled and dynamic modes • AC and AC_BPT services
EVCC: Electric Vehicle Communication Controller	Protocol bridge between vehicle and charging station	Message forwarding, protocol mediation, session coordination	• ISO 15118 message forwarding • Session state maintenance

			• Communication isolation
VCU: Vehicle Control Unit	Vehicle-side client initiating charging sessions	Session initiation, battery management interface, charging process control	• ISO 15118 protocol flow initiation • Battery system interfaces • Charge loop logic • SOC target management

Decision-Making Components

Component	Role	Responsibilities	Key Features
SEDMM: Supply Equipment Decision-Making Module	Charging station intelligence and optimization	Schedule generation, power allocation, grid integration decisions	• Constraint-based scheduling • Reinforcement learning optimization • Grid condition awareness • Dynamic power control
EVDMM: Electric Vehicle Decision-Making Module	Vehicle-side charging intelligence	Charging parameter calculation, schedule acceptance, battery health management	• Optimal parameter calculation • Schedule evaluation • Battery health consideration • Smart charging strategies

Hardware Interface Components

Component	Description	Key Features
OBCController: On-Board Charger Controller	Hardware interface for battery and charging	• FoxBMS battery interface • Real/emulated hardware support

	systems (embedded within VCU)	• CAN bus communication • Power supply control
Battery Models	Multiple battery implementations	• simulated_battery.py - Software simulation • vw_id3_battery.py - VW ID.3 model • foxbms_battery.py - Real FoxBMS hardware • emulated_lab_battery.py - Emulated lab • battery_factory.py - Factory pattern
Charging Station Models	Charging station implementations	• Simulated station (software) • Real station (hardware interface)

Supporting Components

Component	Role	Key Features
TimeService Shared Clock Service	Centralized time management for simulation and evaluation	• Time synchronization across components • Time acceleration (1x to 1000x+) • Deterministic testing • Enabled only in simulation mode
OCPP Client Backend Integration	OCPP 1.6 client for CSMS connectivity	• WebSocket connection to central system • Remote start/stop transaction handling • Status and meter value reporting • Passive mode trigger support
Common Utilities	Shared infrastructure libraries	• Configuration System (config/) • ISO15118SequenceTracker (timeout/validation) • Logging Utilities

		• gRPC Interceptors • Protobuf Utilities

Protocol Definitions

Category	**Description**
API Specifications	Protobuf service definitions • common/ - Shared ISO 15118 messages • SECC/ - SECCService.proto • EVCC/ - EVCCService.proto • VCU/ - VCUService.proto • SEDMM/ - SEDMMService.proto • EVDMM/ - EVDMMService.proto • MCC/ - Mobile Communication Controller • MCSE/ - Matrix Charging SE Interface • OCPPProxy/ - Passive mode triggers

All source code was released as open source at: https://opensource.silicon-austria.com/divergent/core

4.4 Charging Systems Components Integration (WP5)

The OBCController was developed as an intermediary between the vehicle battery, the onboard charger, and higher-level decision-making systems. It is implemented as a threaded Python component supporting constant-power operation and current-ramping operation modes.

The physical integration of components involved several power path sections: Grid to Switching cabinet, Switching cabinet to Matrix charger base, Matrix charger base to Matrix connector, Matrix connector to Switchbox, Switchbox to OBC emulating power supply, and OBC emulating power supply to Battery emulating power supply. An ITECH IT-M3902C-80-40 bidirectional power supply unit was used to emulate the OBC. The battery was emulated using an ITECH IT-M3422 bidirectional power supply.

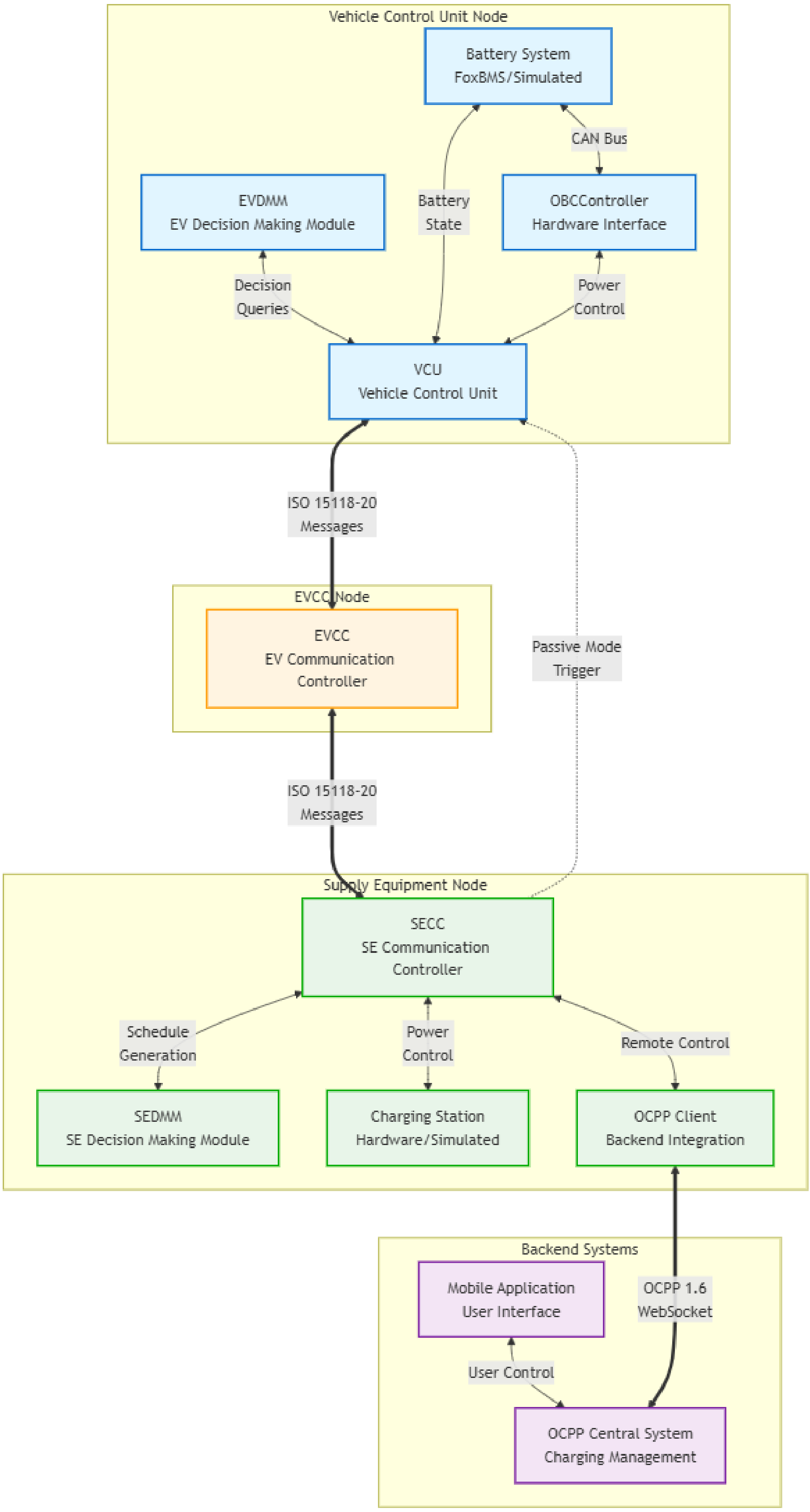

Figure 7: DIVERGENT-Core distributed component architecture.

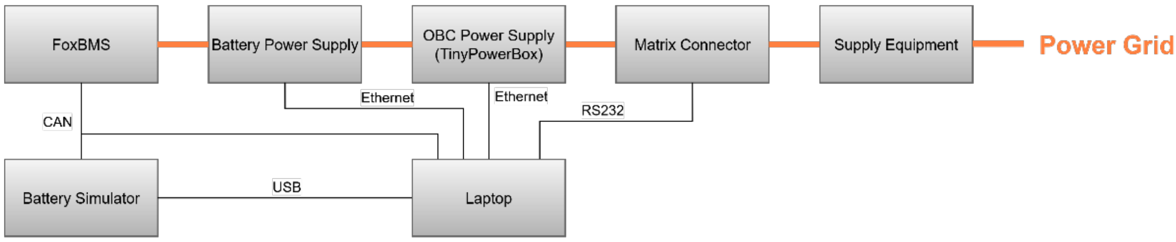

Figure 8: Physical components in the DIVERGENT lab demonstrator and their interconnection.

4.5 Laboratory Demonstrator Development and Evaluation (WP6)

The laboratory demonstrator integrates five coordinated modules: the Vehicle Control Unit (VCU), the Electric Vehicle Decision-Making Module (EVDMM), the Electric Vehicle Communication Controller (EVCC), the Supply Equipment Communication Controller (SECC) with simulated Supply Equipment (SE), and the Supply Equipment Decision-Making Module (SEDMM). The demonstrator includes a Power Supply Interface, Battery Data Aggregator, Battery Simulator, Battery Power Supply, and OBC Power Supply.

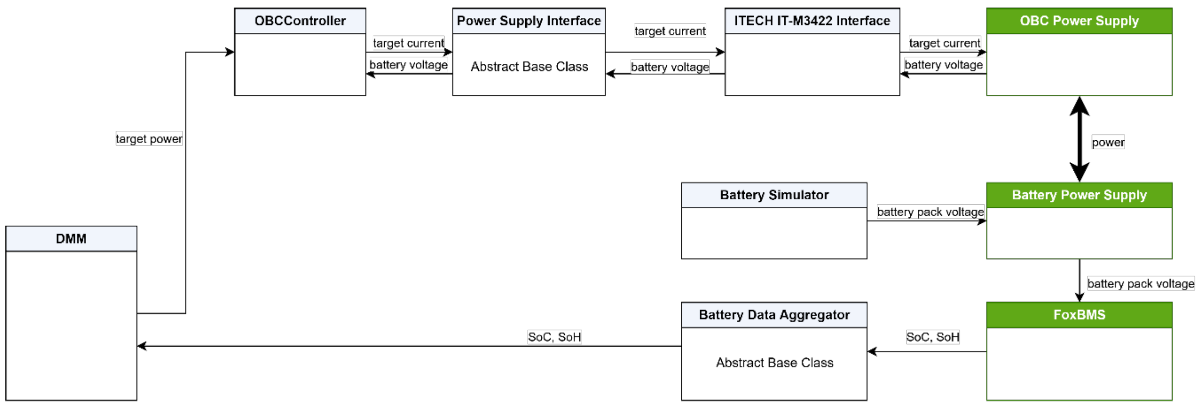

Figure 9: High-level lab demonstrator software architecture.

Figure 10: Assembled DIVERGENT laboratory demonstrator at SAL, Graz.

Evaluation Results

An automated testing solution was implemented to evaluate the quality and compliance of the code. A total of 583 tests were implemented and executed successfully with 0 failures. Overall code coverage reached 66% (7,522/11,359 statements). Component coverage ranged from 43% (SEDMM) to 79% (EVCC). The test suite includes 47 ISO 15118 compliance tests, 23 OCPP integration tests, 15 end-to-end integration scenarios, and 8 FoxBMS hardware integration tests.

The testing approach evaluated the DIVERGENT-Core system across all critical dimensions of ISO 15118-20 bidirectional charging functionality. All key validation use-cases executed successfully, confirming proper operation in scheduled charging, dynamic power control, and bidirectional energy transfer scenarios.

Battery SoH Evaluation

A structured workflow was developed for converting household energy data into electrical and aging insights for battery packs using the RCSolver simulation environment. The results demonstrated that high currents, higher end-SoC, and larger SoC swings all accelerate capacity loss. A similar trend appears in both calendric aging and cyclic aging. The workflow and its Python interface enable accurate analysis of how battery capacity decreases and internal resistance increases over time under real operating conditions.

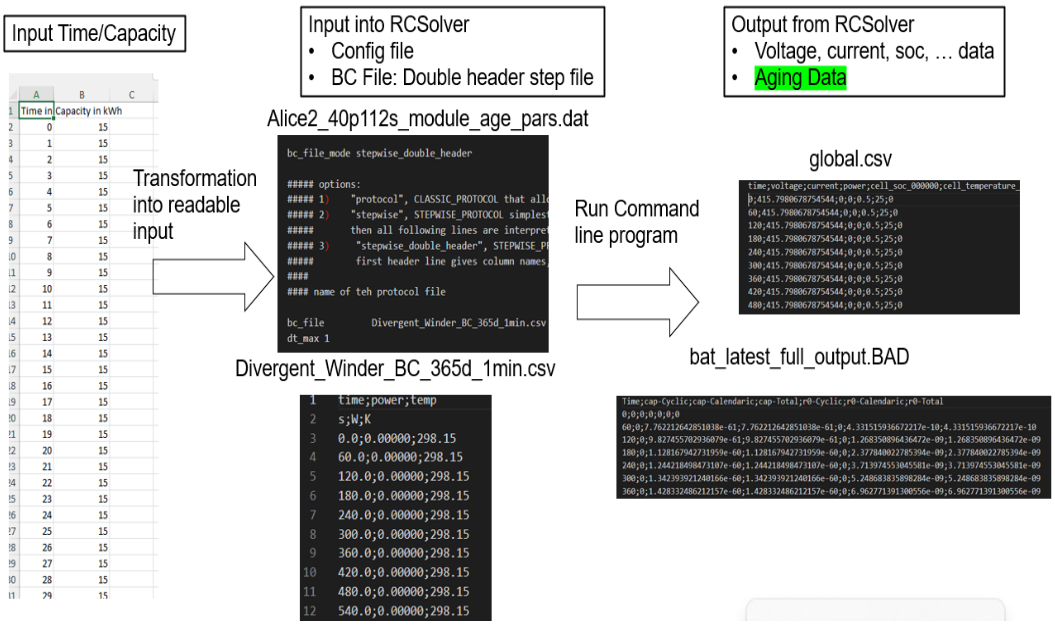

Figure 11: Virtual Vehicle workflow for battery aging simulation using RCSolver.

5 Schlussfolgerungen und Empfehlungen

The DIVERGENT project successfully achieved all three of its main goals: developing decision-making methods for bidirectional EV power profile negotiation, investigating the influence of bidirectional charging on battery state of health and lifetime, and implementing a smart bidirectional automated AC charging system demonstrator.

Key Conclusions

Regarding decision-making methods, the deep reinforcement learning approach, specifically using the Soft Actor-Critic algorithm, proved to be effective for optimizing bidirectional EV charging schedules. The SAC agent outperformed traditional rule-based strategies, with a median monetary gain of EUR 3.35 per three-day episode. The DRL agent effectively adapts to variations in electricity prices, renewable energy availability, and household demand. The analysis revealed a trade-off between battery capacity and monetary benefits: small batteries provide insufficient flexibility, while very large batteries face limitations from extended charging requirements.

Regarding battery health, the investigations confirmed that V2H combined with excess PV charging can be profitable, but profitability strongly depends on the user profile. High currents, higher end-SoC levels, and larger SoC swings all accelerate capacity loss. The efficiency of the discharging process is particularly low when discharging occurs at night, where constant losses are comparable to the household base load.

Regarding the demonstrator, the ISO 15118-20 compliant bidirectional charging software system was successfully implemented and validated with 583 tests achieving 100% pass rate. The system demonstrated proper operation in scheduled charging, dynamic power control, and bidirectional energy transfer scenarios.

The cloud-based energy distribution algorithm for DC microgrids showed that optimized energy management can yield a 6% increase in annual profit for a community of ten households with PV systems, wind turbines, and EVs.

The user workshop confirmed that acceptance of smart charging and V2X technologies exists, particularly when monetary benefits, intelligent functions, and ease of use are offered. Control and transparency are decisive factors for user adoption.

Recommendations

Based on the project results, the following recommendations can be made:

- Future work should focus on enhancing the robustness of reinforcement learning algorithms to handle greater uncertainty and observation noise, improving reliability in real-world deployments with imperfect information.
- Expanding the framework beyond single-household scenarios to address multi-household and community-level energy management challenges would enable cooperative energy trading mechanisms among EV owners and potentially unlock greater system-wide efficiencies while reducing overall grid dependency.

- Improving the forecasting methodology for renewable energy sources would enhance the performance of the cloud-based energy distribution algorithm.
- Target group-specific incentives, transparent communication, and flexible control options are recommended for the successful implementation of smart charging and V2X programs.

The results of the DIVERGENT project serve as a foundation for the follow-up EDISON FFG project (Energieforschung 2024, FFG No. 908601), where RL-based energy management algorithms, the evaluation environment, and the software implementation of energy-management components are considered as a foundation for building a decentralized Virtual Power Plant Platform.

C) Projektdetails

6 Methodik

The DIVERGENT project adopted a multi-disciplinary research approach combining simulation-based methods, machine learning, standards-compliant software prototyping, and hardware-in-the-loop evaluation.

6.1 Simulation Environment for Decision-Making

A modular simulation framework was developed for modeling and analyzing energy flows, incorporating entities such as the energy grid, PV sources, batteries, and household consumers. To ensure realism, open datasets containing historical observations for all key components were utilized, including spot market electricity prices from Germany and Austria (hourly resolution), photovoltaic power generation from residential households in Konstanz, Germany (aggregated to 15-minute resolution), and household electricity consumption data from Sceaux, France (processed at 15-minute resolution).

Since the datasets originate from independent sources spanning different locations and time periods, data alignment was performed based on seasonal variations (for energy prices, PV generation, and household consumption) and day-of-week patterns (for energy prices and household consumption). Battery degradation parameters were derived from existing studies. EV user behavior was modeled using a predefined commuting schedule with stochastic variations to reflect real-world uncertainties.

A train-test split methodology based on calendar days was implemented. Training episodes utilize data from the first half of each month (days 1–14), while test episodes use data from the second half (days 15–31). Each episode spans three days, with decision steps occurring every 15 minutes for a total of 288 steps per episode.

6.2 Deep Reinforcement Learning Approach

The home energy management system (HEMS) scheduling problem was formulated as a Markov Decision Process (MDP). The state representation includes PV production, household consumption, energy price, EV and stationary battery SoC values, EV connection status, future energy prices, and cyclic time encoding. The action space represents the charge and discharge powers of the EV and stationary battery.

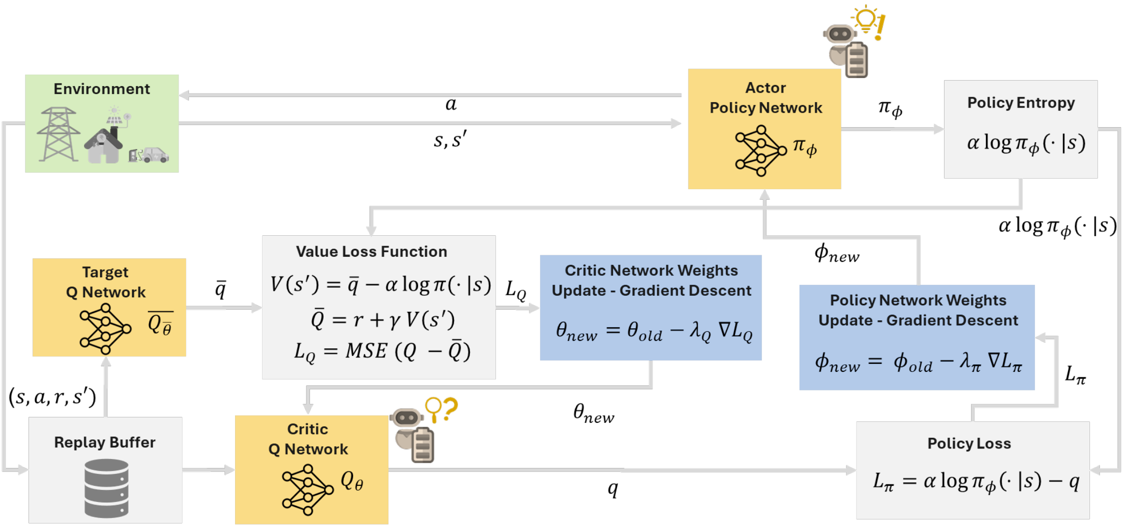

Figure 12: Soft Actor-Critic (SAC) algorithm architecture.

Three state-of-the-art DRL algorithms were benchmarked: Soft Actor-Critic (SAC), Deep Deterministic Policy Gradient (DDPG), and Proximal Policy Optimization (PPO). These were compared against three rule-based baseline strategies based on fixed time windows. The actor and critic networks were implemented as feed-forward neural networks, each with two layers of 512 units. Training was conducted using a learning rate of 0.0001, a discount factor of 0.995, a batch size of 512, a buffer size of 500,000, and completed in 3 hours on an NVIDIA A100 GPU for 700,000 timesteps.

6.3 Cloud-Based Energy Distribution Algorithm

A cloud-based energy distribution mixed-integer non-linear rolling horizon control algorithm was developed, structured into three hierarchical control levels. The primary control level operates on a sub-second time scale for grid stability. The secondary control layer (online phase) operates on a 15-minute time scale and adapts the energy dispatch schedule in response to real-time events. The tertiary control level (offline phase) operates on a one-hour time scale and generates an optimized energy dispatch schedule using energy price forecasts and renewable energy generation predictions. The forecast horizon extends over 36 hours and is divided into 14 time slots. The optimization problem was solved using the APOPT mixed-integer solver provided by the GEKKO optimization library, with the event-driven simulation library SimPy used to model dynamic system behaviour.

6.4 ISO 15118-20 Communication Prototyping

A software-based prototyping approach was used to implement the EVCC and SECC components compliant with ISO 15118-20. The system was implemented using Python 3.11 and gRPC for inter-component communication. Protocol Buffers (Protobuf) served as the interface definition language and message interchange format. The implementation covers the full nine-phase protocol flow from session setup to session termination.

6.5 Hardware-in-the-Loop Evaluation

The laboratory demonstrator integrates hardware components including a battery cells simulator, a battery management system (FoxBMS), a battery emulator (ITECH IT-M3422), an OBC emulator (ITECH IT-M3902C-80-40), the Matrix Charging system by Easelink, and supply equipment. The control application runs as a containerized application under Podman in Ubuntu on a Linux laptop with a PCAN-USB adapter for CAN bus connectivity.

The evaluation methodology covers component tests, integration tests, unit tests, ISO 15118 compliance tests, OCPP integration tests, and hardware-in-the-loop tests. The pytest-based test runner supports marker filtering, coverage thresholds, and HTML reports.

6.6 Battery SoH Evaluation Methodology

A workflow was developed to process household battery-related input data through the RCSolver simulation environment and extract detailed electrical and aging outputs. The workflow consists of three main stages: data preparation, simulation setup and execution, and output generation. Raw household energy-usage profiles are transformed into the required format, and the simulation produces voltage, current, and aging outputs at cell and pack levels.

7 Arbeits- und Zeitplan

The DIVERGENT project ran from October 2023 to September 2025 (24 months). The work was organized into six work packages:

WP	Title	Duration	Key Tasks
WP1	Project Management	10/2023 – 09/2025	Consortium coordination, reporting, dissemination, data management
WP2	Concept and Specifications	10/2023 – 04/2024	Use-case definition, technical requirements, standards study, system architecture
WP3	Decision-Making Methods Development	02/2024 – 07/2025	Data gathering methods, vehicle usage simulation, battery modelling, DM algorithms, mobile app

WP4	Communication Controllers Development	02/2024 – 03/2025	EVCC/SECC architecture design, ISO 15118-20 protocol implementation
WP5	Charging Systems Components Integration	02/2024 – 02/2025	Test environment setup, power path integration, OBC controller development
WP6	Lab Demonstrator Development and Evaluation	10/2024 – 09/2025	Demonstrator assembly, evaluation methodology, SoH evaluation, system evaluation

8 Publikationen und Disseminierungsaktivitäten

Scientific Publications

#	Publication reference	Status	Submission / publication date	Link
1	Lucas Winder, David Url, "Simulation based assessment of a Vehicle-to-Home use case for a single-family house", 14. Internationale Energiewirtschaftstagung an der TU Wien (IEWT 2025).	Published	28.02.2025	https://iewt2025.eeg.tuwien.ac.at/download/contribution/fullpaper/136/136_fullpaper_20250219_153603.pdf
2	M. Stoiber, M. Freiberger and L. Winder, "Cloud-Based Energy Distribution Algorithm for DC-Microgrids Incorporating Renewable Sources and Electric Vehicle Support," 2025 IEEE Seventh International Conference on DC Microgrids (ICDCM), Tallinn, Estonia, 2025, pp. 1-6, doi: 10.1109/ICDCM63994.2025.11144739.	Published	04 June 2025	https://silicon-austria-labs.elsevierpure.com/en/publications/cloud-based-energy-distribution-algorithm-for-dc-microgrids-incor

3	Gei, C., Scherer, J., & Radchenko, G.. Electric Vehicle Bidirectional Charging Control with Deep Reinforcement Learning. In ICECET 2025	In press	May 2025	https://silicon-austria-labs.elsevierpure.com/en/publications/electric-vehicle-bidirectional-charging-control-with-deep-reinfor
4	Martin Stoiber, Manuel Freiberger, Lucas Winder. Enhanced Cloud-Based Energy Distribution for DC Microgrids with Improved Forecasting and Updated Real-World Datasets. Open Journal of Power Electronics	Submitted	November 2025	

Dissemination Activities

Date	Activity	Location / Channel
29.05.2024	DIVERGENT project results presented at VEHICLE & GRID FORUM	Graz, Austria
13.06.2024	DIVERGENT Prototype Integration Workshop	SAL, Graz
13.11.2024	DIVERGENT project promoted on regional TV (ORF)	Austria
20.08.2024	DIVERGENT Integration and Evaluation Workshop	SAL, Graz
18.09.2025	DIVERGENT Results and Insights Workshop	SAL, Graz
24.11.2025	J. Scherer, "Decision-Making and Data-Processing Methods for Vehicle-To-Home Power Flow Management", Klima- und Energiefonds Science Brunch	Vienna, Austria
06.2024, 12.2025	DIVERGENT status reports delivered at Klimafonds workshops	Austria

Open Source Repositories

- DIVERGENT Core: https://opensource.silicon-austria.com/divergent/core
- DRL-HEMS (Deep Reinforcement Learning for Home Energy Management): https://opensource.silicon-austria.com/schererj/drl-hems

Project Website

- https://silicon-austria-labs.com/en/research/projects/details/divergent

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