Development and Experimental Validation of an Integrated EV Testbed for Battery and Motor System Monitoring

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Abstract

The development of a Digital Twin for electric vehicle (EV) battery and motor systems requires an experimental platform capable of operating under controlled conditions while acquiring reliable and synchronized multimodal measurements. Existing laboratory platforms often investigate battery and motor subsystems independently or under simplified conditions, limiting their usefulness for integrated system analysis and subsequent prognostics and health management (PHM). This study aimed to develop and experimentally validate an integrated EV testbed for battery and motor operation, monitoring, and data acquisition. The testbed combines a battery pack and battery management system (BMS), brushless DC (BLDC) motor, DC motor/generator dynamometer, programmable electrical load, battery charger, electrical, mechanical, thermal, and vibration sensors, a data-acquisition system, and supervisory control architecture. Experimental validation was performed under constant-speed motor operation and battery-charging conditions to assess functionality, measurement accuracy, acquisition reliability, synchronization, dynamic response, and repeatability. The results confirmed reliable operation of the integrated battery–motor system and consistent acquisition of synchronized electrical, mechanical, thermal, and vibration measurements. The platform enabled controlled manipulation of motor speed and loading while supporting continuous battery monitoring and charging experiments. Thus, the testbed provides a controlled physical environment for generating reproducible datasets for driving-cycle simulation, Digital Twin development, and subsequent PHM investigations.

Keywords: BLDC motor; electric vehicle; experimental testbed; battery monitoring; Digital Twin; prognostics and health management

I. INTRODUCTION

1.1 Background

The rapid adoption of electric vehicles (EVs) has increased the engineering complexity of traction battery systems, electric machines, power electronic converters, and supervisory control systems. In particular, EV performance, safety, efficiency, and service life depend on coupled interactions between the battery pack, battery management system (BMS), motor controller, traction motor, mechanical load, and environmental conditions(Chau, 2015). These interactions are inherently dynamic: acceleration, regenerative braking, road-gradient changes, payload variation, and charging events produce time-varying current, torque, speed, temperature, and vibration responses. Consequently, the isolated assessment of either the battery or motor subsystem may not sufficiently represent the physical conditions encountered during vehicle operation.

Experimental data are essential for developing, calibrating, and validating physics-based, data-driven, and hybrid models of EV systems. For lithium-ion batteries, operational current profiles and temperature substantially affect voltage behaviour, energy efficiency, state of charge (SOC), state of health (SOH), and degradation rate (Barré et al., 2013). Similarly, the performance and condition of an electric motor are influenced by speed, torque demand, electrical loading, thermal behaviour, and mechanical vibration. Accurate experimental

observations under representative conditions are therefore required to identify system parameters, validate simulation models, and detect emerging faults.

This requirement is particularly important for Digital Twins and prognostics and health management (PHM). A Digital Twin is a continuously updated virtual representation of a physical system that uses measured data and models to support monitoring, diagnosis, prediction, and decision-making (Tao et al., 2018). In EV applications, an effective Digital Twin must be informed by data that capture the interactions among electrical, thermal, mechanical, and control domains. Likewise, PHM seeks to assess present system conditions and estimate remaining useful life or future fault behaviour using condition-monitoring information (Jardine et al., 2006) . The quality and representativeness of the experimental data used to develop these methods strongly influence their reliability when deployed in real operating environments.

Many laboratory studies employ constant-current battery cycling, fixed-speed motor operation, or simplified electrical loads because these conditions improve experimental repeatability and simplify analysis. Such tests remain useful for component characterisation; however, they do not fully reproduce the nonstationary nature of EV use. Real driving conditions impose fluctuating power demand on the battery, and the resulting battery current depends on motor speed, torque, controller efficiency, auxiliary loads, and regenerative operating states(Israr, 2026). Dynamic cycling is especially relevant because battery ageing and thermal behaviour can differ substantially between constant and variable load profiles (Nandi et al., 2005). Therefore, a laboratory platform should enable controlled reproduction of both stationery and time-varying operating conditions.

An integrated experimental platform is consequently required to reproduce controlled EV operating conditions while simultaneously acquiring synchronized electrical, mechanical, thermal, vibration, and operating-condition measurements. Such a platform provides an empirical basis for investigating the causal sequence by which an imposed operating condition influences motor behaviour and, subsequently, battery response. It can also support the production of repeatable multimodal datasets for system identification, fault diagnosis, Digital Twin development, and PHM research(Lei et al., 2018)(Li et al., 2026).

1.2 Problem Statement

The principal technical challenge is not merely to operate a brushless DC (BLDC) motor or monitor a battery pack independently. Rather, it is to establish an integrated, controllable, and instrumented experimental environment in which the coupled relationship between operating condition, motor response and battery response can be observed experimentally and repeatedly.

In this relationship, the operating condition may include commanded motor speed, mechanical or electrical loading, charging state, and programmed transient events. The motor response includes variables such as rotational speed, torque, current, voltage, temperature, and vibration. The battery response includes pack voltage, current, temperature, SOC-related BMS variables, charging behaviour, and potentially indicators relevant to battery health. Because these responses occur across different physical domains and may evolve at different rates, the measurements must be time-synchronized to permit meaningful interpretation of cause-and-effect relationships.

The experimental environment must additionally support both stationary operation and nonstationary operation. Stationary operation is required for baseline characterisation, sensor verification, and repeatability assessment. Nonstationary operation is necessary to emulate time-varying propulsion demand and to create datasets relevant to realistic driving-cycle analysis (Nkengne et al., 2025). Achieving these functions requires coordinated motor-speed control, programmable load control, battery monitoring, charging capability, and reliable data acquisition (DAQ). Without synchronization and controlled actuation, it becomes difficult

to distinguish actual system behaviour from measurement delay, sensor noise, uncontrolled load variation, or differences between experimental trials.

1.3 Research Gap

Existing EV research infrastructures frequently concentrate on a single subsystem. Battery test facilities commonly use programmable cyclers and environmental chambers to investigate capacity, impedance, thermal behaviour, and ageing under prescribed current profiles(Israr, 2026). These platforms provide valuable electrochemical and thermal information but may not reproduce the battery-current demand generated by an operating traction motor. Conversely, motor test benches commonly examine efficiency maps, torque-speed characteristics, thermal performance, and fault signatures using dynamometers, but often employ a regulated power supply rather than a battery pack operating through a BMS.

A further limitation is the widespread use of constant-speed or steady-state motor testing. Although steady-state testing is necessary for establishing baseline motor characteristics, it does not capture transient phenomena associated with acceleration, deceleration, load changes, controller switching, and changing battery voltage. Dynamic load control is therefore required to investigate how nonstationary mechanical demand propagates through the motor-controller system to the battery pack.

In addition, the acquisition of isolated electrical variables alone is insufficient for integrated condition monitoring. Battery and motor faults may manifest through changes in temperature, vibration, rotational speed, voltage, current, or combinations of these variables. Multimodal monitoring namely, the coordinated observation of electrical, mechanical, thermal, and vibration signals can provide complementary evidence for condition assessment. However, if data streams are not synchronized, time-domain relationships between load commands, motor transients, and battery responses may be obscured. This limitation reduces the usefulness of datasets for model validation, fault detection, and machine-learning-based PHM.

The reviewed challenges indicate a need for an EV testbed architecture that physically integrates a battery pack and BMS, BLDC motor and controller, motor/generator dynamometer, programmable electrical load, battery charger, sensors, DAQ hardware, and supervisory control. Such an architecture is necessary not to replicate every aspect of a complete road vehicle, but to provide a controlled and repeatable experimental representation of the principal battery–motor energy pathway. It should permit the reproduction of driving-cycle-inspired speed and load profiles while retaining sufficient measurement fidelity for subsequent Digital Twin and PHM investigations.

1.4 Research Objective

The objective of this study is: "To design and implement an integrated EV experimental testbed capable of reproducing controlled and nonstationary operating conditions for battery and BLDC motor systems". This objective includes the integration of battery operation, motor propulsion, load application, charging, sensing, synchronized DAQ, and supervisory control within a single experimental platform. The testbed is experimentally validated through controlled motor-operation and battery-charging experiments to assess functional operation, measurement reliability, synchronization, dynamic response, and repeatability.

1.5 Research Question

The research is guided by the following question: "How can an experimental EV testbed be designed to reproduce controlled and nonstationary motor operating and battery conditions while enabling synchronized measurement of electrical, mechanical, thermal, vibration, and operating-condition parameters?", Answering this question requires consideration of system architecture, component compatibility, electrical and mechanical coupling, sensor selection, data-synchronization strategy, control implementation, and experimental validation procedures.

1.6 Research Scope

The scope of the study is limited to the design, implementation, and validation of a laboratory-scale integrated EV testbed. The platform incorporates a battery pack, smart BMS, BLDC motor, motor controller, DC motor/generator dynamometer, programmable load, battery charger, electrical sensors, mechanical sensors, thermal sensors, vibration sensors, a DAQ system, and supervisory control functions. Motor-speed control and load control are included to enable both constant and variable operating conditions.

The study focuses on controlled battery–motor experimentation rather than full-vehicle validation. Accordingly, factors such as tyre-road interaction, aerodynamic resistance, vehicle suspension dynamics, and complete vehicle-network communication are outside the present scope. Nevertheless, the controllable speed and loading functions are intended to permit the later implementation of driving-cycle-inspired operating profiles. The testbed is also intended to create high-quality datasets for future Digital Twin and PHM studies; the development of a complete predictive Digital Twin or remaining-useful-life algorithm is not the primary objective of this work.

1.7 Research Contribution

This study contributes an integrated and experimentally validated EV testbed capable of generating repeatable stationary and nonstationary operating conditions while providing synchronized multimodal measurements. Unlike isolated battery cyclers or standalone motor test benches, the proposed platform enables direct observation of the coupled battery–motor system under controlled propulsion, loading, and charging conditions.

The resulting infrastructure supports the collection of synchronized electrical, mechanical, thermal, vibration, and operating-condition data. These capabilities provide a controlled physical basis for validating EV subsystem models, reproducing driving-cycle-like conditions, developing Digital Twin representations, and undertaking subsequent PHM research. By improving the experimental connection between imposed operating conditions, motor behaviour, and battery response, the testbed is expected to facilitate more representative modelling and condition-monitoring studies for EV energy and propulsion systems.

II. METHOD

2.1 Overall Research Methodology

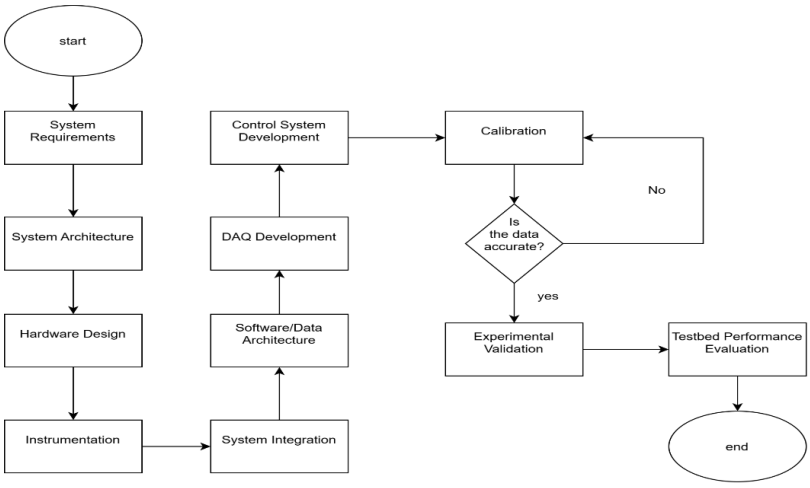

Fig. 1. Research workflow of the integrated EV testbed development and validation.

The research workflow comprises system requirements definition, system architecture development, hardware design, instrumentation, control and DAQ development, software

and data architecture, system integration, calibration, experimental validation, and testbed performance evaluation. The workflow begins by defining the required motor, battery, load, charging, and measurement capabilities. The physical and measurement systems are then designed and integrated with the control, DAQ, and data-processing architecture. After calibration, the integrated testbed is experimentally validated under selected operating conditions. Its performance is subsequently evaluated in terms of functionality, measurement reliability, synchronization, dynamic response, and repeatability.

2.2 System Requirements

Table 1. System Requirements of Integrated EV Testbed.

Requirement	Description
Dynamic speed	Motor must follow time-varying speed reference
Dynamic load	Mechanical load must be controllable
Battery operation	Battery must supply motor under controlled conditions
Charging	Battery must support controlled charging experiments
Multimodal sensing	Electrical, mechanical, thermal and vibration measurements
Synchronization	Measurements must share a common time reference
Repeatability	Identical operating profiles should produce comparable results
Expandability	Platform must support later PHM experiments
Data accessibility	Data must be available for Digital Twin/PHM development

2.3 Overall System Architecture

The proposed integrated EV testbed consists of two main architectures, namely the measurement architecture and the physical architecture. The measurement architecture is responsible for acquiring electrical, mechanical, vibration, and battery-related parameters, while the physical architecture represents the interaction between the battery, BLDC motor, dynamometer, load, charging system, and motor control system. The overall system is designed to enable synchronized acquisition of operating data for subsequent monitoring, analysis, and testbed validation.

The measurement architecture integrates sensors and measurement devices for monitoring the battery, BLDC motor, charging process, and mechanical vibration. The battery pack is monitored using a Jikong BMS, which provides battery-related parameters including cell-level and pack-level information. An ADXL accelerometer is installed to measure motor vibration along the X, Y, and Z axes, enabling vibration characteristics of the motor system to be captured. The BLDC motor is equipped with an encoder to measure rotational speed (RPM). Electrical parameters of the BLDC motor are measured using INA219 sensors, including phase voltage and current. The voltage difference between the U, V, and W phases is also measured to characterize the three-phase electrical behavior of the motor. The measured voltage and current parameters are subsequently processed to obtain the corresponding BLDC phase power. The charging subsystem obtains electrical power from the PLN grid, which is converted into a regulated 24 V DC supply using a power supply before being delivered to the battery. An INA219 sensor is employed in the charging path to measure charging voltage and current, while the charging power is calculated from the measured electrical parameters. In addition, a potentiometer module is used as an input device to generate the motor speed command. The speed profile obtained from the Worldwide Worldwide Harmonized Light Vehicles Test Cycle (WLTC) is converted into a corresponding control matrix and applied to the motor control system to reproduce a time-varying speed profile. All measurement devices are interfaced with an ESP32, which functions as the primary data acquisition node. The acquired data are transmitted through Node-RED for data processing and communication before being stored in an InfluxDB

database. This architecture enables the measured parameters from different subsystems to be collected and stored within a unified data infrastructure.

The physical architecture consists of the battery pack, BLDC motor, DC motor, dummy load, charging system, and motor control system. The BLDC motor serves as the primary propulsion motor in the testbed and is mechanically coupled to a DC motor. The DC motor is connected to a dummy load, which provides a controllable electrical load to the DC motor and consequently introduces a mechanical loading effect on the BLDC motor. This configuration is used to emulate the load experienced by the BLDC motor during vehicle operation. The BLDC motor speed is controlled through a control system using a potentiometer as the speed-command input. For dynamic testing, the WLTP speed profile is converted into a control matrix, which is subsequently used to generate the desired motor speed command. The BLDC motor therefore operates under both controlled speed conditions and time-varying speed profiles. Meanwhile, the coupled DC motor and dummy load provide the loading condition required for evaluating the motor response under different operating conditions. The battery supplies electrical power to the BLDC motor system during operation, while the charging subsystem provides a controlled 24 V DC input to recharge the battery. Through the integration of the physical and measurement architectures, the testbed enables the relationship between motor operating conditions, mechanical loading, vibration, and battery electrical behavior to be observed through synchronized measurements.

2.4 Physical System Design

2.4.1 Battery System

The battery system uses Li-ion 18650 cells with a rated capacity of 1200 mAh, nominal voltage of 3.7 V, and rated energy of 4.44 Wh per cell. The battery pack consists of six cells connected in series (6S), resulting in a nominal pack voltage of approximately 24 V. A Jikong Smart BMS is used for battery monitoring and protection, with Bluetooth as the communication interface. The measured battery parameters include cell voltage (Vcell), pack voltage (Vpack), pack current (Ipack), cell temperature (Tcell), and state of charge (SoC).

2.4.2 BLDC Motor System

The BLDC motor system uses an 8-pole, three-phase BLDC motor with a nominal voltage of 24 VDC. The motor has a rated speed of 4000 ±10% RPM, rated torque of 0.0716 N·m, and output power of 30 W. The no-load speed is specified as 6800 ±10% RPM, with a maximum no-load current of 0.3 A. The motor has a phase-to-phase resistance of 1.8 Ω, back-EMF constant of 4.36 V/kRPM, and torque constant of 0.042 N·m/A. The motor uses Class B insulation and is equipped with a 1000 P/R encoder for rotational speed measurement. The encoder provides A, B, and Z phase outputs, while Hall sensors are provided for U, V, and W phase commutation.

The motor is controlled using a SYS-BLD-70 brushless DC motor driver, which supports a 12–30 VDC supply, up to 3 A output current, and speed control through an external 10 kΩ potentiometer or analog voltage input. The driver provides U, V, and W phase connections and Hall-sensor interfaces. The BLDC motor is mechanically coupled to a DC motor using a flexible coupling, with the DC motor connected to a dummy load to simulate the motor loading condition. The BLDC motor is selected as the representative EV propulsion motor because its high efficiency, strong starting torque, and controllable speed characteristics are suitable for representing the basic operating characteristics of an electric propulsion system.

III. RESULTS AND DISCUSSIONS

A. Result

A.1 Implemented Physical Testbed

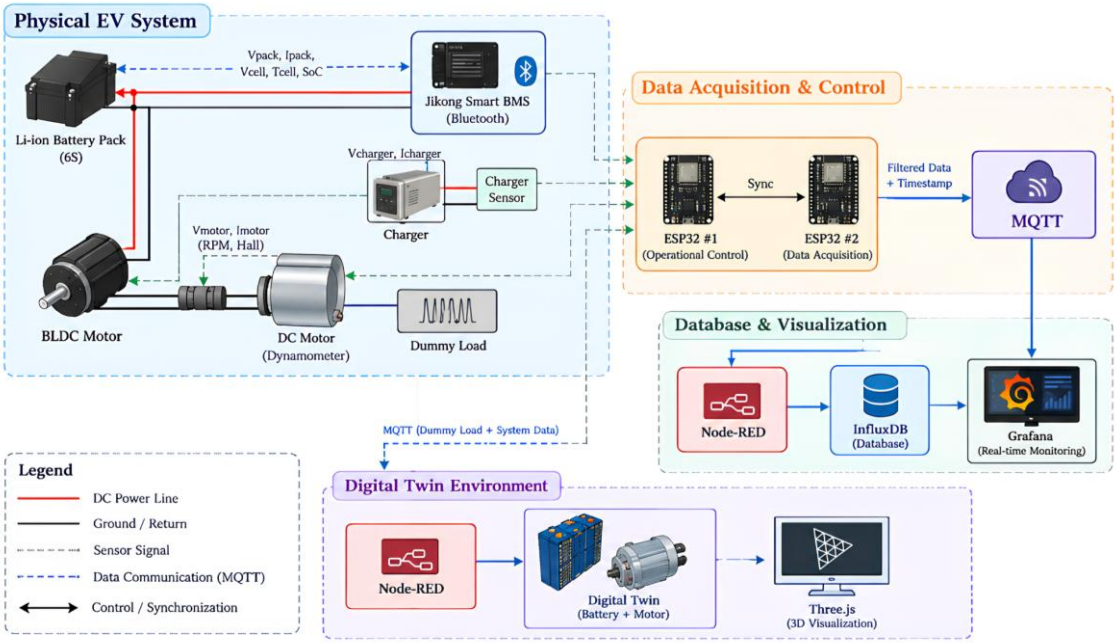

Fig. 2. system diagram of Integrated EV Testbed.

Figure 2 is a system diagram of the testbed, showing the battery, BMS, BLDC motor, programmable load, charging system, sensors, DAQ, and control system. During motor operation, variations in motor current correspond to changes in motor power, while the battery current follows the overall electrical demand of the propulsion system. The battery system serves as the main electrical energy source for the BLDC motor and is monitored by the BMS to obtain battery operating parameters, including cell voltage, pack voltage, current, temperature, and state of charge (SoC). The BLDC motor is mechanically coupled to a DC motor/generator connected to a dummy load, allowing the motor operating condition to be varied during the experiment. The charging subsystem is used to restore the battery energy after operation and provides additional measurement data for evaluating the charging behavior of the battery system.

The measurement and control functions are implemented using two ESP32-based units. The DAQ system collects measurements from the battery, motor, and charging subsystems, while the control system generates the motor operating commands according to the selected operating profile. The acquired measurements are processed and timestamped before being transmitted through the MQTT communication protocol. Node-RED is used to integrate the data from the different measurement sources and to manage data transmission to InfluxDB for time-series storage. The stored data are subsequently visualized through Grafana, while selected measurement data are also transmitted to the Digital Twin environment for real-time system representation. This architecture enables the physical testbed to provide synchronized measurement data from different subsystems and supports the execution of both constant-speed and time-varying operating conditions.

The implemented configuration therefore provides an integrated experimental platform in which electrical, thermal, and motor operating parameters can be monitored during different test conditions. The combination of controllable motor operation, battery monitoring, mechanical loading, and centralized data acquisition allows the response of the individual subsystems and their interactions to be observed over time. This capability is

particularly relevant for experiments involving nonstationary operating conditions, where changes in motor speed and loading can produce corresponding variations in electrical and battery parameters.

A.2 Electrical System Characterization

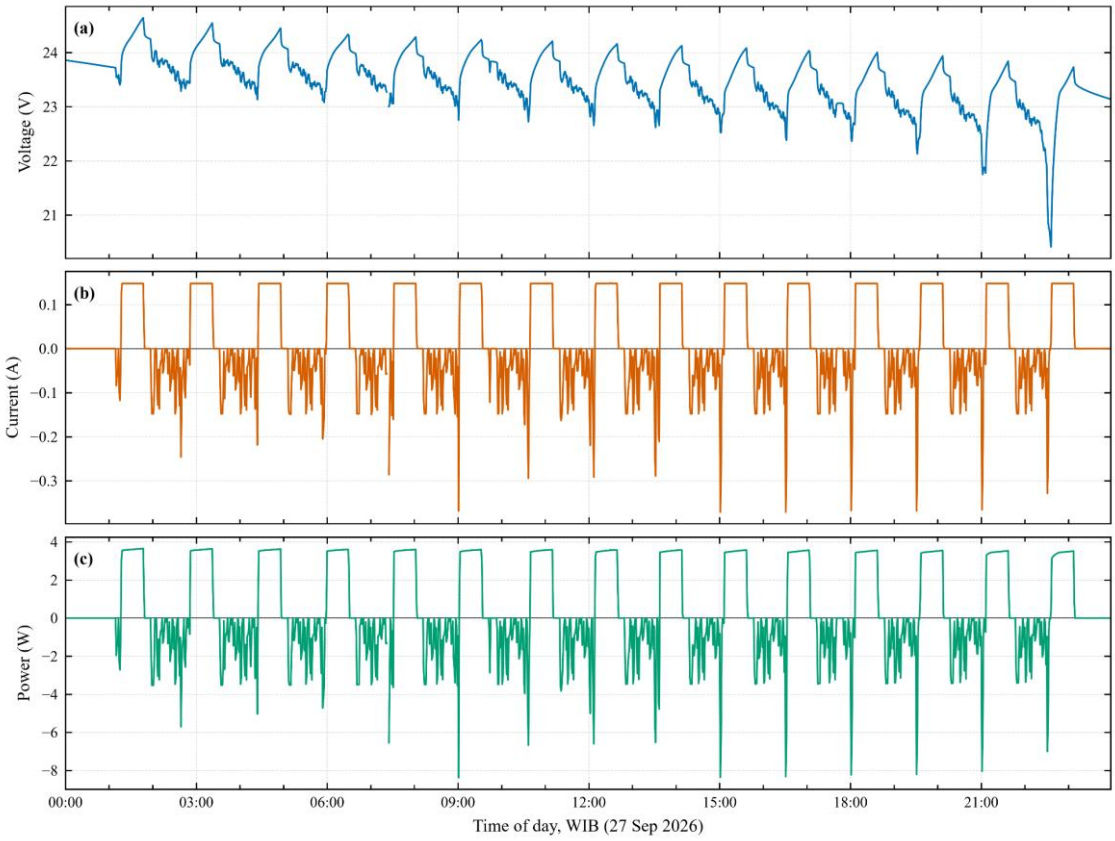

Fig. 3. Time-series electrical characteristics of the battery including voltage, current, and power measurements.

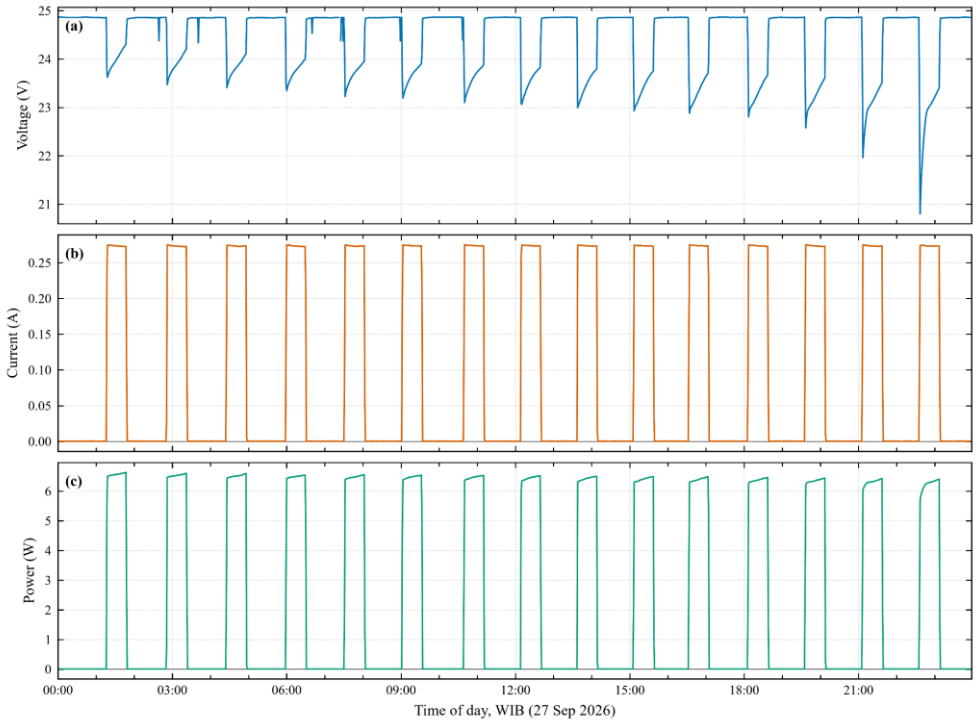

Fig. 4. Time-series electrical characteristics of the charging system including voltage, current, and power measurements.

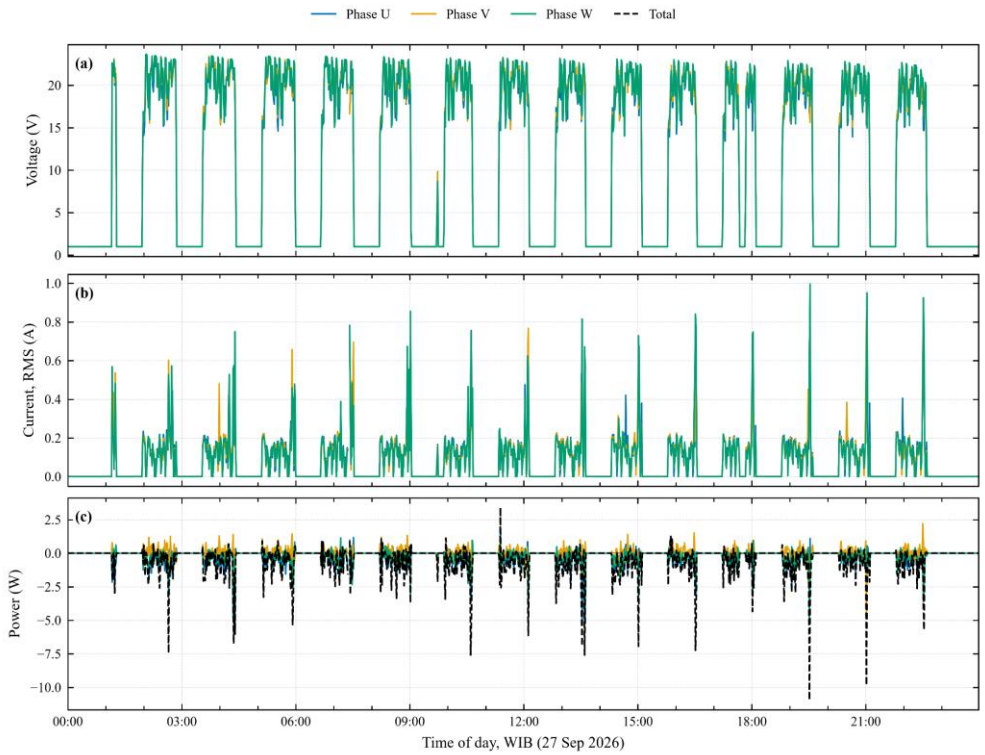

Fig. 5. Time-series electrical characteristics of the BLDC motor, including voltage, current, and power measurements.

Figure X presents the electrical characteristics of the integrated EV testbed, including battery voltage and current, motor voltage and current, and charger voltage and current. Battery and motor power are calculated from the measured voltage and current according to

$$P = V \times I$$

The results show the electrical response of the battery and motor under the applied operating conditions, while the charging measurements characterize the electrical input during the battery charging process. The motor-speed performance was evaluated under constant-speed and WLTP-derived operating conditions by comparing the reference speed, , with the actual motor speed, , measured using an encoder. Under constant-speed operation, the motor's ability to maintain the target speed was assessed. Under WLTP-derived operation, the motor's tracking performance was evaluated by comparing its actual speed with the time-varying reference profile. These results provide an assessment of the testbed's capability to reproduce both steady-state and dynamic motor-speed conditions.

A.3 Motor-Speed Performance in Dynamic WLTP Speed

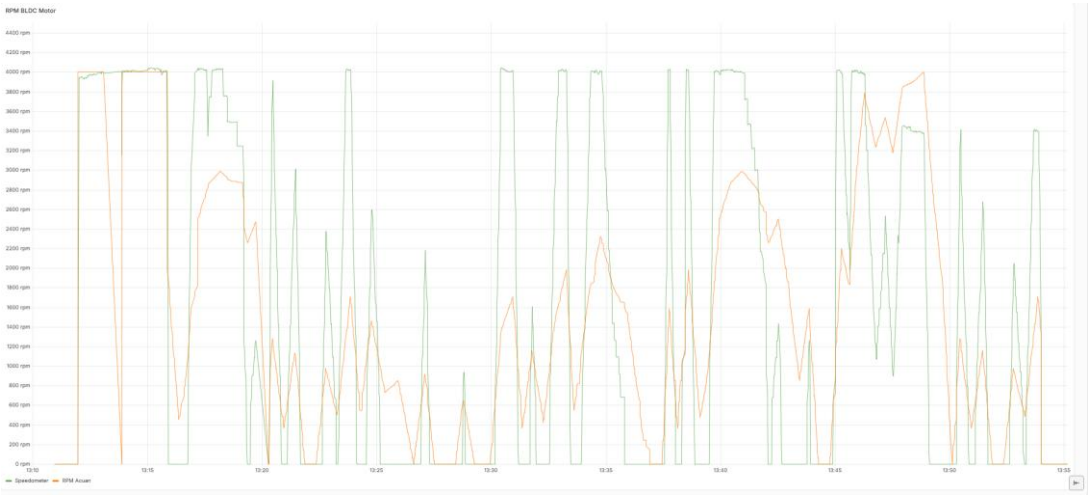

Fig. 6. Comparison between actual speed and WLTP speed.

Figure 6 compares the WLTC-derived reference speed with the actual BLDC motor speed measured using an encoder. The reference profile is mapped from a vehicle speed range of 0–131 km/h to a motor speed setpoint of 0–4000 rpm, corresponding to the configured maximum motor speed of the testbed. The speed profile is generated as a time-varying command so that the motor is required to continuously increase, decrease, and maintain its rotational speed according to the corresponding reference points. This configuration allows the testbed to reproduce the dynamic characteristics of a driving-cycle-based operating condition rather than operating only at a constant motor speed. The measured motor speed generally follows the changing pattern of the reference profile, indicating that the control system is capable of responding to variations in the commanded speed. However, noticeable differences between the reference and actual motor speed can be observed throughout the experiment. The deviation becomes more apparent during periods with relatively rapid changes in the reference speed, where the actual motor speed does not immediately reach the corresponding setpoint. In several sections, the measured speed also exhibits fluctuations and intermittent drops to zero. These responses indicate that the motor requires a certain response time to follow changes in the commanded speed and that the implemented control mechanism does not yet provide continuous correction of the actual motor speed. The observed deviations can be related to several characteristics of the implemented motor control system. The motor speed command is generated by converting

the reference RPM into discrete digital potentiometer steps, which limits the resolution of the speed adjustment. Consequently, small changes in the reference speed may not always result in an equivalent change in the control input. In addition, the response of the motor driver and the dynamic behavior of the BLDC motor can introduce differences between the commanded and measured speed. The mechanical coupling between the BLDC motor, DC motor/generator, and dummy load may also affect the motor response, particularly when the required motor torque changes as the operating condition varies. Another factor is the conversion of the WLTC-derived vehicle speed into motor rotational speed. In the current implementation, the conversion uses a linear relationship between 0–131 km/h and 0–4000 rpm. This approach provides a practical method for generating a dynamic motor command; however, it does not directly represent the complete longitudinal dynamics of an actual electric vehicle. The results nevertheless demonstrate that the developed testbed can operate the BLDC motor under a continuously varying speed command and can acquire the resulting motor-speed response through the encoder. This capability is important for subsequent experiments because battery current, voltage, temperature, and motor operating parameters can be observed while the operating condition changes with time. The resulting time-series data can therefore be used to investigate the relationship between dynamic motor operation and the electrical response of the battery system. Although the testbed can execute time-varying speed commands, accurate WLTC speed tracking has not yet been achieved. The present control approach does not employ closed-loop speed regulation in which the measured encoder speed is continuously compared with the reference speed and used to correct the motor control input. Future improvement can therefore focus on implementing encoder-based feedback control, increasing the resolution of the motor command, and calibrating the relationship between the driving-cycle speed and motor operating point.

A.4. Multimodal Measurement and Data Communications

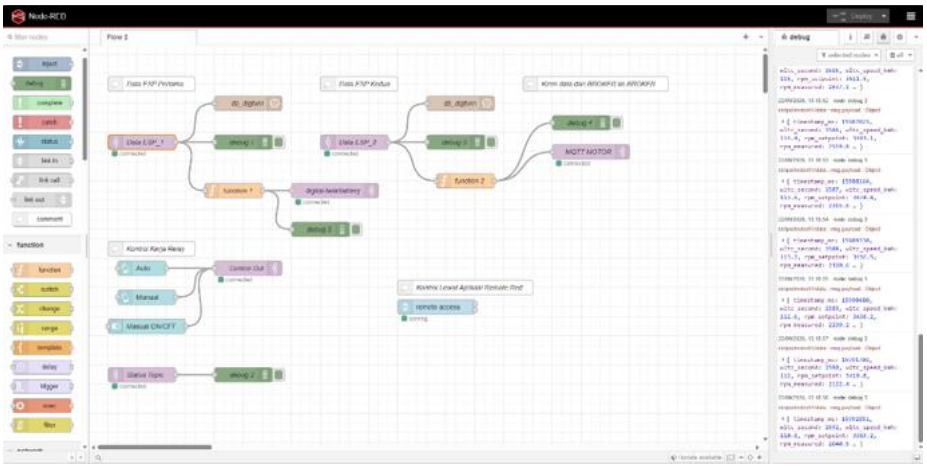

Fig. 7. Node-RED communication flow used to integrate measurement data from two ESP32 units.

Figure X illustrates the Node-RED communication flow used to integrate measurement data from two ESP32 units. Each ESP32 acquires data from different subsystems of the EV testbed and packages the measured parameters into an MQTT payload before transmitting them to the communication network. The payload contains measurement information from the corresponding subsystem, including battery, motor, charging, and operating-condition parameters. MQTT is used as the communication protocol between the ESP32 units and Node-RED, allowing measurement data to be transmitted continuously during the experiment. Within Node-RED, the received MQTT messages are processed before being forwarded to the subsequent data-processing and storage stages. The MQTT payload received from the ESP32 is passed through a Function

node, where the incoming data structure can be interpreted, selected, reorganized, and converted into the format required by the next processing stage. This function-based processing allows parameters from different ESP32 units to be handled within a common data flow and facilitates the separation of measurement variables according to their respective functions. The processed payload can then be forwarded to InfluxDB for time-series storage and to the Digital Twin environment as an input for system visualization. Thus, Node-RED acts not only as a communication interface but also as a middleware layer for integrating and preparing measurement data from multiple sources.

A.5. Battery Charging Results

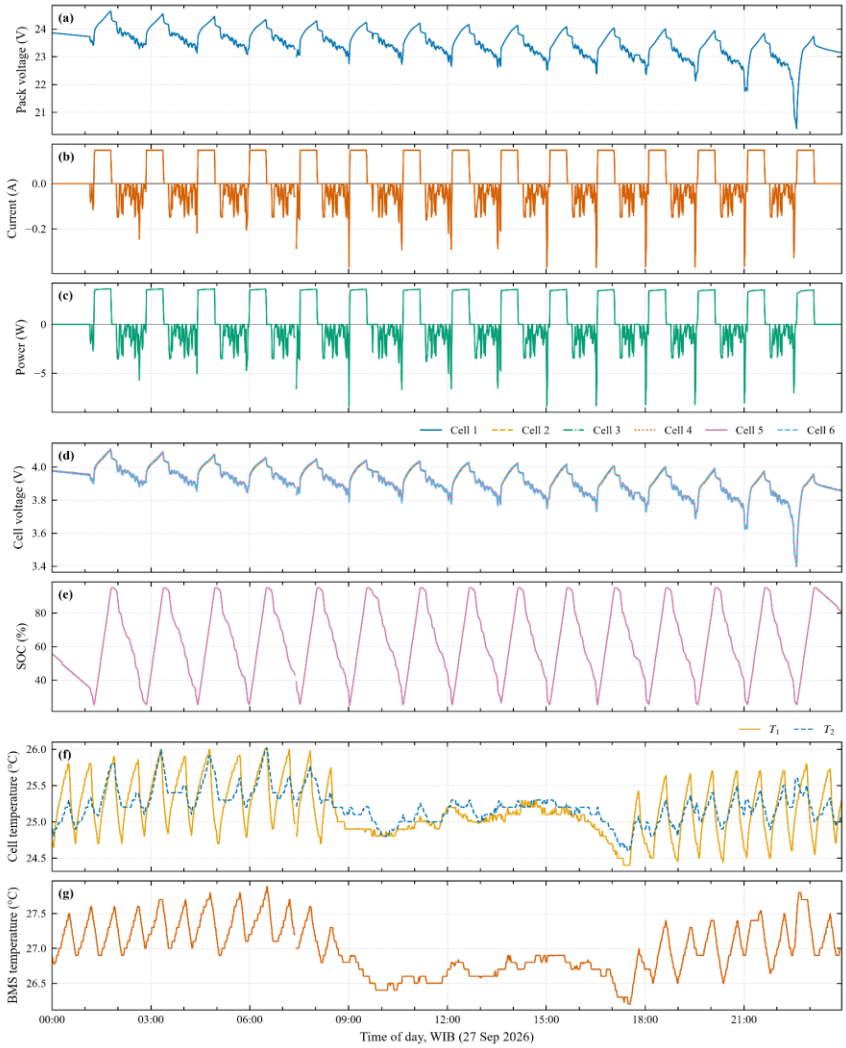

Fig. 8. Time-series graph of the system response during the battery charging process.

Figure X presents the battery charging characteristics, including charger voltage and current, battery pack voltage and current, state of charge (SoC), and cell temperature during the charging process. These parameters are monitored to characterize the electrical and thermal responses of the battery under charging conditions. The charger and battery measurements provide information on the charging input and battery response, while SoC and cell temperature are used to observe changes in the battery's charge state and thermal condition. The results demonstrate the testbed's capability to monitor battery charging parameters through the integrated BMS and sensor-based data acquisition system.

B. Discussion

B.1. Capability for Stationary and Nonstationary Experiments

The EV testbed supports stationary motor operation and nonstationary experiments using a WLTC-derived speed profile. However, the current system has not yet fully reproduced the reference driving cycle, as deviations between the reference and measured motor speeds were observed. This limitation is partly related to the implementation of the speed profile, which maps vehicle speed linearly to the motor RPM range (0–4000 RPM) and then converts the RPM setpoint into discrete steps of the X9C103S digital potentiometer. Since the motor speed is controlled through the driver's potentiometer interface without closed-loop correction based on encoder feedback, the actual motor speed may not precisely follow the reference profile, particularly during rapid speed transitions. In addition, the mapping between the driving-cycle speed and motor RPM has not yet been fully calibrated to represent equivalent vehicle operating conditions. Therefore, although the testbed can execute time-varying speed commands, further improvement in speed mapping, control resolution, and feedback-based speed regulation is required to achieve more accurate WLTC reproduction.

B.2. Measurement and Synchronization Capability

The measurement and data acquisition system integrates battery, BLDC motor, and charging parameters through two ESP32 units. The acquired data are processed, timestamped, and transmitted via MQTT to Node-RED, which serves as the communication interface for data integration and storage in InfluxDB. This architecture enables measurements from different subsystems to be recorded and aligned based on their timestamps, supporting synchronized monitoring and correlation of multimodal data. The integrated system provides a centralized data acquisition framework for monitoring the EV testbed. However, quantitative evaluation of timestamp offsets and communication delays between the ESP32 units is required to verify the synchronization accuracy.

B.3. Limitations

The proposed EV testbed is a laboratory-scale platform developed at the Faculty of Engineering, Universitas Jenderal Soedirman, and does not represent a complete electric vehicle or its full driving dynamics. The road-load condition is simplified using a dummy load to simulate uphill driving; however, the applied load remains relatively static and does not reproduce the continuously varying load experienced by a vehicle on an actual slope. The operating range of the motor and battery is also limited by the testbed configuration and the capacity of the Li-ion 18650 battery pack. Furthermore, sensor accuracy may be affected by their mounting method, as the sensors are attached to component surfaces rather than fully integrated into the measured components. Data acquisition is also subject to MQTT broker-related sampling and communication limitations, which may affect the temporal resolution of the recorded measurements. In addition, the Jikong BMS does not provide direct battery State of Health (SoH) measurements, limiting the testbed's ability to monitor battery degradation directly. These limitations should be considered when interpreting the experimental results and indicate areas for future system improvement.

B.4. Readiness for PHM Research

The integrated EV testbed provides a suitable experimental foundation for future Prognostics and Health Management (PHM) research by generating time-series data from multiple subsystems under both stationary and nonstationary operating conditions. PHM generally relies on condition-monitoring data to support anomaly detection, fault diagnosis, and prognostics, including Remaining Useful Life (RUL) estimation. In the proposed testbed, battery parameters such as cell voltage, pack voltage, current, temperature, and SoC are acquired together with BLDC motor operating parameters, including reference speed and measured RPM, as well as charging parameters. The timestamped and centralized data architecture enables these measurements to be correlated with changes in operating conditions and system responses.

The availability of multimodal time-series data under changing speed profiles provides opportunities for developing data-driven PHM methods that consider nonstationary operating behavior. For example, deviations from normal voltage, current, temperature, or motor-speed patterns can be used as inputs for anomaly detection and fault diagnosis, while long-term battery degradation data can support health-indicator construction and RUL estimation. Data acquisition is an important foundation of prognostics because degradation and operational histories provide the information required for subsequent health assessment and RUL prediction. Previous studies have also demonstrated the use of data-driven methods for Li-ion battery health diagnosis and RUL prediction using operational battery data.

Therefore, the current testbed should be considered PHM-ready at the data acquisition and experimental platform level, rather than as a completed PHM system. The present work does not implement anomaly detection, fault diagnosis, or RUL prediction; instead, it establishes the hardware, sensing, communication, and data infrastructure required for these future tasks. Further experiments involving controlled fault conditions and long-term degradation measurements are required to generate suitable labels and degradation trajectories for training and validating PHM models. This makes the proposed testbed a basis for future research on data-driven PHM of integrated EV battery and motor systems under nonstationary operating conditions.

IV. CONCLUSION

This study developed and experimentally validated an integrated EV testbed for monitoring battery, BLDC motor, and charging system parameters under stationary and nonstationary operating conditions. The results demonstrate that the testbed is capable of acquiring and integrating multimodal measurements through BMS, sensors, ESP32-based data acquisition, MQTT communication, Node-RED, InfluxDB, and Grafana, while also providing data input for the Digital Twin environment. The experimental results confirm that the system can execute time-varying speed commands and continuously monitor the responses of the battery and motor, although deviations in WLTC-derived speed tracking, simplified mechanical loading, sensor limitations, and communication-related sampling constraints remain. Overall, the developed testbed provides a functional laboratory-scale platform for integrated EV system testing and establishes the data acquisition foundation required for future PHM research, including anomaly detection, fault diagnosis, and RUL estimation under nonstationary operating conditions.

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