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Research Article

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Design of Cooperative Converter with Optimized Deep Learning based Control Mechanism of Battery Cell Balancing for Automotive Applications

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Abstract: This paper presents a high power density battery cell balancing system for the electro-mobility application that integrates a voltage step-up and a cell balancing function in one converter topology. The Co-operative conversion technique is used and realized by means of a number of dual active bridge (CO-DAB) converter modules. The converter processes only a portion of the output power, proportional to the difference in voltage of the battery pack and the converter output, thus a smaller converter can be designed than conventional solutions. Furthermore, it does lead to more efficient power processing at the system level as well. The modular structure of the converter allows multiple connection to each battery cell for online cell balancing in the case of standstill, charging, and discharging modes. System is controlled through practical Deep Balancing Network (DBNet) Layer controller, which can perform cell balancing and output voltage regulation simultaneously. Simulation results of a cooperating converter for a 24-48 V, 250 W, and 120 kHz converter for small automotive motors have shown that the cooperative converter combines both functions and leads to physically smaller and more efficient power processing elements than traditional DAB and boost converters. The Co-operative DAB converter runs with a peak efficiency of 96.4% and extracts 64% of the output power.

Index Term: Co-operative Converter, Dual Active Bridge, Deep Learning, Battery Cell Balancing, State-of- Charge, State-of-Health, Depth-of-Discharge.

1. Introduction

With the development of electric vehicles (EVs), lithium-ion batteries have become the mainstream choice of energy storage media. The battery packs consist of several cells put together in series and parallel combinations in order to reach desired voltage and capacity. One challenge faced is to keep the state-of-charge (SOC) well balanced among all cells for desired battery performance and long life. Cell imbalance occurs when there is a discrepancy in the cells' SOCs, voltages or the cells' internal resistances due to manufacturing differences, aging and disparities in operational stresses [1]. These discrepancies result in lowered effective capacity of the battery pack, a faster rate of capacity fading and ultimately it becomes a potential safety concern such as cell overheating or failure in the most awful scenario [2].

These cells require battery management systems (BMS) that monitor and regulate them to keep cell balancing, among other tasks such as voltage, current, temperature protections [3]. These BMSs' complexities are important because imbalanced cells hinder battery performance, lower driving range, and even potentially lead to early battery pack launch of life issues. Correct balancing of cells not only prolongs the life of cells but also enhances the reliability and security in EV battery system design. These strategies need to react dynamically based on the real-time data of the cell, and avoid overbalance to maximize the capacity for a consolidated pack [4].

A central Make use of converters-helper is served by patrol-based are powering full active advanced balancing state-of-charge (SO Passive balancing, that dissipates extra energy as heat in high charged cells, if different from active balancing where power electronics converters dump energy from higher cells' cells to low charged cells. Supporting the power re-distribution work is a group of power converters, e.g., bidirectional DC-DC converters, switched capacitor converters, etc., which provide a regulated environment for such energy re-

allocation to occur, so that power loss is restricted and capacity is better utilized [5].

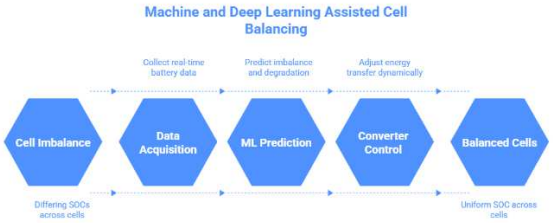


Figure.1 Deep Learning based Cell Balancing

There are two categories in balancing mechanism passive and active. Passive balancing typically uses resistor shunts which dissipate surplus energy as heat, providing a simple, but energy-inefficient approach [6]. In contrast, active balancing includes assisting converters to transfer energy between cells or to/from external sources which in turn improve energy efficiency and assists in achieving even cell usage. These approaches can significantly mitigate thermal stress, enhance overall battery performance, and extend the life-span of a battery [7]. Furthermore, active balancing through help converters offers real-time dynamic control via adaptive power flow control, which is essential in today's EV applications that highly request for not only efficiency, but also safety levels [8].

The use of machine learning (ML) as the basis of algorithms for BMSs is a revolutionary method in the design and running of such systems. Because of the complexity, nonlinearity, and time-varying character of lithium ion battery cells, many traditional model-based approaches to estimating SOC, state-of-health (SOH), and RUL face problems with uncertainties and dynamic environmental conditions. ML approaches offer the possibility to learn from data and predict battery state with higher accuracies for various usage behaviours and environmental conditions [9].

In addition, those data-driven algorithms for SOC and SOH estimations can improve the accuracy of the estimates by taking complex battery behaviours into account. They also promote proactive control, predict degradation trend and adjust balancing strategies in real-time to compensate for cell imbalance before it triggers the detrimental influence on battery, rather than solving battery management problems passively [10]. Among many ML realizations, it is worth to mention ensemble, and hybrid models such using ML state estimation technologies in conjunction with deep learning that emerged recently and show improvement in prediction accuracy. These advancements reinforce a future where BMSs are based not only on ML for state estimation, but also on ML for fault detection, thermal control, and intelligent control of convertors of assistive power [11].

2. Related Work

The cell balancing is generally divided into passive, active, and hybrid [12]. Passive balancing practices consume surplus stored energy by generating heat in shunt resistors connected to fully charged cells to balance SOC. These methods are simple and low cost, but they are not appropriate for large-capacity or high-performance battery packs because of energy loss and heat management problem [14].

Active balancing methods use power electronics to move energy between cells or modules using assistive DC-DC converters such as switched capacitor converters, inductive transfer or bi-directional DC-DC converters [15]. This charge shuttling keeps the charge in the system so that the energy efficiency and capacity utilization are enhanced. In general, the active techniques are more complex, more expensive but they bring the best performance and thermal behaviour [16].

Hybrid approaches, such as associating passive and active strategies, can adjust balancing methods on demand and system conditions to provide a trade-off among the cost, complexity and balance effect [17]. Decentralized BMS architectures replicate the monitoring and control functionality, to push the intelligence further down to individual cells or modules. This significantly increases reliability, scalability and permits finer control for better active balancing. Hybrid architectures like this represent a compromise and target scalable system dimensions that can be handled because it reduces the complexity of the entire system, with the large number of cells found in large EV battery packs is often being managed this way [18].

There are challenges for implementation of balancing algorithms based on these architectures (such as communication latency, accurate measurement synchronization and fault-tolerance etc.) to realize desired and safe control actions [19]. Supporting converters enable energy transfer for active cell balancing, and have been implemented in several topologies such as switched capacitor converters, buck/boost converters, and bidirectional DC-DC converters [20]. Switched-capacitor converters use capacitors as transfer components to transfer the charge from one cell to another in series or parallel. They are simple but often exhibit power handling limitations and poor efficiency.

The estimation of the SOC is also a key role in BMS. Machine Learning (ML) provides a number of models to improve SOC estimation under numerous operating conditions [21]. Conventional regression techniques such as SVR [22], RF [22] yield interpretable models and have low computational complexity to train and efficient generalization.

Deep learning methods such as the long short-term memory (LSTM) and gated recurrent units (GRU), as well as convolutional neural networks (CNN) are well suited to time series and non-linear feature representation

and modelling of battery behaviour. These models enhance the prediction performance by taking into account temporal dependencies and small characteristics of voltage and current waveforms [23]. Ensemble and hybrid methods, combining regression and deep learning models, further enhance SOC estimation robustness against noise and operational variability by leveraging strengths across algorithm types [24].

3. Methodology

The proposed Co-operative Dual Active Bridge (CO-DAB) employs a novel Deep Balancing Net (DBNet) structure, as shown in Fig. 3. This model includes multiple inputs to the battery cells (connected directly) and a single output to the output capacitor V_{cg} (at the top of the battery pack to create V_{out}. It follows that the converter is required only to deliver a fraction of the total power. This has the advantage of alleviate the power processing requirement on the converter and may allow to use smaller, more efficient converter and enhance the system- level power process efficiency.

The Proposed CO-DAB converter puts much less burden on the conversion stage. In particular, the converter has to supply only a small portion of the overall power requirement, proportional to the difference between the sum of the total output voltage,V_{out} and the sum of the battery pack voltages $V_{battery}$. The reason behind this reduced amount of balancing workload is that the DBNet carries out most of the balancing work internally and this enables the power converter to work under minimum demanding conditions. This direct consequence is that the system can use a smaller and more efficient converter device that not only reduces the size and cost of the component, but also the thermal management and reliability of the system. This effective partitioning of the DBNet and the converter eventually enhances the whole system-level power processing efficiency that results in longer operating lifetimes and performance in applications that require high energy density and tight power regulation.

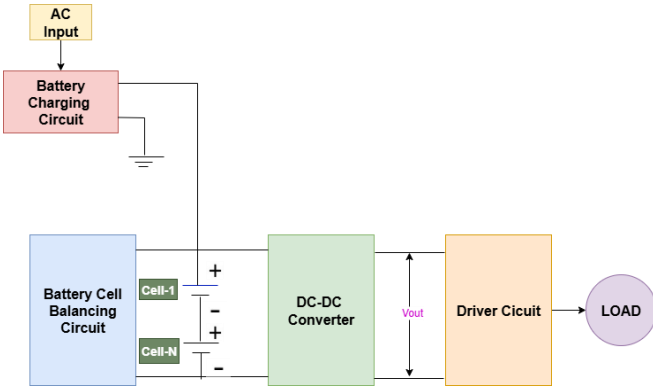


Figure.2 Conventional Battery Cell Balancing and Management Procedure for Automotive Applications

An important aspect of the proposed integration is the use of the same controller for controlling the step-up conversion and cell balancing at the same time. The use of one controller not only simplifies the control structure, but it also assures reliability, because synchronization among the functions controlled is more easily coordinated within a consistent controller architecture. This stands in strong contrast to a standard system depicted in Fig. 2 [28], with use of two different controllers for two different functions, the hardware cost is increased and also the complexity is increased and control coordination problem between two controllers is possible. This 'combined' controller simplifies the electronic elements needed and contributes to making the unit more compact and efficient. Furthermore, the single control structure of the proposed configuration allows the application of advanced operational schemes, e.g., dynamic load distribution and adaptive balancing, that provide a performance improvement at different operating conditions. Combining these functions, the converter can respond quickly to the changes of the system, regulate the output voltage steadily, and extend the life of cells with the well-balanced condition without additional hardware cost.

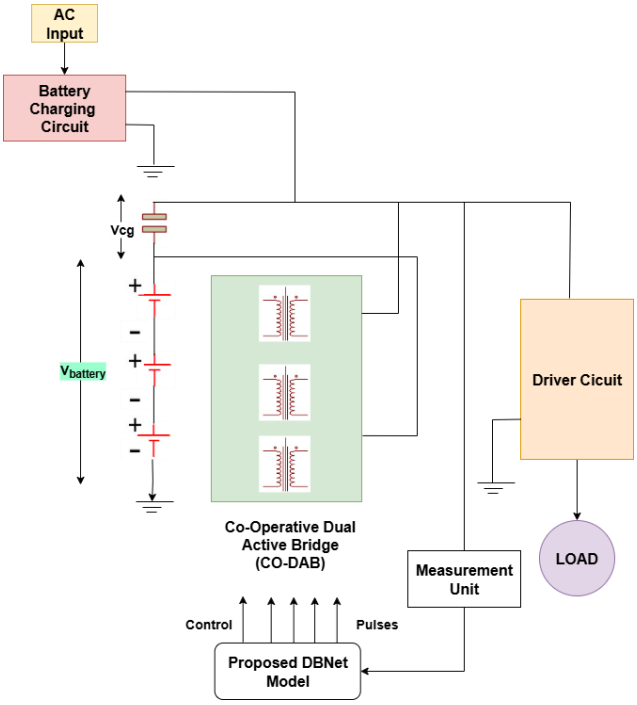


Figure.3 Proposed CO-DAB-DBNet Model Architecture

3.1 Step up function and system level efficiency

The Assisting DAB operation is graphically represented by the block diagrams in Figures 3 and 4, which give a visual inception of the system configuration and operation. Fundamental to this architecture is a principle to increase the collective output voltage -and power- by using two voltage sources: A battery stack voltage, referred to as $V_{battery}$, and an output voltage,V_{cg} produced by a proposed bi-directional multi-input single-output converter. This circuit is designed to distribute power at the level of battery cells, so as to realize more flexible power contributions that are extracted from individual battery cells, without having to depend on

only the battery pack as a whole. The battery pack in conjunction with the converter increases system efficiency by balancing the load and providing an optimal power transfer.

The bi-directional converter is not the single element producing all the output voltage and powers, as would be the case for a standalone source. It supports the battery pack with a part of a total power required by the system. Doing a division in this process also facilities the burden on the battery pack, which should increase battery life and reliability. As the converter taps the power of each cell, it is able to actively manage for variation in particular regions of the battery pack, allowing for precision control and stable output characteristics. This cooperative operation reduces the voltage drop and keeps desired voltage output in dynamic load.

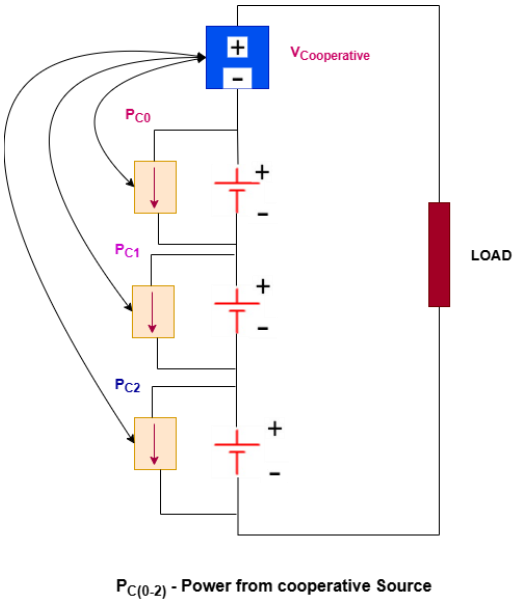


Figure.4 Proposed Multi-Input Cooperative Converter

A key parameter in such architecture is the cooperative power $P_{cooperative}$, which reflects the power contributed by the converter to support the pack. This power is directly related to the voltage difference between the output voltage desired and the actual voltage of the battery pack. Particularly, $P_{cooperative}$ is proportional to this difference, i.e., when the difference between the target output voltage and the battery voltage becomes large, the converter's power contribution increases proportionally. Such relation allows for a responsive and adaptive power sharing between the two, with the converter dynamically controlling its output to be the best fit to fill the battery pack. Mathematically, this process is as follows:

$$P_{co-operative} = (power)_{out} \frac{V_{out} - V_{battery}}{V_{out}} \qquad (1)$$

Referring to Fig. 4 and equation (1), the collective power of all the converter modules, $P_{cooperative}$ can be defined as the sum of the power of each module $P_{cooperative1} + P_{cooperative2} + \ldots + P_{cooperativeN}$. Here, $(Power)_{out}$ is the entire power converted to the load; $V_{battery}$ is the battery pack voltage and V_{out} is the converter output voltage. With a reduction in the power processing load, a smaller converter can be used than would be the case with conventional solutions as shown in Fig. 2. The same reduction enables the realization of greater efficiency in power processing at the system level. The efficiency gains could be explained further by looking at the following equations that relates system efficiency.

$$\eta_{sys} = \frac{(power)_{out}}{(power)_{out} + (power)_{losses}} \qquad (2)$$

With the reference of equation (1) and (2)

$$\eta_{sys} = \frac{1}{1 + \frac{(V_{out} - V_{battery})}{V_{out}} \left(\frac{1}{\eta_{coopeative}} - 1\right)} \qquad (3)$$

The losses in the assisting converter, represented by the $P_{lossess}$, are therefore very important for the total efficiency of the power conversion system. These losses are mainly caused by conduction and switching losses taking place inside the components of the converter. Alongside, the efficiency of the cooperative converter represents how efficiently the cooperative converter converts from the input power to the output power without left-over. The cross- coupling between these quantities plays an important role in the overall system performance, as the proposed Assisting converter supports the combining converter and does not intend to handle all the output power.

An important assumption is that power delivered from the battery to the load is considered lossless when analysing system efficiency. This assumption has the advantage of simplifying the model by limiting the losses to just inside the cooperative and assisting converters. Analytical expressions (1-3) express the power flows and the losses among the components which formalize the principle that the overall system efficiency outperforms the efficiency for the cooperative converter operating alone. This result is due to battery bypassing of the cooperative converter, which reduces the proportion of power that must be converted with associated losses. Therefore, the cooperative converter is released from working with the whole load, contributing to the overall efficiency improvement.

3.2 Cell Balancing during Load Movement, Charge Source connect, and Full stop Modes of Operation

Under Load conditions, the electric Load works under two modes (Though it is applied it is applicable under both Load as well as No Load running) one is motoring mode; where the machine operates as a Motor

and drives the load; next is the regenerative braking mode: means it acts on a generator. In either mode, the battery charger is disconnected, as depicted in Fig. 5. In the motoring mode, the Proposed Assisting converter controls the DC output voltage V_{out} for driving the motor and balancing the battery cells. This balancing operation changes the currents of individual cells passing through, with bigger current contributions being provided for cells with higher SOC.

During regeneration, motor drive operates as a rectifier to output a voltage. Since it is a bidirectional converter (Fig. 3), and in this mode it functions as a step-down stage, with the recuperated braking energy from the motor being returned to the battery pack on input. Cell balancing keeps occurring at the same time, using exactly the same approach as per the the motoring mode.

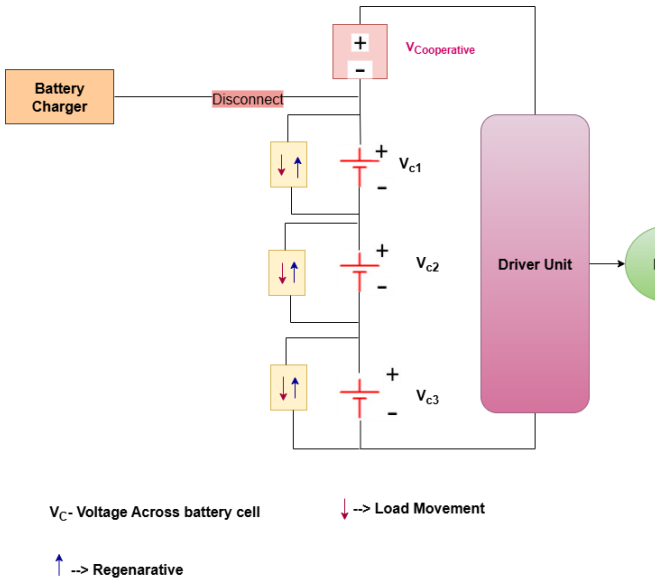


Figure.5 Load Enabling Mode Operation of Proposed Design

In the Charge Source Connect mode, the system sets a condition that the load will be protected from power up as the charging interlock is active. This interlock is a safety feature which prevents the current flowing to the motor drive, so as not to allocate any power to the load in this mode. As a result, the motor drive remains totally at rest and does not draw electrical energy. This purposeful isolation prevents the motor mechanism from being accidentally activated and damaged when a charge is being received.

The motorization drive is shut down and the cooperative converter takes a leading role as an active balancing circuit. Its main function is to allow the energy transfer between cells in the battery pack to achieve cell balancing. This is crucial as it allows cells to reach the same charged state - key for a battery's life-span and performance. During the Charge Source Connect mode, the output voltage is controlled to remain within its limits. This voltage regulation is important because it allows for the exchange of charge, not only from higher-voltage cells to lower-voltage cells as discussed above, but also from lower-voltage cells to higher-voltage cells, and will optimize overall battery pack balance.

Switch to the Full Stop state, in which is also limited motor to work the drive generates no current work well and the power is virtually cut off. Furthermore, the battery charger is deactivated in this mode to minimize power consumption and maintain system integrity in an idle state. Even without motor drive and battery charger activity in Full Stop mode, cell balancing never stops. There is still energy transfer between the cells to keep the charge distribution even from cell to cell (Passive balancing) and to prevent its degradation but such energy is now (converter parameters permitting) provided by the drivers in order to keep the output in the required range for this effect. This persistent balancing during both operation and standstill modes of the charging process emphasizes the focus of the proposed system's design on battery robustness and efficiency.

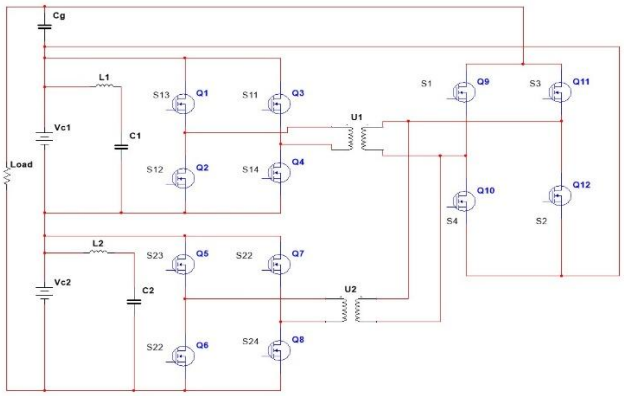


Figure.6 Proposed CO-DAB Circuit Design

The detailed construction of the proposed Assisting Converter is demonstrated in Fig. 6, and fundamentally depends on the multi-phase transformer-isolated dual active bridge (DAB) converter topology. Such a configuration leads to lossless bi-directional power flow between system parts, an attribute important for applications calling for both energy storage and energy release characteristics. Such requirements are naturally satisfied by the DAB topology, due to the inherent flexibility of operation and its potentiality to work also as load compensator in any direction of power flow.

It is one of the major advantages of using the DAB converter for this purpose that it enables a high power processing efficiency to be obtained. Such high efficiency results primarily from the fact that the converter is operated under zero voltage switching (ZVS) and/or zero current switching (ZCS) conditions. These soft switching methods have been developed to reduce the switching losses in a converter, thus improving the converter performance over that which is available using conventional hard-switching topologies. Therefore, DAB converter allows high frequency operation with no accompanying increase in electromagnetic interference

or thermal load on devices, which are typical in conventional converter designs.

In addition, the inductor size of conventional hard-switching and resonant converters is effectively reduced over the DAB converter. The volume and mass of inductors are known to limit overall compactness and integration of the system, so this size reduction can be quite meaningful. As inductance is reduced, the power density of the converter is also increased, and this property is particularly beneficial for portables or space-limited applications. This compactness is enhanced by making use of the leakage inductance of the transformers in the system thereby enabling the possibility of total elimination of discrete inductors in some cases. By taking advantage of transformer leakage inductance, not only is the part count lowered, but also reliability is enhanced and parasitic losses are reduced.

The architecture in Figure 6 includes multiple isolated transformers having their primary windings coupled one to one to separate battery cells. Such a structure allows for all cells to simultaneously provide power processing and provides for improved galvanic isolation. The windings of each transformer on the secondary side are linked by small inductors to a shared output capacitor. This configuration in turn offers a compact means for harvesting energy and then delivering the power to the load or to the store elements while acting as an isolative barrier between the multiple battery cells. The effective control of a numerous transformers as well as inductors within the system, which leads to fully scalable and modular power conversion solutions in line with the requirements of this modern multi-cell battery management systems.

3.3 Measurement Unit

At compare with traditional combustion engine vehicles, in our analysis the EV-Load based measurements are taken, electric vehicles (EV-Load) are the significant progress by using electric energy as its main energy source. An electric motor, powered by high-powered rechargeable batteries, which are at the heart of operation of each and every EV-Load. These batteries are key elements, they define driving distance, acceleration potential and overall operational efficiency of vehicles. The performance of an EV-Load is heavily depended on the characteristics of battery cell system such as capacity to store electrical energy and deliver when demanded under different conditions.

Leaving aside the fact that our envisioned system of battery cell is indeed very efficient for EV-Loads applications, it carries a complex set of issues which are intrinsic to battery chemistry and operation. Firstly, the energy density of batteries restricts the energy that they can store for a given weight and volume, hence placing a direct impact on the vehicle range and design aspects. Temperature maintain is essential here because batteries will produce heat once they are on the charging and discharging side, and the suitable temperature range can help prevent our components from getting burned and under safe condition. Batteries are degraded over time, decreasing their total capacity and power, which in turn may challenge the reliability of the system, so predictive maintenance strategies are also required. State of Charge (SOC) and State of Health (SOH) have to be accurately estimated in order to monitor batteries status in real time, as this can facilitate the precise control of charging methodologies and extend battery life. These are complex algorithms and sensor integration that need to ensure efficient data for battery cell management systems that protect performance and safety are maintained.

Accurate observation of the State of Charge (SOC) is fundamental in improving battery systems in EV-Loads performance. Proper SOC estimation allows managing the energy and preventing both, over-discharges and overcharges as they both lead to rapid battery wear. Also, SOC data generated using our DBNet Model can be used to make accurate predictions of the vehicle range, and this enhances user confidence and operational scheduling. Simultaneously, the State of Health (SOH) is continuously monitored and used to determine possible signs of capacity degradation or higher internal resistance and ensure that failures are not unexpected, thereby maximizing battery life.

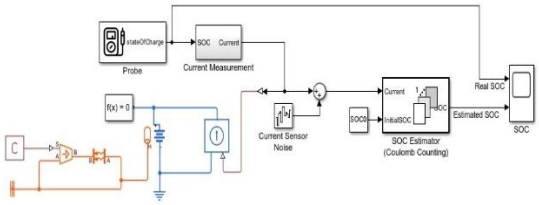


Figure.7 Proposed Model based Measurement Unit

The unit estimate the SOC of the battery cells by using the coulomb counting method and the kalman filtering protocol.

$$SoC_{cell} = SoC_{cell}(t_0) + \frac{1}{C_{rated-value}} \int_{t_0}^{t_0+\delta} I_{battery_{cell}} \qquad (4)$$

Where $C_{rated-value}$ represents the nominal capacity of the battery cell and the battery cell current denotes as $I_{battery_{cell}}$

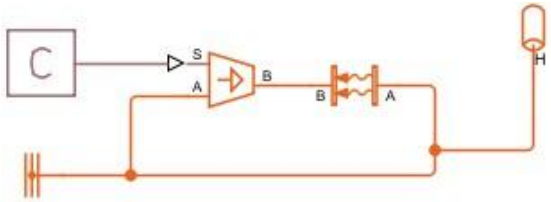


Figure.8 Thermal Network Design

Connection mechanism of a battery with environment is important for performance and safety. Cool battery cells work less effectively, as do hot ones, and extreme heat can set off a dangerous condition called thermal runaway. Although the model offers advantages such as high capacity and high energy density, the situation is risky because the battery generates heat more quickly than it can dissipate it, raising concerns of fire or explosion.

Heat transfer between the battery and the surrounding environment mainly involves conduction and convection. Conduction is the transfer of heat through the battery's internal components. Electric resistance and electrochemical reaction reactions develop heat within the battery while charging and discharging. This heat then makes its way through the materials of the battery until it finally arrives at the surface. Convection transfers heat to the ambient air or coolant outside the surface. This convection heat transfer is affected by variables including the temperature difference between the battery surface and the ambient surroundings the battery exposed surface area and the velocity of the air or fluid passing over the surface.

The Figure.8 shows the convective heat transfer block, it represents the heat transfer the connection in the middle of the battery cell and the proposed CO-DAB model design. The newton law of cooling describes the heat transfer as follows,

$$Q = k.A.(T_{Cell-A} - T_{Env-B}) \quad (5)$$

The parameter Q represents the flowing of the heat and measured in terms of watts, the variable k represents the transfer of heat coefficients, the surface area denoted as A, the battery cell temperature noted as T_{Cell-A} and the environment temperatures as T_{Env-B}.

State of Charge (SOC) is difficult to measure directly, because it is not a measured parameter (like voltage, temperature and current). SOC does not reflect the battery's internal chemical status, which is influenced by battery age, temperature and discharge rate. As a result of these difficulties, it is not possible to directly measure the SOC. To solve it, our model uses the Kalman filter to estimate SOC. The Kalman filter is a method to estimate the states of linear dynamic systems subjected to noise. Here, it estimates the future SOC of the battery and subsequently updates this estimate with the arrival of new measurements. This technique generates accurate SOC estimates from noisy inputs, adjusts to battery behaviour changes over time, including aging, and combines multiple types of measurements, i.e., voltage, current, and temperature, for improved SOC accuracy.

The measurement starts with the one-time constant dynamics as follows,

$$\frac{dSoC}{dt} = -\frac{i_{cell}}{3600.Ah} \quad (6)$$

$$\frac{dV_{pol}}{dt} = \frac{i_{cell}}{C_{pol}(SoC,T)} - \frac{V_{pol}}{R_{pol}(SoC,T).C_{pol}(SoC,T)} \quad (7)$$

$$V_{cell-terminal} = V_0(SoC,T) - iR_0 - V_{pol} \quad (8)$$

V_{pol} R_{pol} C_{pol} Represents the polarization voltages and $V_{cell-terminal}$ denotes the cell terminal voltage value.

3.4 Proposed Deep Balancing Network Layer (DBNet) Model

We propose an integrated deep learning-based Layer Protocol to improve the accuracy and efficiency of the balancing operation in the load-storage systems, the proposed model's flow shown in Figure.9. Fundamentally, the protocol leverages sophisticated neural network structures which process real-time battery data, allowing on-the-fly decision making at the cell level based on cell state, and cell behaviour. The protocol learns from historical and operational datasets, so it gradually adjusts its balancing strategy, and outperforms the traditional static algorithms. This approach, which not only simplifies control of the system but also is able to predict and avoid possibly imbalances, results in long battery lifetime and high level of system reliability.

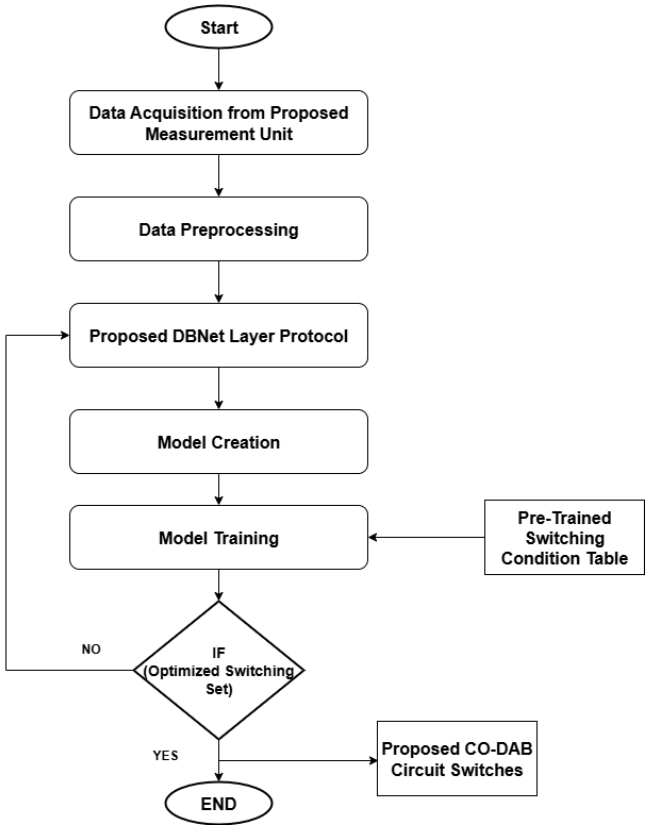


Figure.9 Proposed DBNet Model Flow Diagram

It is enhanced with intelligent balancing algorithms (both passive and active) which also assist in charging the cells at the optimal rates. Passive balancing is defined as a mechanism which eliminates the surplus charge by converting it into heat making it energy inefficient if used in pure form. Active balancing, on the other hand, moves energy from higher charged cells to lower charged cells, increasing overall efficiency while lowering the power loss. Combining these two mechanisms allows the system to harness the benefits of both methods, where passive balancing can be utilized during low-demand stages and active balancing during the fast-imbalance-stages to bring rapidly the states to their balance-points. This combined technique allows the deepened protocol, which optimizes energy consumption and the associated thermal damage to the cells.

The decision of choosing a balancing switching pulse shown in Figure.10, the measurement and set of rules that determine when and how cells are balanced is based on a joint consideration of measurement and the pre-trained table of value. Measuring variables such as cell voltage, temperature, and state-of-charge of each battery unit give an efficient overview on the current condition of the cell. These measurements are processed by the deep learning model to obtain optimal switching actions by referring the pre-trained value table, which encodes learned policies and expected outcomes from the previous extensive training phases. The integration allows the accurate timing and the degree to which the balancing pulses are modulated, resulting in the distribution of the energy into the optimal location and avoiding overcorrection or the excessive cycling of the balancing components. Combined, these elements provide a unified framework that exploits data-driven intelligence combined with hybrid hardware techniques to provide an efficient, durable battery-management system.

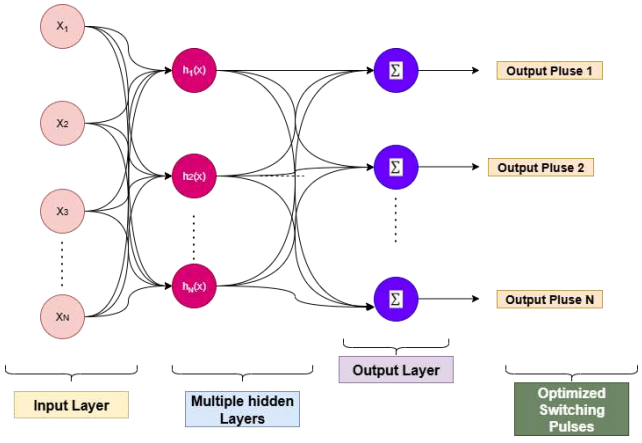


Figure.10 Proposed DBNet Model Architecture

The important feature mapping and representation means of the hidden layer nodes in the DBNet is a set of nonlinear radial basis transformation functions. They transfer the input data through radial basis functions that simply calculate the distance between input vectors and receptor points, and enable features in data space to be represented in nonlinear and complex relationships. The advantage of the transformation is that the inputs are projected into higher-dimension spaces in which clustering and pattern separation become easier, and learning capacity as well as generalization improve.

The training of the network is divided in two separate but interrelated phases. The hidden layer parameters are first optimized through a variant parallel back-propagation and stochastic approximation algorithm. This hybrid training technique allows for adaptive adjustment of the weights of hidden layer by stochastically minimizing error to enhance convergence stability and avoid local minima's. After this optimization procedure, in the output of the hidden layer, a clustering method is performed to find some cluster centres, which can be interpreted as receptor locations in the transformed feature space. This method finds the best position for each receptor and the spread of the radial basis function of every hidden node that is the receptive field with which the node works well. These spread parameters are responsible for the sensibility of each Gaussian to the variance of the input data and are the balance between the specificity and the generalization.

After the hidden nodes are characterized, the second stage is utilized to update the orthonormal weighting gatherers between the hidden layer and the output layer. During this phase, each hidden node linearly combines inputs via the computed radial basis function to produce output values, characterizing local activations. The generated output clusters indeed represent the discovered receptors in clustering, which in turn hold semantic feature groupings extracted from the transformed input data. In the end, it is this two-stage training that allows the input vectors to be projected in a complex transformation space where the structure of the data is represented, i.e. the objective of the training. The overall architecture of BDNet is schematically presented in Figure 10, which shows M dimensional inputs passing through H hidden nodes, which apply radial basis transformations, and resulting in Y dimensional outputs.

4. Result and Discussion

In order to justify the developed model an experiment was performed with a specially designed laboratory test bench with four serially connected lead-acid cells. Each of the cells is of 6.2 V 12 AH, which combined together supplies the desired nominal power output. Such a configuration ensures full power capability (250 W), a necessity for a realistic evaluation of the converter behavior at load. The use of the lead-acid cells was based on the wide application in automotive by their reliable performance and a very well-known electrochemical behaviour.

The topology of the converter consists of isolated proposed Co-operative Dual Active Bridge (CO-DAB) stages at higher switching frequency of 120 kHz.

Since such high frequency operation is necessary for efficient power conversion and different types of associated passive components such as inductors and capacitors are important to the size and stability of the converter, this frequency of operation is important. The system also stabilizes its output voltage to 48 V to be compatible with a typical auxiliary power in automotive applications. The infrangible voltage regulation is essential for consistent performance when powering electric loads as small electric motor.

Based on the given operating pair, the converter exhibits potential to effectively manage around 92% of its rated load. This figure of merit reflects high efficiency both in power transfer and in regulation signal in the converter system; this is especially important in the automotive power electronics circuit, where losses affect fuel economy and car emissions. The power handling of this down converter also fits the automotive benchmarks, demonstrating its potential use in the 48 V power supply system for low power electric actuators and motors used in vehicles. This focus design not only verifies the feasibility of the model, but also demonstrates its applicability for real-world automotive applications requiring a high power density and the efficiency respectively.

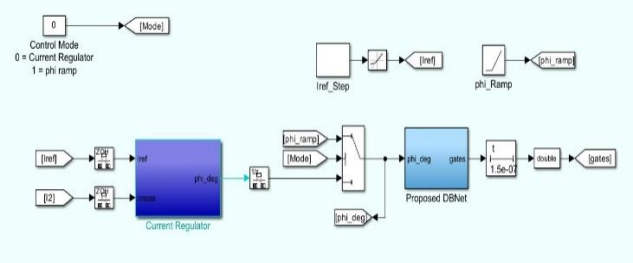


Figure.11 Proposed DBNet Simulink Model Design

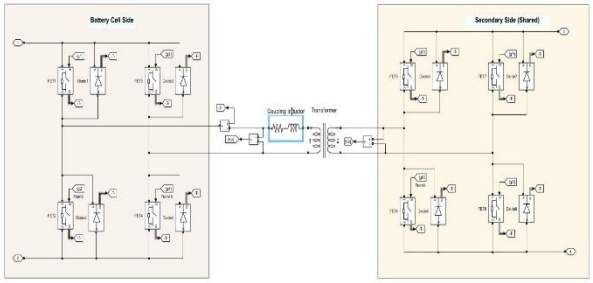


Figure.12 Proposed CO-DAB Circuit Simulink Model Design

Figures 11 and 12 depict more details of our proposed model structure, which is realized with MATLAB Simulink. We note that this simulation platform is designed to simulate the battery cell side (several cells in series or parallel with different SOC). Modelling the SOC dispersion among individual cells, the model accurately reproduces the dynamical characteristics while the battery is operating under the practical conditions and identifies effective analysis and control of the cell balancing and energy management.

The battery cells are linked with the secondary side of the system (referred to as the shared unit) using cooperative dual active bridge (CO-DAB) circuit model. These circuit model enable bidirectional power flow between the battery cells and the common unit with high efficiency and with efficient controllability. This synchronization between the two active bridges guarantees the zero-transient behavior during switching actions contributing to the reduction of losses and, ultimately, the system efficiency. This architecture encourages the remaining battery cells with low State of Charge (SOC) to be charged-up and therefore increases the capacity of the battery pack while prolonging the battery pack life and performance.

A critical feature of this design is the addition of a coupling inductor, employed in such a way as to reduce current stress during cell balancing. The inductor filter's transient currents and quiets on stressed of peaks of power electronics, providing an increased system reliability and longer life. Due to reductions in the current ripple and stress, the coupling inductor also tends to promote more stable and controllable energy transfer to assure balancing operation to be safe and efficient.

In addition, Figure 12 describes the connection method for a single battery cell of the system in more detail. This comprehensive diagram shows the connection interrelation among the single cell and supporting components such as the dual active bridge transformers and the coupling inductor. In our laboratory/Simulation test, four cells were used with this connection configuration, which permits a systemic validation of the proposed balancing strategy at different SOC levels.

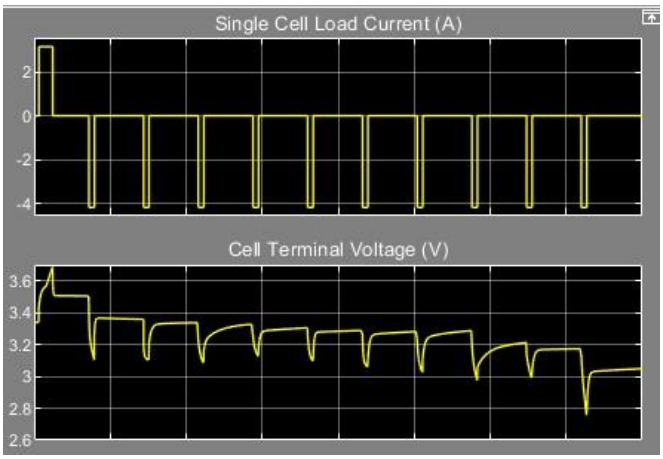


Figure.13 Battery Pack Single Cell Load Current drawn and Terminal Voltage Graph

Figure 13 shows the electrical value of a single-cell battery pack during load operation which focuses on the current consumption and terminal voltage. The figure contains information on how the discharge current varies with the SOC of the cell, which is maintained at reasonably high level of 92 %. This SOC value is important because it corresponds to approximately full charge condition of the battery, which can be used to monitor the behaviour at normal working condition, when the battery is not deeply discharged. Current consumption at this SOC shows the impact of load requirements on the internal dynamics of the cell, and the relationship between electrical draw and cell response.

Voltage at the terminal drops from 3.6 volts to some 3.01 volts as the load current on the cell goes up. Such a voltage drop is a measure of the internal resistance and electrochemical limitations of the cell under high load. In particular, the decline of terminal voltage demonstrates that higher current loads result in higher polarization losses and voltage drop along the cell/more severe loss of voltage retention at higher loads. The insight into such voltage behaviour contributes to model the actual useful operational domain of the battery cell under different load current profiles, offering useful information for the battery management systems striving for performance and lifetime.

The data also shows a dynamic relationship between current consumption and voltage output for a given SOC, revealing the non-linear nature of battery performance under load. The voltage drop is non-linear with current increase but it is characteristic of resistive changes, electrochemistry rates, and thermal dependence, all of which change as the battery is discharged under high load. Critical aspects of cell health, efficiency and application profile suitability can be deduced if the curve is analyzed, and as a result models for cell behavior under “real-world” conditions can be developed with increased accuracy. This investigation highlights the necessity of concurrent measurement of current and terminal voltage used to accurately access battery efficiency and potential performance loss during deep discharge cycling.

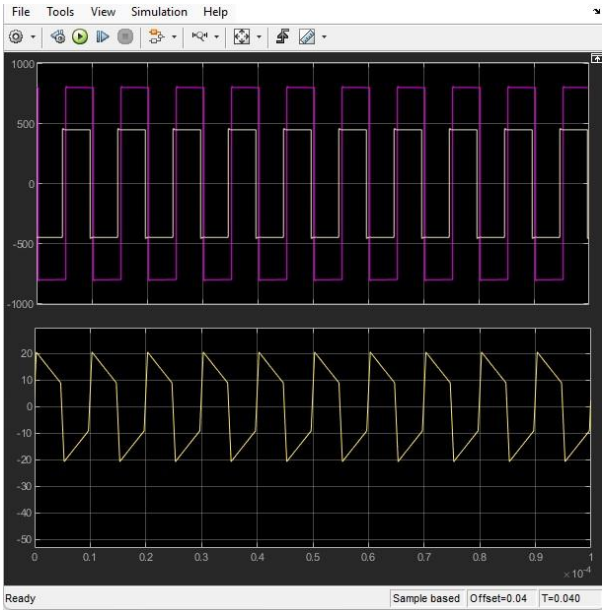
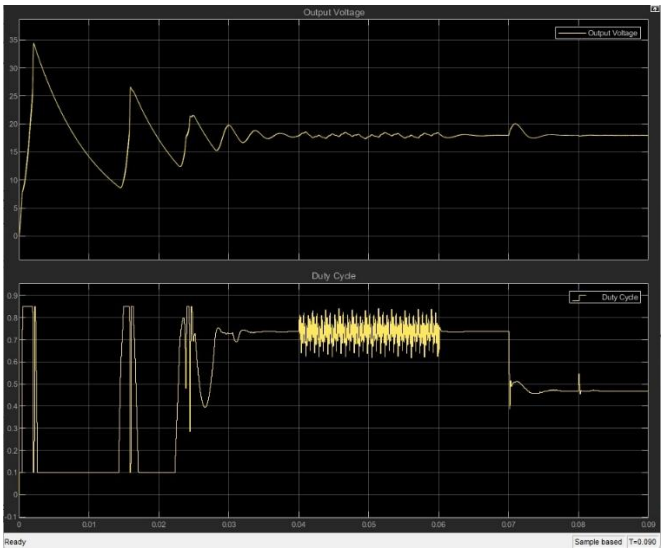


Figure.14 Cooperative DAB model’s Inductor Current Waveform

The currents from the primary side of the each phase, and the output side voltage, when the cells are balanced are given in Fig. 14. These primary side currents act as a direct indication of the power supplied by each of the phases and provide useful information on the load sharing of the converter. From the analysis of these current wave shapes, it can be see that the converter equally shares the input power among the parallel phases so that no individual phase is significantly overloaded.



Figurre.15 Proposed DBNet Model Balancing Cell Voltage using Optimized PWM Control Signal

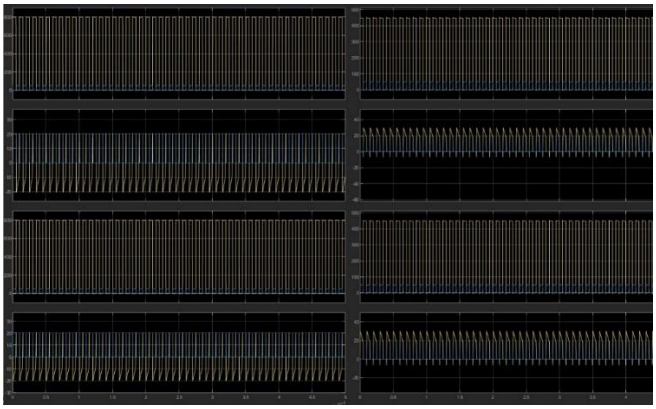


Figure.16 Proposed DBNet Model's Gate Pulses and Switching Voltages

Figure 15 and Figure.16 shows a well-regulated output voltage for balanced cells as well as balanced current usage. The voltage waveform appears smooth and forms a regular form curve, indicating that the converter is able to maintain the target voltage level despite the multi-phase power distribution complexity. This fine-tuned voltage regulation is vital for downstream devices to rely on a superior power supply, which is a key factor in maintaining system stability, efficiency, and ensuring components last longer. The observed proof of equal current sharing and stable output voltage underscores the effectiveness of the converter's control strategy, which adaptive-tunes the contribution of each phase for enhanced total performances. Furthermore, the results displayed in Fig. 15 also highlight the inherent synchronization of the phase currents between the cells regardless of the discrepancy on the characteristics of each individual cell or externally-induced perturbations. This synchrony reflects powerful control algorithms, which continuously observe and adapt to changes, finely controlling transitions from one phase to the other in real time.

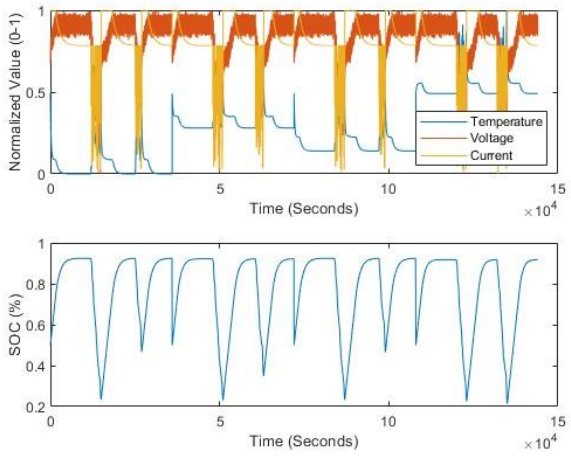


Figure.17 Pre-Trained Database Parameters

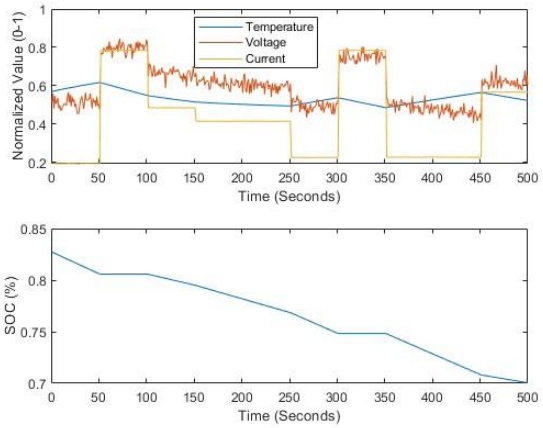


Figure.18 Pre-processed Pre-trained Database Parameters

Figures 17 and 18 show how our proposed DBNet learner feature details to learn useful feature representations from a pre-trained switch table. This switching table is the reference data set for the model, and is formed across various states of charge (SOC) to represent the dynamic operation of the battery cell. The table provides a complete integration of all relevant parameters such as cell voltage, cell current and temperature as the impacting SOC parameters. By does so recording this multi-dimensional data along the shift among different SOC levels, the switching table acts to normalize the complex electrochemical environment in battery and provides the DBNet with high context critical to accurate learning.

The accumulated data in the switching table are pre-processed in an organized fashion to improve the quality of data and thus its usability for training of the model. This pre-processing usually includes cleaning, normalization and structuring of the dataset in order to be able to serve it to the model in an appropriate way. Such pre-processing can help the efficient learning of broader representative features and relieve the learning the DBNet. After pre-processing, the dataset is processed with the Kalman filter, a statistical model that estimates the actual SOC value iteratively by minimizing errors between measurements obtained by noisy sensors. The use of Kalman filter also has the effect to map the feature set better capturing the underlying battery condition during the training phase of the DBNet, contributing to an improved predictive capability.

The structure of the model is specifically designed to capture the interactions between voltage, current and temperature that occur at various SOC levels and, therefore, the model is capable of efficiently mapping these non-linear relationships. Training the DBNet on this augmented data allows for the extraction of discriminative feature embedding that captures very sensitive battery behavior differences. At last, this procedure enables the model to estimate SOC more accurately and reliably, which is superior to the common

SOC estimation methods and it represents a great leap into the development of balancing strategies for battery cells.

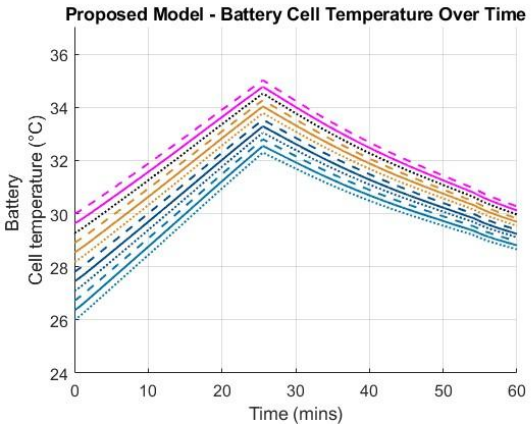


Figure.19 Proposed C)-DAM-DBNet Model Cell Temperature over Time

The temperature of a battery cell changes with time and is affected by a number of factors such as charge/discharge rates, environmental conditions, and the internal chemistry of the cell. In the initial stages of battery use, there may be rapid temperature rise as the electrochemical reaction becomes more active, and internal resistance changes electricity to heat. In figure. 19 all battery cell temps goes from 26 degree Celsius to 34 degree Celsius. This heat dissipation rate is very current dependent, with larger currents leading to increased resistive losses and faster rise times. Furthermore, environmental effects like ambient temperature and cooling in the heating process control the heating rate and magnitude.

Since the battery system according to our model settles to a steady state in terms of battery utilization, the temperature evolution will reach a steady state corresponding to the balance between heat generation and dissipation. This is a region of thermal equilibrium and is a function of the battery system: heat capacity of the cell materials, the thermal conductivity and efficiency of the cooling proposed.

The balancing DBNet control algorithm always keeps track of the state of charge (SOC) of each cell in the battery pack. It starts to balance if the SOC difference is over 0.55% between the two successive cells. Then, according to the SOC of the battery, the control unit autonomously controls the charging/discharging of the inductors for balancing.

The control part of the DBNet first continuously reads the SOC values of all cells to implement balancing feature set selection. The control unit triggers the associated switches through short pulse, when the SOC difference of any two cells exceeds 0.55%. For instance (Ref. figure 12) these switches are turned ON to result in charging of inductors L1 and L3 to enable energy transfer into cells S11 to S12 and S13 to S14 respectively.

For instance, when cells S1 and S2 have stabilized at an SOC corresponding to 54.5% and cells S3 and S4 have stabilized at an SOC corresponding to 79.5%, switch S4 is turned on by the control unit. This allows transfer of power from the S3-S4 cell pair to the S1-S2 cell pair, while balancing battery pack. From Figure 20, we see that the whole pack will be balanced at a SOC value as high as 83.5 % in only 68 s.

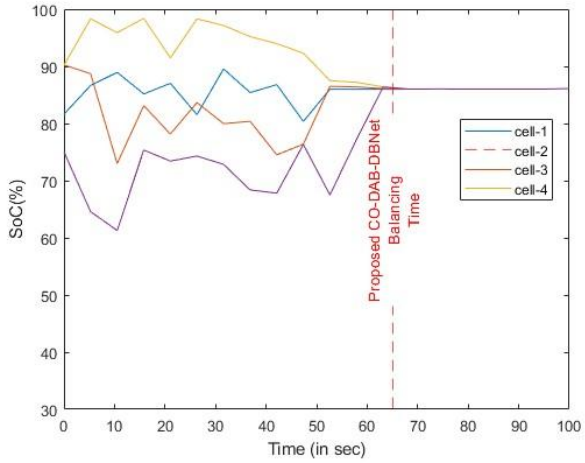


Figure.20 Proposed Model based Balancing of Battery cell's SOC

5. Conclusion

A new system dedicated to Electro-Mobility with an integrated battery balancing and step-up voltage. This novel (CO-DAB-DBNet) methodology can satisfy the two most challenging problems of the electric vehicle power management; achieving a uniform cell voltage of the battery pack and reaching an optimal voltage level for the systems. By performing these roles at once, the system simplifies the power-conversion process and improves the efficiency of energy management overall, which, in turn, could help extend battery life and vehicle range. The Co-operative Dual Active Bridge (DAB) converter architecture constitutes the core of this configuration. The difference of this architecture from traditional converters is that it processes, differently from the voltage conversion from the battery pack to the output, only the voltage difference between the battery pack and the output voltage to obtain a broad gain range with small demagnification factor. Such selective processing reduces the power load on the converter a great deal. It thereby reduces the power stress that would normally burden the step-up stage to facilitate a more practical and easy power conversion. This targeted voltage difference processing also relaxes the challenge of employing an efficient converter, as the latter is less demanding in this case in its performance specifications, potentially leading to cost reduction. In order to prove the feasibility and benefits of this concept a prototype using four single cells was developed, built and experimentally

tested in a cooperative DAB converter connection topology. This demonstrator provide key input for the real-life operation and benefits of the structure. The collaborative DAB system has been tested and it showed that it was working better than the normal single-stage step-up converters. In particular, a smaller power stage was used to make the conversion, which resulted in smaller and simpler components. Furthermore, it had improved power processing efficiency, which was of great importance for the energy-sensitive mobility environment like the electro-mobility systems. These enhancements in the system performance further demonstrated the advantages of co-operative DAB converters in enhancing the energy control for EVs.

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1.https://drive.google.com/file/d/12s4220kHr4xrXiJNo608qtI0dExFUe1s/view?usp=drive_link