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SVM-Based EV Battery Monitoring with Dual Active Bridge Converter

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Abstract

Estimating the health status of batteries used in electric vehicles is essential in ensuring safe operation and maximizing their life expectancy and reliability. Precise lifespan prediction reduces expenses and increases confidence. However, existing prediction techniques lack sufficient real-world battery degradation data, suffer from non-linear degradation patterns due to differences in usage cases, and require heavy computational capacity. To solve the above issues, this research work introduces a battery prognostics algorithm that uses the SVM algorithm to predict key parameters of lithium batteries' health state, including their SOH and RUL. The developed prognostics system is combined with a DC–DC converter. Thus, it allows transferring power in both directions between the converter and the vehicle battery. The power transfer control unit is based on the PWM generator and the digital signal controller dsPIC30F4011 that controls the operation of the system by controlling the power distribution. Besides, the system has voltage and current sensors that monitor the battery's parameters continuously. Finally, the developed system enables not only to predict but also charge the EV battery. TLP250 drivers help generate gate pulses to control the switching process, while the web-based monitoring service created using the ESP32 microcontroller helps to visualize data.

Keywords: Electric Vehicle (EV), Battery Health Prognostics, State of Health (SOH), Remaining Useful Life (RUL), Multiport DC–DC Converter, Support Vector Machine (SVM), Space Vector Modulation, dsPIC30F4011 Controller.

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1. Introduction

Electric vehicles (EVs) are gaining more popularity with time, thereby increasing the need for battery monitoring and efficient energy management. Lithium-ion batteries are commonly used in electric vehicles because of their higher energy density, longer life span, and better performance than traditional batteries. Nonetheless, with the passage of time, there is a reduction in the capacity of lithium-ion batteries, adversely impacting the efficiency, safety, and life span of the electric vehicle system [9] [10]. Hence, monitoring and prediction of the parameters of health of batteries, including SOH and RUL, are crucial.

With an increasing number of electric vehicles being purchased by people all over the world, there is now increased attention in the field of battery health prognostics. Traditional ways of monitoring batteries are often based on simple techniques of estimation that may not be able to capture the complexities of how a battery ages due to different factors such as changes in temperature, charge-discharge cycle, and load [11]. This calls for innovative ways of prediction and analysis of the data.

Another trend seen in modern charging systems for electric vehicles is that these systems rely increasingly on renewable energy sources such as wind energy or solar energy, which helps contribute to making energy systems sustainable. In order to ensure stability in the system and to achieve optimal energy utilization, it is vital to achieve efficient power management between the EV battery and other sources of power. One viable option in this regard would be multiport DC–DC converters.

2. Literature Review

Berecibar et al. (2016) developed an advanced multiple state of health (SOH) assessment technique that uses a combination of electricity, heat, and impedance parameters. The results reveal that it is possible to achieve greater accuracy through the use of various data coming from different types of sensors rather than using just one type. It becomes important to incorporate the use of data collected at the converter level in terms of electricity alongside the heat and impedance information to attain high efficiency in SVM [1].

In another investigation, Barré et al. (2013) have proposed a generic multi-port Neutral Point Clamped Dual Active Bridge (NPC-DAB) architecture with closed-loop control. They conducted hardware-in-the-loop (HIL) testing to validate their concept. This fault-tolerant and modular design provides an effective solution for bidirectional energy conversion. It is observed from the experimental investigation that faulty control in the converter side, as well as impedance variation, can produce unique electrical fingerprints due to battery aging. Therefore, the use of the converter in diagnostic applications is promising, which can be used for health prediction with machine learning techniques in the future [2].

X. Hu et al. (2012) compared different machine learning techniques including SVM, RF, CNN, and LSTM for SOH prediction. Their results showed that deep learning approaches such as LSTM are superior to the other models when handling bigger datasets; however, for small, engineered datasets, SVM still works effectively. This shows how complex a decision-making process is, involving considerations of model complexity, prediction accuracy, and computational power [3].

A different approach by W. Waag et al. (2014) proposed an advanced form of SVM that provides predictions with associated confidence intervals. By doing so, this improves its performance when used for predicting battery health status under realistic conditions where data can be inconsistent. Such an advancement enhances its robustness and helps develop more effective adaptive control techniques [4].

Vetter et al. (2005) introduced a strategy that incorporates data-driven approaches with rules-based BMS safeguards to increase safety. This strategy involves superimposing the algorithm's output with constant restrictions in order to prevent the risk associated with state-of-health uncertainty. This combination of systems led to a decline in cases of overcharging, overheating, and early failure, hence providing a safer means for predicting the state of the battery in an electric vehicle [5].

In the same vein, Eddahech et al. (2012) studied different multi-input converters, including the Multiport Dual Active Bridge Converter and the Triple Active Bridge Converter, as a means of accelerating the charge time for electric vehicles. The results from their study have shown that by incorporating circuits capable of controlling the power flow from the grid, solar energy and battery packs, increased adaptability and reliability can be achieved. Furthermore, by studying the behavior of signals in the process of converting power, they were able to establish some trends in order to gauge the condition of the batteries without having to use extra sensors [6].

The study conducted by Plett et al. (2004) explored the connection between impedance pattern changes and battery degradation in order to improve the prediction of its state of health. Its method uses electrical perturbations caused by power converters and applies them as markers of variations in internal resistance, thus providing a cheap substitute for traditional electrochemical impedance spectroscopy that involves costly equipment. By harnessing the already existing patterns in the system, the researchers have managed to gain insights about its behavior from ordinary energy transactions. The introduction of impedance characteristics into SVM classifiers improved the prediction rate significantly and allowed for efficient health monitoring of vehicular power electronics without introducing new sensors [7].

The research by He et al. (2011) focused on current approaches to Prognostics and Health Management and reviewed machine learning methods for quantifying uncertainties based on non-invasive sensors. The proposed workflow includes data acquisition, diagnostics, and lifetime forecast stages and highlights the usage of externally measured electrical signals of power converters as substitutes for invasive measurements. Such techniques, combining indirect signals and intelligent analysis algorithms, as well as transparent artificial intelligence models, contribute to reliable decision-making under various conditions [8].

The major limitation of previous studies is the fact that research on prognostics and control systems has been carried out independently without much collaboration. Many of the studies have concentrated on either prognostic systems through the use of machine learning algorithms to predict battery condition, while others have focused on power management systems designed to increase efficiency during battery charging processes in electric vehicles [12], [13].

In addition, most of the research conducted has been limited by its inability to consider real-world scenarios since most systems are designed based on off-line data. Current monitoring solutions have tended to prioritize the collection of data and its presentation rather than implementing algorithms for the assessment of the State of Health (SOH) or the Remaining Useful Life (RUL) of the batteries. Consequently, there is a need to integrate machine learning techniques for prognostics, efficient energy management through the use of multiport DC-DC converters, and real-world implementation within electric vehicles [14], [15].

3. Proposed System

The designed model consists of the integration of different systems responsible for real-time monitoring of the batteries' state, intelligent control, and effective power distribution. The system measures different parameters, such as voltage, current, and temperature, in real-time while the battery charges or discharges through different sensors. It is integrated with a dsPIC30F4011 microcontroller, where the information is preprocessed and analyzed to evaluate the battery's state of health. Afterward, it enters the support vector machine (SVM) algorithm, which calculates the SOH and RUL, increasing the accuracy of prediction. The power distribution system uses a multport DC-DC conversion with the capability to move bidirectionally and maintain a constant DC voltage level. The model applies pulse-width modulation (PWM) using space vector modulation (SVM). It enables real-time wireless updates using the ESP32 module with internet access for sending information about the charge state and predicted lifetime of batteries to mobile phones or computers. This system raises an alarm immediately if any measurement exceeds a threshold value to increase the safety and longevity of batteries.

3.1 System Architecture of Battery Health Monitoring

The architecture layers of EV Battery Health Monitoring System have been depicted clearly in Fig. 1 below. The figure brings out the hierarchical arrangement of the components as well as interaction between various layers.

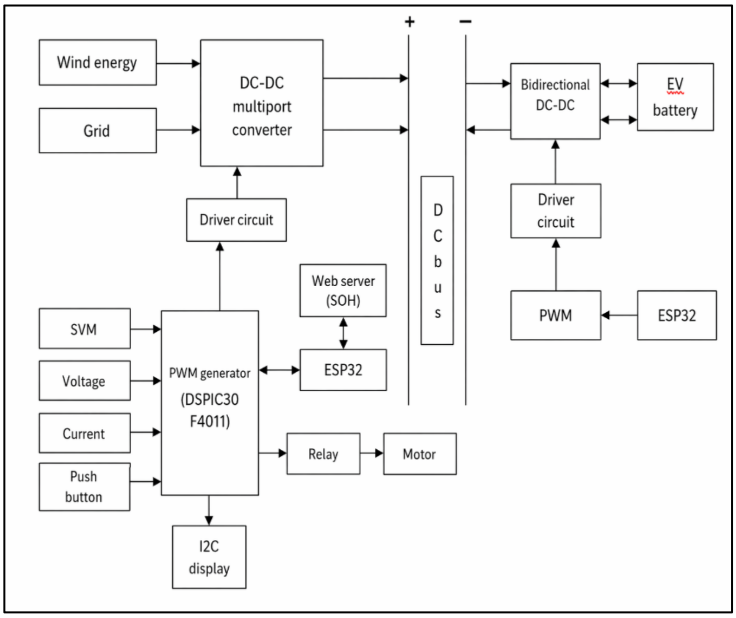


Figure 1. Architecture Layers of EV Battery Health Monitoring System

- **Sensing Layer:** This layer uses sensing devices that collect live data on voltage, current, and thermal activity in the battery. The sensor monitors any change in performance and sends output signals from this monitoring process, which are vital to evaluate the performance and condition of the battery.
- **Processing Layer:** This layer involves the use of dsPIC30F4011 chips as its basis, where real-time processing of data collected by the sensors is done. The processing of such data includes forming precise PWM output in order to improve control action of the device. It controls a multiport DC–DC converter in accordance with the current real-life operation of the system, ensuring efficient results despite various operating conditions.
- **Communication Layer:** Real-time data collected in the battery is transmitted to the cloud by means of ESP32 chips. The latter use Wi-Fi to transmit the information on operational metrics of the battery.
- **Application Layer:** This layer consists of the user interface via mobile apps or websites, which provide real-time data about the state of the battery and its performance. The system is capable of warning the users in case of any unusual metric in the battery's operation.

3.2 Working Flow of the Proposed System

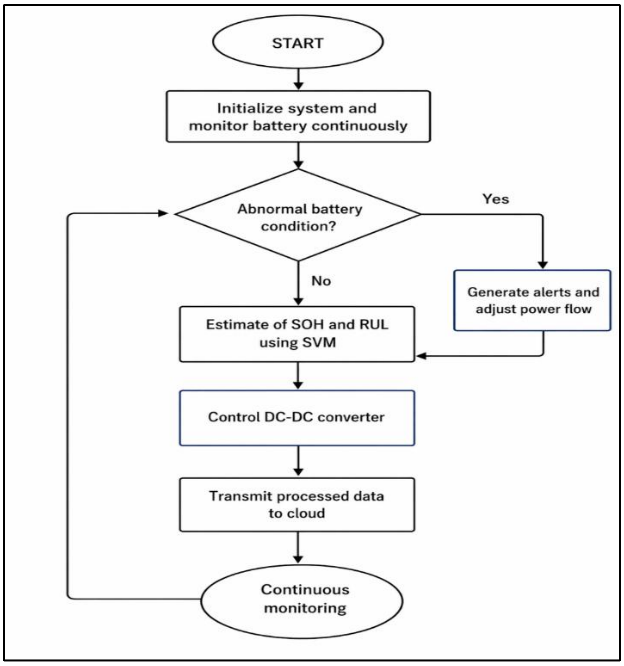


Figure 2. Overall Workflow of SVM Model

3.3 Flow Logic (Battery Monitoring & Control)

1. Start

   The monitoring process tracks electric vehicle battery voltage, current, and heat levels through sensor inputs - updating without pause. While readings flow in, each value gets analyzed on the fly. Voltage shifts appear alongside thermal trends, tied by live data streams. Sensor outputs are continuously evaluated, enabling correlations to be established across multiple parameters. As conditions shift, updates reflect in real time, connecting one moment to the next.

2. Data Processing

   Sensor information arrives at the dsPIC30F4011 unit where it gets examined. While signals move through circuits, computations begin without delay. Processing takes place once raw inputs reach the chip. After entry, data shifts into evaluation mode automatically. The controller handles each reading as it appears. Once inside, measurements undergo transformation step by step. Information flows steadily toward internal logic pathways.

3. Battery Condition Check

   When battery values stay inside acceptable boundaries

   - Normal operation continues.

     If unusual situations occur - such as voltage too high, heat beyond limits, or current that exceeds normal range - the system responds accordingly

   - Alert notification is generated.
   - If the battery parameters are within safe limits

     Normal operation continues.

   - If abnormal conditions are detected (over-voltage, high temperature, or excessive current)

     Alert notification is generated.

4. Battery Health Prediction

   Using processed information, the SVM method predicts how healthy a battery remains along with its remaining lifespan. What comes out shapes estimates without needing exact measurements upfront.

5. Converter Control

   The findings guide the controller in forming PWM outputs, shaping how power moves through the multiport DC-DC unit alongside the two-way converter. Efficiency emerges as these signals adjust flow across both systems dynamically.

6. Cloud Monitoring

   From the ESP32 chip, raw information moves into online storage spaces. A website or phone interface then allows live observation of results.

7. Continuous Monitoring Looping continuously, the system tracks battery status while forecasting its condition ahead of time. Each cycle updates live data without pausing, keeping assessments current through constant repetition.

The overall workflow of the SVM model is explained below and illustrated in Figure 2 Starting at the sensor level, raw measurements flow without pause into the monitoring setup. Real-time tracking of voltage, heat levels, and electric flow happens across several embedded detectors. Rather than functioning independently, these components transmit data directly to a central microcontroller. This central chip, specifically the dsPIC30F4011, takes charge of managing incoming signals. Processing tasks begin only after all inputs arrive in sequence. The system checks incoming signals against set thresholds, spotting issues like voltage spikes, too much current, or overheating. Meanwhile, a predictive algorithm built on Support Vector Machines analyzes the data - forecasting key metrics such as battery wear and expected lifespan. Though detection happens instantly, estimation relies on learned patterns from earlier performance trends. Each signal contributes to both real-time alert generation and long-term degradation analysis.

From the data gathered, the controller produces PWM signals that manage both the multiport and bidirectional DC-DC converters. While handling energy flow, these signals coordinate movement among renewables, the grid, and the electric vehicle battery. Stability in battery performance emerges through this coordination. System-wide efficiency rises as a result of precise regulation. Despite transmitting prediction outcomes alongside processed battery metrics via the ESP32 module, information reaches a cloud environment where monitoring occurs using either a website interface or smartphone software. Stored details include voltage levels, current readings, heat measurements, plus forecasts on battery condition - useful later when reviewing performance trends.

Extra features boost how well the battery system works, stays dependable, yet smart over time. Filtering happens first when sensors collect information, removing interference so voltage, current, and heat readings stay precise. Better raw inputs mean predictions and decisions turn out more trustworthy. Instead of fixed rules, safety margins shift as the battery wears down or faces changing environments - adjusting voltage and heat boundaries on the fly. Shutdowns become rare because limits respond intelligently, without risking protection.

With respect to timing of processes performed by sensors, processors, and controllers, synchronization can limit delays and enhance response time when there are unexpected variations in workload or malfunctions. The DC-DC converter used in the system limits variations to facilitate efficiency and increase clarity of the power supply process. In terms of security, ESP32 ensures that all communications between the system and the cloud are secured and continuous to minimize potential information leaks. While not clear from the outset, keeping a record of battery behavior throughout the system's use helps one detect gradual changes, as such data facilitates accurate predictions by showing consistent patterns of wear and tear. This model is flexible and easily incorporates additional modules and sources of power without major modifications. Also, in the event of any malfunction, safety features keep the system running efficiently and safely despite any single malfunctioning unit. Stability of the system is achieved through real-time modification based on actual performance. When operating in smart grids, there is coordination of all activities concerning power generation, storage, and consumption.

3.4 Hardware Model and Components

The hardware design of the developed system examines a DC–DC multiport converter with bi-directional power transfer for EV battery charging along with predicting the battery status. Some major blocks are the wind energy generator source (regulated DC supply), grid input, multiport converter, bi-directional DC–DC converter, EV battery, controller block, driver circuitry, sensor elements, and monitoring system. The hardware system uses regulated DC power supply for simulating wind energy for uniform experimentation conditions. This multiport converter includes the use of MOSFET switches, inductor, capacitor, and diode elements for connecting the source blocks and regulating the DC bus voltage. The PWM signals for switching operations in converters are generated by using the microcontroller DSPIC30F4011, whereas an amplified signal for proper MOSFET switching is produced by the TLP250 driver circuitry.

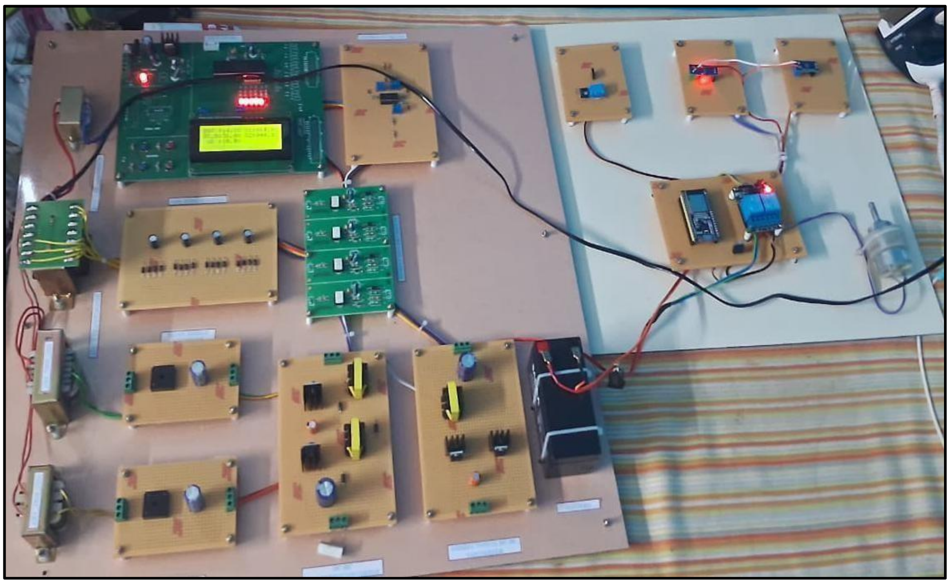


Figure 3. Hardware Implementation of EV Battery Monitoring System

The regulated DC bus is connected to a bi-directional DC-to-DC converter that controls the charge and discharge processes in the selected EV battery with parameters that match the design of the entire system. The bi-directional DC-to-DC converter guarantees the secure and efficient transmission of energy between the battery and the DC bus. The sensor values are processed using the support vector machine algorithm for the estimation of parameters characterizing the battery state, such as SOH and RUL. The system performance is monitored using the ESP32 controller, while voltage and current values are collected and transmitted to the web server via an HTTP protocol. For manual control of the system operation, a push button is used, while the values of the system parameters are shown on a local I2C display.

4. Results and Discussion

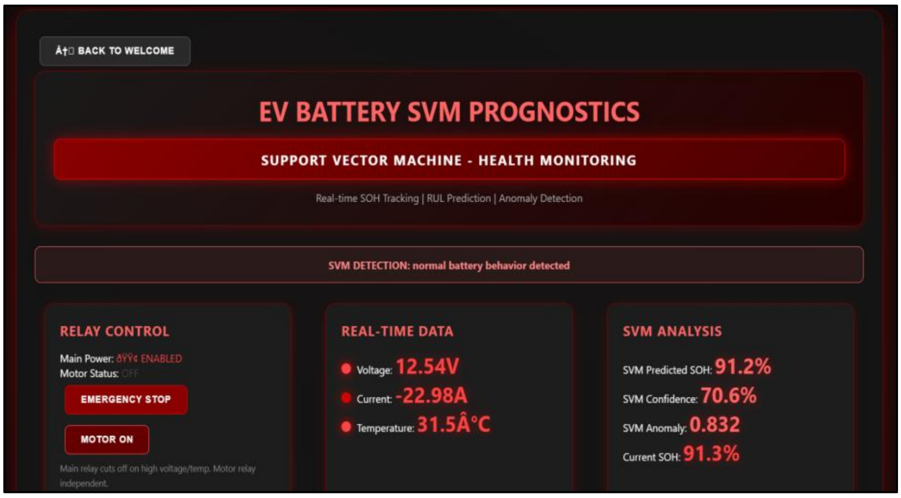
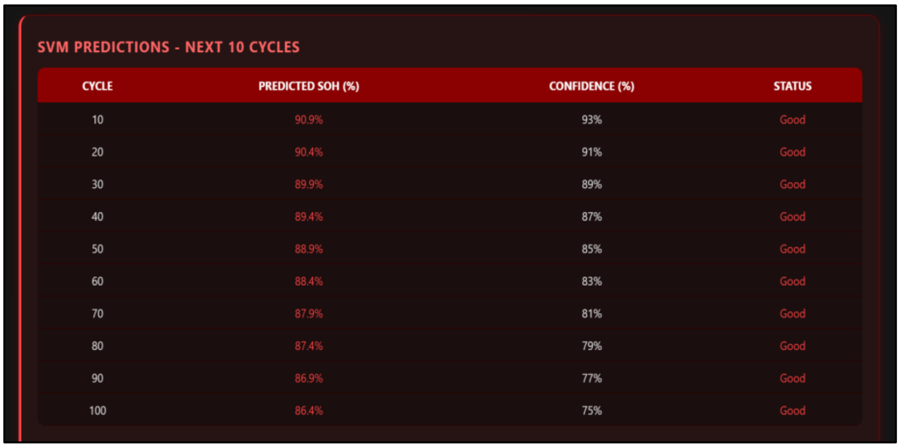


Figure 4. Real-Time SVM-Based Battery Health Monitoring Output

Real-time analysis of the battery metrics such as voltage, current, and temperature together with SVM's predictions about SOH and remaining useful life is another important aspect of the system. The monitoring process occurs on a regular basis, ensuring quick detection of abnormal behavior and allowing making informed choices. Real-time data, shown in figure 4 below, shows the data provided by SVM with SOH, probability, and anomalies being the key features. The presence of control measures like emergency stop and motor start allows ensuring that the battery performs normally in terms of the established standards. As can be seen from the outcomes, there is a relatively high SOH around 93% with low anomaly score. The results also highlight strong correlation between input parameters and predicted values as shown in the figure 5. This improves confidence in decision-making and supports timely maintenance planning.



SVM PREDICTIONS - NEXT 10 CYCLES

CYCLE	PREDICTED SOH (%)	CONFIDENCE (%)	STATUS
10	90.9%	93%	Good
20	90.4%	91%	Good
30	89.9%	89%	Good
40	89.4%	87%	Good
50	88.9%	85%	Good
60	88.4%	83%	Good
70	87.9%	81%	Good
80	87.4%	79%	Good
90	86.9%	77%	Good
100	86.4%	75%	Good

Figure 5. SVM-Based Battery Health Analysis Results Under Different Operating Conditions

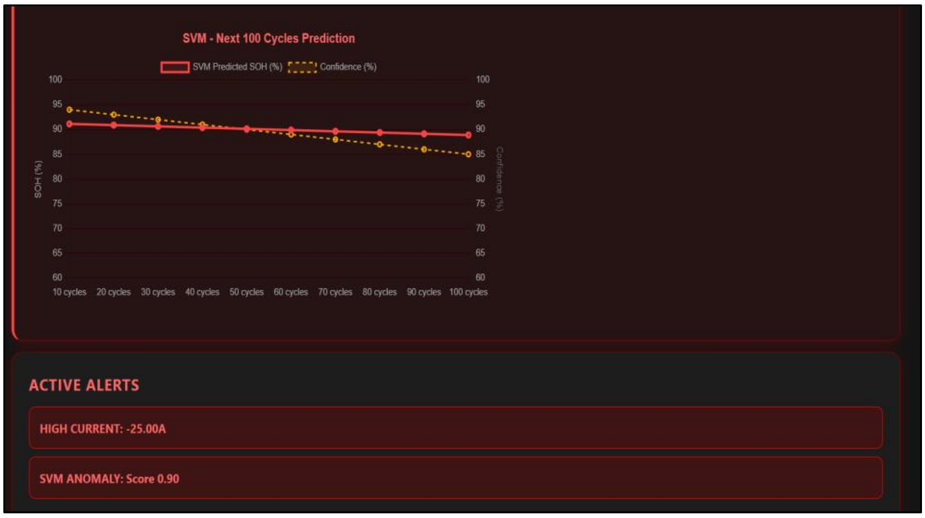


Figure 6. SVM Cycle Prediction

Even though there are no significant deviations from the normal voltage values, the dips are quickly compensated. The current deals effectively with variations in load without exceeding borders. Heat is kept stable without spikes; this is another sign of effective cooling. Battery health does not show any deviations, remaining within the boundaries predicted by SVM. Stable and predictable output of the system is achieved due to the lack of drift or abrupt changes regardless of the load. Energy transfer efficiency can be easily seen through the measured results obtained from testing. The figure 6 displays a graph of SVM-based prediction for the next 100 cycles with regard to battery SOH showing degradation in the predicted performance. The trend of prediction confidence is also shown on the chart, which decreases slightly with an increase in the number of cycles. Alerting signals above the chart include the high current alert and SVM anomaly detection score.

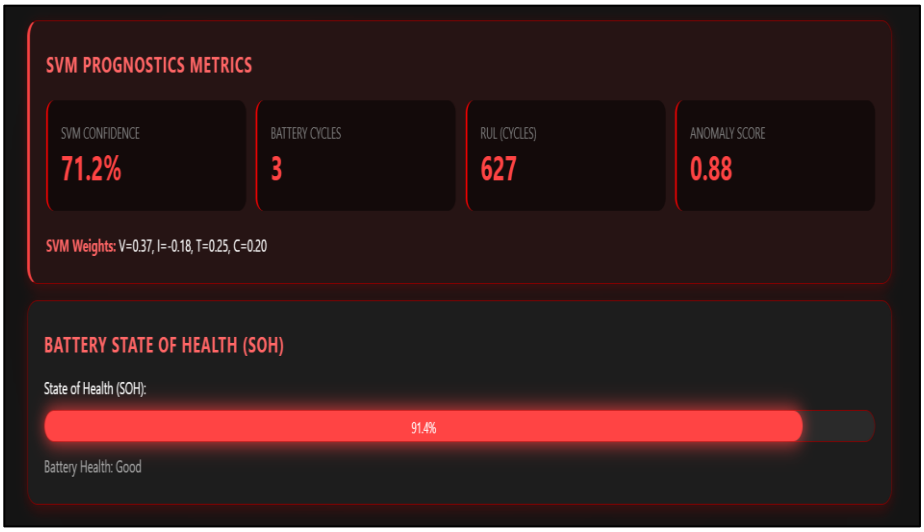


Figure 7. SVM-Based Battery Health and Prognostics Analysis

The figure 7 demonstrates the outcomes of the Support Vector Machine (SVM) model which was used for monitoring the battery state and predicting its behavior. It shows crucial performance indicators, including SVM confidence level, battery cycle number, Remaining Useful Life (RUL), and anomaly score. The accuracy of prediction made by the model can be evaluated by high SVM confidence of 71.2%. The battery experienced three cycles of charging/discharging, and the predicted RUL equals to 627. Therefore, the system is predicted to have a relatively long lifetime. Furthermore, the 0.88 anomaly score demonstrates that the model does not differ considerably from the expected one and is stable. The condition of the battery is shown with the help of State of Health (SOH). According to the indicator, SOH is 91.4%, and thus, the battery works normally.

5. Conclusion

This study presented an innovative method for monitoring electric vehicle battery status, utilizing machine learning in conjunction with power electronics. It connects voltage, current, and heat sensors to a dsPIC30F4011 microcontroller to collect performance data in real time. Using a Support Vector Machine method, the condition of the battery can be predicted, including its health level and remaining lifespan. Built-in multiport, two-way DC-DC converters make it possible for renewables, the power network, and electric vehicle batteries to transfer energy more efficiently. The ESP32 chip facilitates real-time communication, allowing performance to be monitored remotely through a mobile application or web interface. One test demonstrates the effectiveness of the new design in tracking battery life and predicting its degradation over time. Safety is enhanced when faults are detected early, supported by continuous data flow across modules. Performance gains emerge not just from speed but also smarter power distribution under load. With real-world use in mind, each function adapts without extra hardware. Scalability follows naturally from modular architecture rather than forced integration. Practical outcomes stand out where other models overcomplicate. Modern EVs gain sharper control through this streamlined method alone.

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