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ARTIFICIAL AND COMPUTATIONAL INTELLIGENCE

Interval type 2 fuzzy PI-enhanced state space model for battery management in battery electric utility vehicles operating in an indoor logistics environment

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Abstract. This research presents an advanced control approach for battery management in battery electric utility vehicles (BEUV) operating in indoor logistics environments. The proposed approach utilizes a combination of proportional-integral (PI), fuzzy PI, and interval type 2 fuzzy PI (IT2fuzzyPI) control structures to augment the state space model for battery management. The state space model incorporates the voltage and current of each battery cell as state variables and considers the current demand from the electric motor as an input. By integrating fuzzy logic with PI control and considering uncertainty, the IT2fuzzyPI structure offers improved control recital and system robustness in the occurrence of nonlinearities, uncertainties, and turbulences. The outcomes of the simulation validate the effectiveness of the proposed scheme in managing the battery pack system's state of charge and controlling the rates of charging and discharging. The IT2fuzzyPI control significantly improves the overall proficiency and longevity of the battery system, making it suitable for battery electric utility vehicles in logistics environments. This research contributes to the field of battery management systems, providing a valuable tool for designing and evaluating high-performance electric vehicles with enhanced control capabilities.

Keywords: fuzzy network; battery electric utility vehicle; state-space; battery management systems; interval type 2 fuzzy.

1. INTRODUCTION

Electric vehicles (EVs) [1] have arisen as a promising solution aimed at sustainable transportation [2], offering reduced emissions and energy consumption compared to conventional vehicles. In indoor logistics environments, EVs are crucial in the efficient transportation of goods within warehouses and distribution centers. However, effective battery management [3] is essential to ensure reliable operation, extended battery life, and optimal performance of these vehicles [4].

Effective battery management systems (BMS) [5] are integrated into these electric vehicles to ensure efficient operation and extend the lifespan. The BMS [6] monitors and controls various parameters such as current, voltage, temperature, and state of charge for each battery cell. Proper battery management [7] is essential for uninterrupted vehicle operation, cost-effectiveness, and environmental sustainability.

One crucial aspect of battery management is regulating the charging and discharging processes. The widely adopted control algorithm in battery management systems is the PI controller [8–10], which holds a significant position in regulating system performance. The PI controller is responsible for adapting the control output by considering the error and integrating the error over time, guaranteeing the battery operation within safe and optimal boundaries. The incorporation of the PI controller into the overall battery management system, alongside techniques like state-of-charge (SOC) assessment [11], wavelet neural network and BP neural network, charging of electric vehicles [12], battery volume estimation, and thermal management, leads to the establishment of a comprehensive system for managing electric vehicles (EVs) in indoor logistics environments [13, 14].

Apart from the utilization of the PI controller, there has been growing interest in the application of fuzzy logic control methods within battery management systems [15, 16]. Fuzzy logic controllers utilize linguistic variables to capture expert knowledge and emulate human-like decision-making processes. The inclusion of fuzzy logic alongside the PI controller in the form of the fuzzy PI controller [17] leads to improved control performance and robustness, specifically in dealing with the uncertainties and nonlinearities present in battery systems. To tackle the uncertainties that arise in conventional fuzzy logic controllers, a promising approach recognized as interval type 2 fuzzy logic (IT2-FL) has gained attention [18]. IT2-FL goes beyond traditional fuzzy logic by integrating the notion of uncertainty through the utilization of upper and lower membership functions [19]. This enhancement enables better modeling and control capabilities, especially in complex systems like battery management in EVs operating in indoor logistics environments.

The impartial of this work is to create an enhanced state space model for battery management in electric vehicles operating in indoor logistics environments, using interval type 2 fuzzy PI (proportional-integral) control [20]. The proposed approach combines the benefits of interval type 2 fuzzy logic with

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PI control to effectively address the challenges of battery management in these specific operational conditions. By effectively capturing and handling uncertainties, the model aims to enhance the reliability, efficiency, and safety of EVs in indoor logistics operations.

Through comprehensive simulations and experimental validations, this research seeks to exhibit the efficacy of the interval type 2 fuzzy PI-enhanced state space model for battery management. The study will investigate the model performance in terms of accurate state estimation, optimal control of charging and discharging processes, and overall battery health management. The outcomes of this research will make significant contributions to the advancement of battery management systems for battery electric utility vehicles (BEUVs), facilitating their extensive usage in indoor logistics environments and encouraging the adoption of environmentally friendly transportation practices.

The subsequent sections will present the state space modeling, fuzzy-based controller design, implementation in battery electric vehicles, results, and discussions of the proposed IT2 fuzzy PI enhanced state space model for battery management in BEUVs operating in indoor logistics environments.

2. BATTERY ELECTRIC UTILITY VEHICLE (BEUV) IN INDOOR LOGISTICS ENVIRONMENT

Battery electric utility vehicles (BEUVs) serve as indispensable assets within indoor logistics, facilitating the seamless movement of goods and materials through confined spaces. With their electric powertrain operating at 24V, BEUVs provide smooth acceleration and precise control, ensuring compatibility with indoor infrastructure. These vehicles boast a payload capacity of up to 600kg, making them adept at efficiently transporting various materials. Their compact dimensions, typically around 1.1 meters wide, enable agile navigation through narrow aisles and congested areas. Equipped with advanced safety features such as collision detection sensors and emergency braking systems, BEUVs prioritize operator safety and bystander protection. Additionally, ergonomic design elements, including comfortable seating and intuitive controls, enhance operator comfort and productivity during extended use. Integration of connectivity and telematics systems enables remote monitoring and fleet management, while a sophisticated battery management system (BMS) ensures optimal performance and longevity of the battery pack [21].

To ensure the optimal performance and longevity of the battery system in BEUVs, a sophisticated battery management system (BMS) is essential. The BMS is responsible for monitoring the health and status of individual battery cells, managing charging and discharging processes, and implementing safety protocols to prevent overheating, overcharging, and other potential hazards. Our research focuses on developing an advanced BMS tailored specifically for BEUV applications. By integrating state-of-the-art monitoring and control algorithms, we aim to maximize the efficiency, reliability, and safety of the battery system, thereby enhancing the overall performance of BEUVs in indoor logistics operations.

In our research, we utilize a 24V battery system to power the battery electric utility vehicles (BEUVs) employed in indoor logistics operations. This battery pack comprises eight lithium-ion cells, providing the necessary voltage and energy capacity to operate the vehicles efficiently within indoor environments. To ensure optimal performance and longevity of the battery pack, a comprehensive battery management system (BMS) is essential.

A 12V 12 000mAh LiFePO4 (lithium iron phosphate) battery typically comprises four cells, with each cell contributing 3.2 volts to the overall voltage of the battery pack. When these cells are connected in series, their voltages add up to provide the desired 12.8V output. LiFePO4 chemistry offers advantages such as high energy density, long cycle life, and enhanced safety, making it a popular choice for various applications, including electric vehicles, renewable energy storage, and portable electronic devices.

To meet the 24V requirement for battery electric utility vehicles (BEUVs) in indoor operations, eight cells are needed. Each cell typically has a nominal voltage of 3.2 volts, commonly found in LiFePO4 batteries. When eight cells are connected in series, their voltages add up to provide a total voltage of 25.6 volts, effectively meeting the 24V requirement for the BEUV.

For charging the eight LiFePO4 cells connected in series to achieve a total voltage of 25.6 volts (to meet the 24V requirement for the BEUV), the typical charging voltage range would be between 30.4V to 31.2V. This range ensures that each cell receives sufficient voltage for charging while avoiding overcharging. The specifications of the LiFePO4 battery are listed in Table 1.

Table 1
LifePo4 battery specifications

Parameters	Value
Type	LifePo4 battery
Charging voltage	14. 6 V
Current	12 A
Nominal voltage	12.8 V
Capacity/nominal current	12 000 mAh
Dimensions ($L \times W \times H$)	150 mm × 98 mm × 94 mm
Weight	1450 gms

This configuration ensures that the BEUV receives the necessary power supply to operate its systems efficiently within indoor environments. LiFePO4 batteries are often preferred for such applications due to their high energy density, long cycle life, and enhanced safety characteristics.

2.1. State space modeling of the battery pack unit

A comprehensive state-space model for the battery pack used in BEUVs is derived in this section. This model captures the dynamic behavior of individual lithium-ion cells and their interactions within the pack, allowing for accurate prediction and control of key parameters such as state of charge, and voltage.

Equations (1), (2), and (3) elucidate the electrical characteristics and behavior of an individual cell denoted as i. These equations mathematically capture the dynamic interactions and relationships among different variables within the cell. Additionally, Fig. 1 provides a visual representation of these electrical dynamics, facilitating a clearer understanding and visualization of the system

$$\dot{\mathrm{SoC}}_i(t) = -I(t)/Q_i \,. \tag{1}$$

Equation (1) relates the rate of change of the state of charge (SoC) of cell i to the current flowing through it ($I(t)$) and the cell's capacity Q_i

$$\dot{V}_{1i}(t) = -\frac{1}{R_{1i}C_{1i}} \cdot V_{1i}(t) + \frac{1}{C_{1i}} \cdot I(t), \tag{2}$$

where $\dot{V}_{1i}(t)$ is the time derivative of the voltage across the capacitor C_{1i} of the cell I; $V_{1i}(t)$ is the voltage across the capacitor C_{1i}, R_{1i} and C_{1i} represent the polarization resistance and cell i capacitance, respectively, and the current flowing through cell i is $I(t)$

$$V_{Ti}(t) = V_{oci}\,(\mathrm{SoC}_i) - V_{1i}(t) - I(t)R_{0i}\,, \tag{3}$$

where $V_{Ti}(t)$ is the overall voltage of cell I; $V_{oci}\,(\mathrm{SoC}_i)$ is the open circuit voltage of cell i at the assumed SOC; $V_{1i}(t)$ is the voltage through the capacitor C_{1i}; $I(t)$ is the current flowing over cell i, and R_{0i} is the series resistance of cell i.

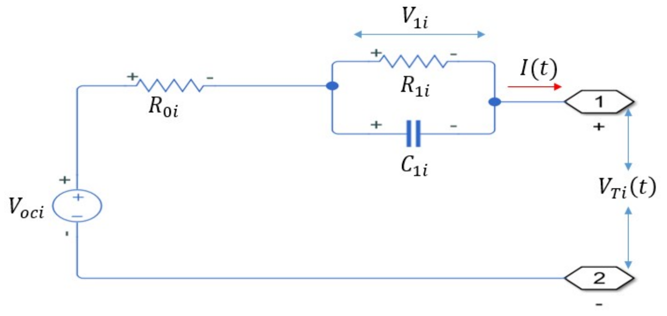

Fig. 1. Circuit diagram of a single-cell

These equations describe the electrical dynamics of a single cell in the battery pack. The dynamics of the entire battery pack can be modeled by applying Kirchoff's voltage law to the series-connected cells.

Eight lithium-ion cells are connected in series to create a 24V battery module with a nominal voltage of 25.6V, which is modeled as a lithium-ion battery pack to power BEUVs in indoor logistics using KVL based on equations (1), (2), and (3)

$$V_{T1}(t) + V_{T2}(t) + \ldots + V_{T8}(t) = V_{\mathrm{pack}}(t), \tag{4}$$

where $V_{\mathrm{pack}}(t)$ is the voltage across the entire battery pack. By applying suitable initial and boundary conditions, the electrical dynamics of the eight-cell battery pack using R and C elements are simulated. By incorporating the equations specific to each cell and employing Kirchhoff's voltage law for the cells connected in series, it is possible to derive the state-space model for the eight-cell battery pack. The state variables are described in equation (5)

$$x_1 = \mathrm{SoC}_1(t), \quad x_2 = V_{11}(t), \quad y = V_{\mathrm{pack}}(t), \quad u = I(t). \tag{5}$$

Then, the state space prototypical for the eight-cell battery pack is given by

$$\dot{x}_{1i} = -\frac{1}{Q_i}u, \tag{6}$$

$$\dot{x}_{2i} = -\frac{1}{R_{1i}C_{1i}} \cdot x_{2i} + \frac{1}{C_{1i}} \cdot u, \tag{7}$$

$$y = \sum_{i=1}^{8} \left(V_{\mathrm{oci}} x_{1i} - x_{2i} - u(R_{0i} + R_{\mathrm{total}})\right), \tag{8}$$

where $\dot{x}_1, \dot{x}_2$ denote the time derivative of the state variables x_1, x_2 respectively; y denotes the output of the battery pack and u is the current smoothing over the cells. Simulating the electrical dynamics of the eight-cell battery pack and devising control algorithms for the system can be accomplished by utilizing the state space model. The matrix custom of the state space prototypical is utilized to express it concisely and systematically.

$$A = \begin{bmatrix} A_{11} & 0 & \ldots & 0 \\ 0 & A_{22} & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & A_{88} \end{bmatrix}, \quad B = \begin{bmatrix} B_1 \\ B_2 \\ \vdots \\ B_8 \end{bmatrix}, \tag{9}$$

$$C = \begin{bmatrix} C_1 & C_2 & \ldots & C_8 \end{bmatrix},$$

$$D = \begin{bmatrix} D_{11} & D_{12} & \ldots & D_{18} \\ D_{21} & D_{22} & \ldots & D_{28} \\ \vdots & \vdots & \ddots & \vdots \\ D_{81} & D_{82} & \ldots & D_{88} \end{bmatrix}, \tag{10}$$

where

$$A_{ii} = \begin{bmatrix} 0 & 0 \\ 0 & \dfrac{-1}{R_{ii}C_{ii}} \end{bmatrix}, \quad B_i = \begin{bmatrix} \dfrac{-1}{Q_i} \\ \dfrac{1}{C_{1i}} \end{bmatrix}, \tag{11}$$

$$C_i = [V_{oci} \quad -1], \quad D_{ii} = [-(R_{0i} + R_{\mathrm{total}})]. \tag{12}$$

Open-loop simulations are performed based on the battery specifications enumerated in Table 2 and it is depicted in Fig. 2. The system is controllable and observable, but it is unstable in open-loop system analysis.

Table 2

Single cell specifications

Parameters	Values
R_{11}	0.02 ohm
C_{11}	500 F
Q_1	12 000 mAh
V_{oc1}	12.8 V
R_{01}	0.2 ohm

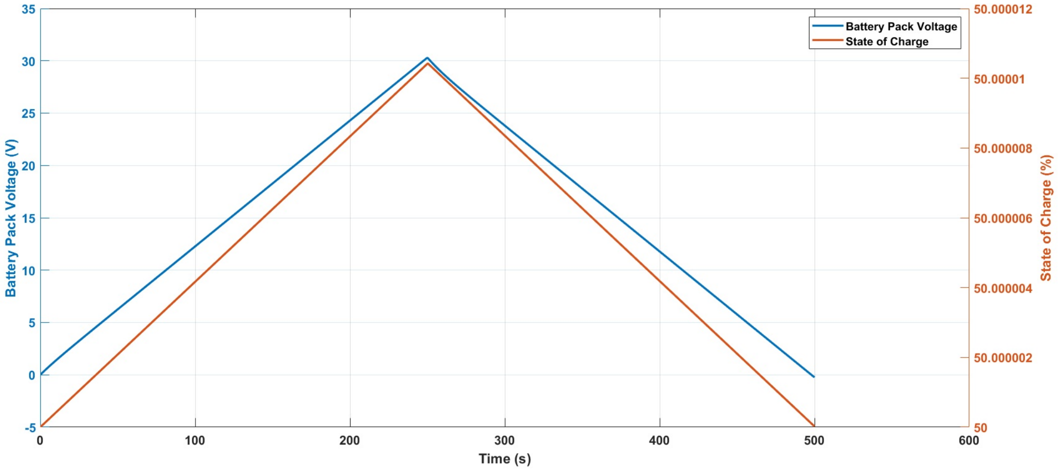

Fig. 2. Open loop battery pack response with SoC

3. PI-BASED BATTERY CONTROLLER DESIGN

The PI controller can be designed to measure the battery voltage and current [22] and use this information to adjust the charging and discharging currents accordingly. The proportional component of the controller allows for fine-tuning the charging or discharging current based on variations in the battery voltage. On the other hand, the integral component helps rectify any persistent discrepancies in the battery voltage, ensuring accurate regulation during steady-state conditions. The PI controller can be incorporated into the state equations by modifying the input vector u. In the state space model with the PI controller, the input vector u is

$$u = \left[I, u_1\right], \tag{13}$$

where I is the input current and u_1 the yield of the PI controller.

The PI controller output u_1 can be calculated as

$$u_1 = k_p e(t) + k_i \int e(t) = k_p e + k_i e_{\text{int}}, \tag{14}$$

where k_p and k_i are the proportional and integral gains of the PI controller; $e = e(t)$ is the error amid the anticipated and real yield voltage, and $e_{\text{int}} = \int e(t)$ is the integral of the error.

The modified state space model with the PI controller incorporated can be expressed as

State variables:

$$x = \left[\text{SoC}_i; V_{1i}; e; e_{\text{int}}\right] = \left[x_{1i}, x_{2i}, x_{3i}, x_{4i}\right]. \tag{15}$$

State equations:

$$\begin{aligned}
\dot{x}_{1i} &= -\frac{1}{Q_i} u_1, \\
\dot{x}_{2i} &= -\frac{1}{R_{1i} C_{1i}} x_{2i} + \frac{1}{C_{1i}} u_1 + k_i x_{3i}, \\
\dot{x}_{3i} &= e, \\
\dot{x}_{4i} &= e_{\text{int}}.
\end{aligned} \tag{16}$$

Output equations:

$$y = \sum_{i=1}^{8} \left(V_{oci} x_{1i} - x_{2i}\right) - u_1 \left(R_{0i} + R_{\text{total}}\right) - k_p e, \tag{17}$$

where x_{1i}, x_{2i}, x_{3i}, and x_{4i} represents the state of charge, the voltage across the capacitor, the error, and the integral of the error term for cell i respectively. Q_i, R_{1i}, C_{1i} and V_{0i} are the parameters specific to each cell; e is the error between the desired and actual output voltage; e_{int} is the integral of the error; I is the input current; u_1 is the control signal for the PI controller, and k_p and k_i are the proportional and integral gains, correspondingly.

An additional state variable e_{int} was added to represent the integral of the error signal, and it was included in the state vector x. The corresponding input k_i was added to the input matrix B.

When using a PI controller for battery pack control, the controller adjusts the output voltage to maintain a constant voltage level. During the charging process, the controller will raise the voltage to uphold the desired set point, while during discharging, the controller will lower the voltage to sustain the set point. This ensures that the battery operates within safe limits and that the performance is optimized. However, if the voltage is maintained at a constant level for too long, it can lead to a decrease in the state of charge (SOC) of the battery. This is because the constant voltage prevents the battery from fully charging or discharging, leading to a lower SOC over time. Hence, regular set point adjustments of the PI controller are crucial to guarantee complete charging and discharging of the battery, besides preventing a gradual decline in the state of charge (SOC) over time.

4. FUZZY PI-BASED BATTERY CONTROLLER DESIGN

The fuzzy PI controller structure, illustrated in Fig. 3, offers a fundamental and effective solution for battery pack management. To enhance the voltage regulation of a battery pack, it is possible to integrate a fuzzy PI controller [23–25] into the state space model. This integration consents for real-time alteration of the proportional and integral gains, considering the current error and its rate of change. By adapting to variations in load and other disturbances, the fuzzy PI controller can provide a more efficient response, ensuring better overall performance. The control accomplishment of the fuzzy PI regulator can be assimilated into the overall structure model by altering the effort matrix, B, and the yield matrix, C, of the state space model.

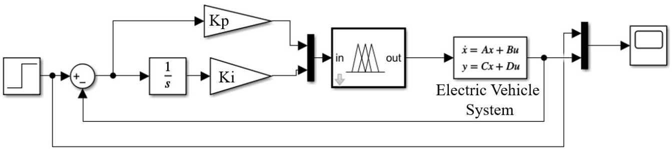

Fig. 3. Fuzzy PI control structure

The input matrix B (11) represents the effect of the control input u on the state variables. To incorporate the regulator accomplishment of the fuzzy PI controller, input Matrix B is modified by multiplying it with the control action equation (14). Then the modified input matrix B' is represented in the equation (18)

$$B' = B\left[k_p e(t) + k_i \int e(t)\,\mathrm{d}t\right]. \tag{18}$$

The modified input matrix B' is dogged by the specific configuration of the fuzzy PI governor equation and how the control action is linked to the state variables in your control strategy. This customization ensures the alignment of the input matrix with the control approach, accounting for the interplay between control actions and the system state variables.

The output matrix C (12) relates the state variables to the yield of the structure. To integrate the control action, the output matrix C is modified to include the effect of the control action u_1 on the output. One possible modification is to add a term that represents the influence of u_1 on the output voltage. The modified output matrix C' can be formulated as

$$C' = \begin{bmatrix} V_{oc1} & -1 & V_{oc2} & -1 & \dots & V_{oc8} & -1 & u_1 \end{bmatrix}. \tag{19}$$

The adjustment of the output matrix depends on how the control action is related to the output variable within your control strategy. The specific modification is tailored to ensure compatibility and appropriate mapping between the control action and the system output variable. With this modification, the behavior of the battery pack with the fuzzy PI controller can be simulated, and the performance in terms of regulating the output voltage can be evaluated.

4.1. Fuzzy logic tuner design

The inference structure centered on Mamdani's fuzzy sense methodology is a regulator that utilizes rules and input values to calculate the control output. Fuzzification involves transforming crisp input data into association values by likening them to fuzzy sets, thereby capturing the degree of membership to each set. This involves assigning degrees of membership to each fuzzy set based on the similarity between the effort rate and the faces of the uncertain set.

In this fuzzy PI controller, both fuzzy logic and the proportional-integral (PI) governor procedure are used to generate the control output. The fuzzy controller employs fuzzy logic and membership functions to handle system nonlinearities. On the flip side, the PI controller employs integral control through the integration of the error signal over the period, which enables the eradication of steady-state errors and boosts the system performance during steady-state conditions.

The regulator yield of the fuzzy PI structure is obtained by combining the outputs of both the fuzzy logic controller and the PI controller. The fuzzy logic controller provides linguistic decision-making and handles complex system behaviors, while the PI controller contributes integral control to improve steady-state performance. By combining these two components, the fuzzy PI controller achieves a balance between precise control action and the ability to handle system uncertainties and nonlinearities.

The Mamdani-based fuzzy PI controller [26] utilizes a rule matrix based on expert knowledge, which incorporates five Gaussian-shaped membership functions: Negative Large (NgL), Negative Small (NgS), Zero (ZE), Positive Small (PoS), and Positive Large (PoL). This rule matrix allows for the effective mapping of input variables and facilitates the fuzzy inference process. The error input range is configured to span from −15 to 50, while the range of response variation is set from −7.5 to 25. The output range, on the other hand, is defined from −25 to 50.

To execute fuzzy inference within the Mamdani inference system, the Max-Min strategy is employed. This strategy entails identifying the minimum membership value for the antecedent of each rule and subsequently aggregating them to compute the complete degree of instigation for every rule. For defuzzification, the largest of maximum (LOM) technique is utilized. This technique selects the output value with the highest membership degree among all the activated rules as the final control output. The rule matrix, which specifies the relationships between the linguistic variables and the control actions, is provided in Table 3.

Table 3
Fuzzy rule matrix for fuzzy PI structure

C\DC	NgL	NgS	ZE	PoS	PoL
NgL	Diminution	Diminution	Diminution	Retain	Retain
NgS	Diminution	Diminution	Retain	Retain	Upsurge
ZE	Diminution	Retain	Retain	Upsurge	Upsurge
PoS	Retain	Retain	Upsurge	Upsurge	Upsurge
PoL	Retain	Upsurge	Upsurge	Upsurge	Upsurge

Within Table 3, the charging level is denoted by the rows, while the discharging level is represented by the columns. The aforementioned linguistic rapports are employed to depict the fuzzy sets corresponding to the charging and discharging levels. The table entries represent the corresponding control output based on the combination of the charging level and discharging level. The control outputs are linguistic terms such as Diminution, Retain, and Upsurge.

The Mamdani-based fuzzy inference system employs If-Then rules to execute learning-based thoughts for control behavior. The fuzzified response from the fuzzy PI controller is obtained using the Mamdani technique. To use it in the battery pack state space model, the fuzzy output is de-fuzzified to obtain a crisp control response.

In general, the fuzzy PI improves the recital of the control scheme by capitalizing on the advantages of both fuzzy sense and PI control. It effectively manages nonlinearities and facilitates linguistic decision-making, while the PI controller offers integral control to rectify steady-state errors.

5. INTERVAL TYPE 2 FUZZY PI (IT2 FUZZY PI) BASED BATTERY CONTROLLER DESIGN

By integrating indeterminacy into the membership utilities, the IT2 fuzzy PI controller [27] extends the capabilities of the conventional fuzzy PI controller. It allows for more robust control by considering the indeterminacy in the system and adjusting the control action accordingly, leading to improved adaptability.

Indeterminacy is inherent in battery systems due to variations in parameters and operating conditions. The IT2 fuzzy PI controller addresses this uncertainty through interval arithmetic or alpha cuts. Interval arithmetic considers the range of possible values for fuzzy membership degrees, while alpha cuts provide a more precise representation of uncertainty.

The TSK (Takagi Sugeno Kang) model [28, 29] is a fuzzy rule-based approach utilized for modeling and control systems with a large number of variables. V2G Battery charging station using various techniques [30, 31], fuzzy rubrics are employed, resembling an “IF this happens, THEN do that” structure. Instead of fuzzy consequents, the TSK model is distinguished by functional-type consequents. Despite utilizing a concise set of rules, the TSK (Takagi Sugeno Kang) model excels in accurately capturing intricate nonlinear systems. In contrast to the Mamdani fuzzy model, the TSK model provides enhanced versatility when representing complex relationships.

TSK fuzzy rules are specified as

$$\begin{gathered}\text{Rule}_i: \text{ if } r_1 \text{ is } s_{i1} \text{ and } r_2 \text{ is } s_{i2} \text{ and } r_k \text{ is } s_{ik}\\ \text{Then } \text{fun}_i(r_1,\, r_2,\, \ldots\, r_k), \text{ where } i = 1,2,\ldots,n\\ \text{or}\\ \text{Rule}_i: \text{ if } r_i \text{ is } s_i \text{ Then } \text{fun}_i(r), \quad i = 1,2,\ldots,n,\end{gathered}$$

where

$$\text{fun}_1\ \text{fun}_2 \ldots \text{fun}_n \text{ are functions,}$$

$r_1, r_2, \ldots, r_n$ are input variables,
$s_{i1}, s_{i2}, \ldots, s_{in}$ are designated fuzzy sets across input regions $r_1, r_2, \ldots, r_n$.

The rules are aggregated to obtain a unified function

$$\text{Rule}(r) = \frac{s_1(r)\text{fun}_1(r) + s_2(r)\,\text{fun}_2(r) + \ldots s_n(r)\,\text{fun}_n(r)}{s_1(r) + s_2(r) + \ldots s_n(r)}. \tag{20}$$

IT2 fuzzy sets have membership values ranging from 0 to 1. To represent IT2-FLS and manage suspicions in the instruction, the third aspect of type-2 fuzzy sets is bounded by the constraints of whichever 0 or 1. IT2-FLS incorporates an additional form-lessening procedure. The functional diagram of the IT2-FLS arrangement is prearranged in Fig. 4.

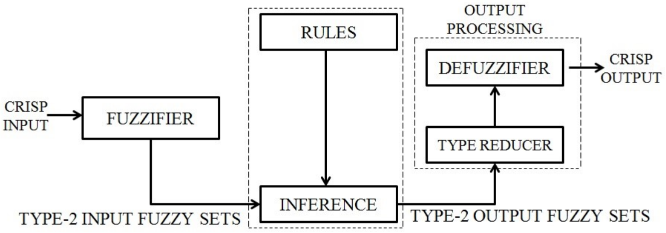

Fig. 4. Functional diagram of an interval type 2 fuzzy logic diagram

The IT2-FLS toolbox [28] incorporates the TSK kind for intuitive operations, catering to all stages of control design. It is designed as an extension of the viable Fuzzy Logic Toolbox accessible in MATLAB, with the addition of new functions specifically tailored for the type reduction (TR) procedure. The structure of the IT2-FLS toolbox is denoted by the file extension ‘*.it2fis’.

5.1. Type 2 fuzzy rubrics and membership utilities

The IT2 fuzzy PI control structure based on the TSK model utilizes a rule matrix derived from knowledge, incorporating ten membership functions. Out of ten, five membership functions for error (charging): Slow Charging, Moderate Charging, Fast Charging, Rapid Charging, Peak Charging, and other five membership functions for change (discharging): Slow Discharging, Moderate Discharging, Fast Discharging, Rapid Discharging, and Peak Discharging. The output membership functions are Upsurge, Diminution, and Retain. Membership functions in type 2 fuzzy logic are outlined by a lower membership function (LMF) and an upper membership function (UMF), which together form the path of uncertainty (POU).

The type 2 trapezoidal membership functions are used to leverage suspicions. The error input spans a range of −15 to 50, the derivative of error varies from −7.5 to 25, and the regulator yield extends from −25 to 50. The K_p, K_i, K_a, and K_b are the effort and yield ascending aspects, respectively. The IT2-FLS structure is elevated with $N = 25$ rules delivered in Table 4. The enhanced Karnik Mendel (EKM) procedure is employed as the technique for type lessening and defuzzification in this context. The parameter values for scaling in IT2 fuzzy PID are set as K_p = 150, K_i = 15, K_a = 0.2, and K_= 10 toward examining the effect of the type lessening tactic on the controller’s accomplishment.

The structure of the interval type 2 fuzzy PI-controlled state space model of the battery package is exposed in Fig. 5. The membership functions of error (charging) and change (discharging) are depicted in Figs. 6 and 7, respectively, using type-2 trapezoidal shapes. Table 4 displays the fuzzy rule matrix for the interval type 2 fuzzy PI controller.

Table 4
Fuzzy rule matrix for IT2 fuzzy PI controller

Error (charging)\ Change (discharging)	Slow discharging	Moderate discharging	Fast discharging	Rapid discharging	Peak discharging
Slow charging	Retain	Diminution	Diminution	Diminution	Diminution
Moderate charging	Upsurge	Retain	Diminution	Diminution	Diminution
Fast charging	Upsurge	Upsurge	Retain	Diminution	Diminution
Rapid charging	Upsurge	Upsurge	Upsurge	Retain	Decrease
Peak charging	Upsurge	Upsurge	Upsurge	Upsurge	Retain

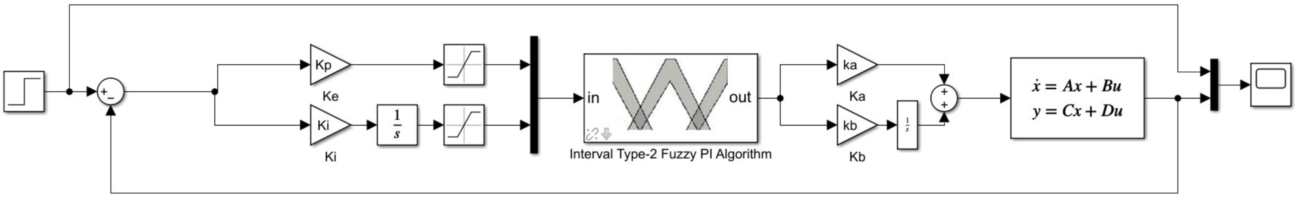

Fig. 5. Interval type 2 fuzzy PI control structure

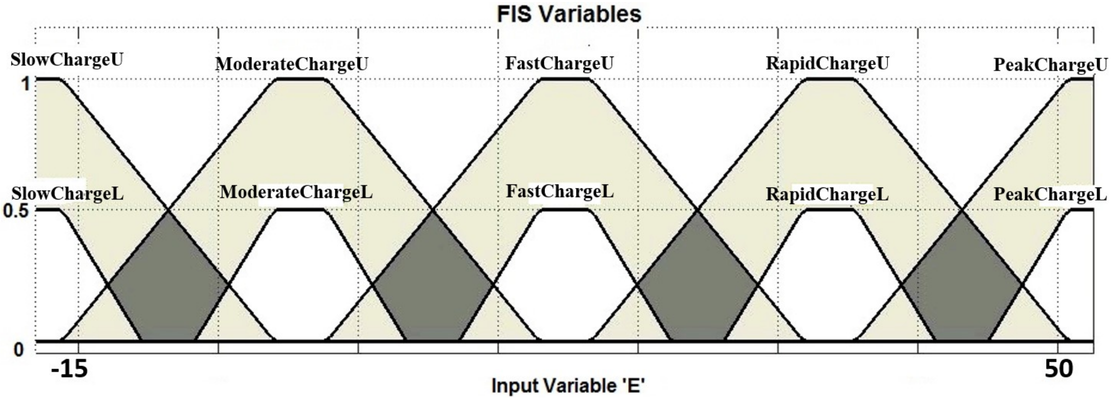

Fig. 6. The membership function representing the error (charging) utilizes a trapezoidal shape

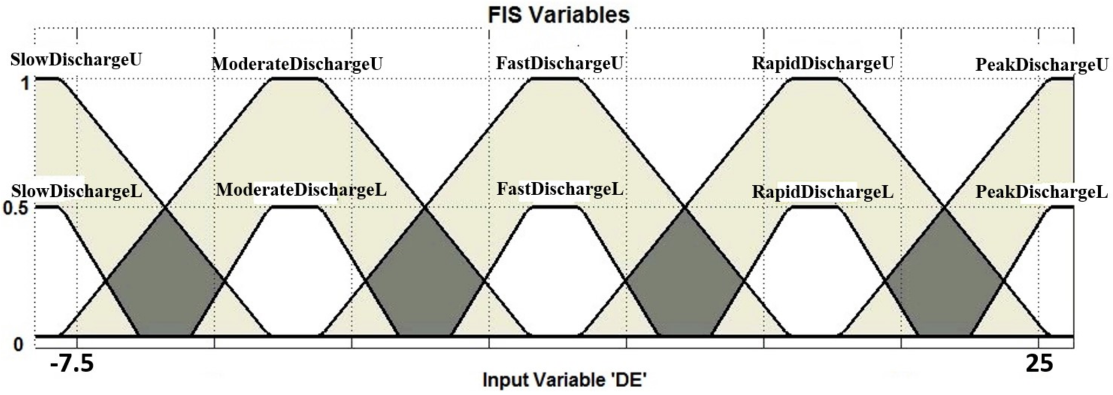

Fig. 7. The membership function representing the change in error (discharging) employs a trapezoidal shape

6. IMPLEMENTATION OF IT2 FUZZY PI-BASED BATTERY CONTROLLER FOR BATTERY MANAGEMENT SYSTEM IN BEUVS OPERATING IN INDOOR LOGISTICS ENVIRONMENT

An evaluation of the effectiveness of the interval type 2 fuzzy PI (IT2FPI) centered battery controller for battery utility electric vehicles (BEUVs) in an indoor logistics environment is conducted through simulation using SIMULINK, as depicted in Fig. 8, within the battery management system (BMS). The imitation model encompasses a battery model that captures the battery dynamic behavior, an indoor logistics environment with servo and regulatory conditions, and the IT2FPI battery regulator that syndicates interval type 2 fuzzy logic and PI mechanism. The simulation process includes battery initialization, indoor logistics environment simulation, computation of the SOC error amid the anticipated and real values, utilization of fuzzy logic control to determine the appropriate control action, adjustment of charging and discharging currents using the PI control algorithm, and subsequent update of the battery.

7. SIMULATION RESULTS AND DISCUSSIONS

This section aims to compare the recital of three different controllers: proportional-integral (PI), fuzzy PI, and interval type 2 fuzzy PI, in the context of battery management intended for BEU vehicles operating in indoor logistics environments. The objective was to evaluate their effectiveness in regulating the battery charging and discharging processes, with a particular emphasis on their servo and regulatory responses. To assess the performance of the controllers, several key metrics were considered, including the battery state of charge (SoC) and the integral of error, which reflects the cumulative error between the desired setpoint and the actual response. These metrics provide insights into the controllers' ability to track set points and maintain stable battery operation accurately. To meet the 24V requirement for the battery electric utility vehicle (BEUV), eight LiFePO4 cells are connected in series, resulting in a total voltage of 25.6 volts. For effective charging, the typical voltage range is between 30.4V to 31.2V, ensuring that each cell receives sufficient voltage without the risk of over-

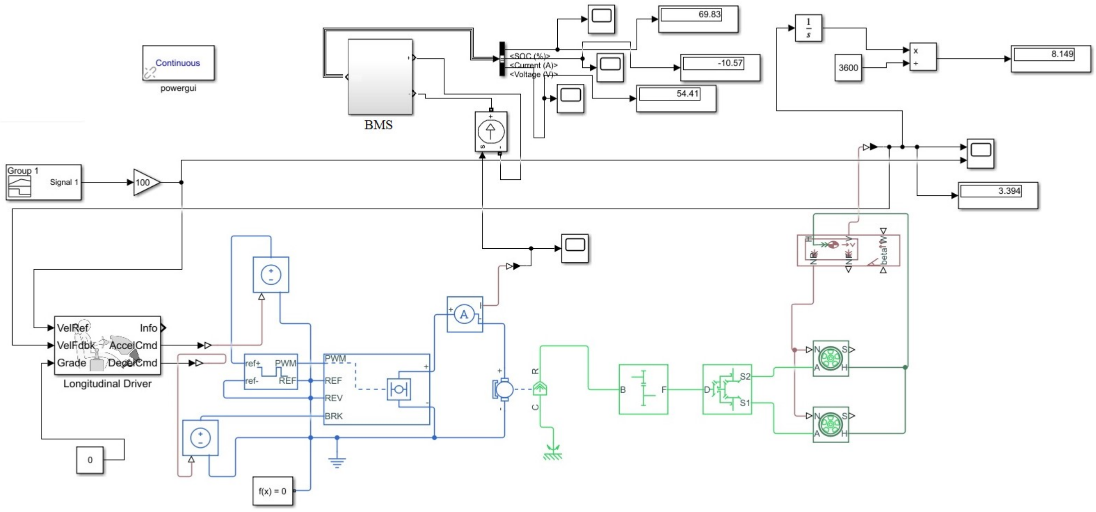

Fig. 8. Simulink model of implementing battery management system (BMS) in battery electric utility vehicle

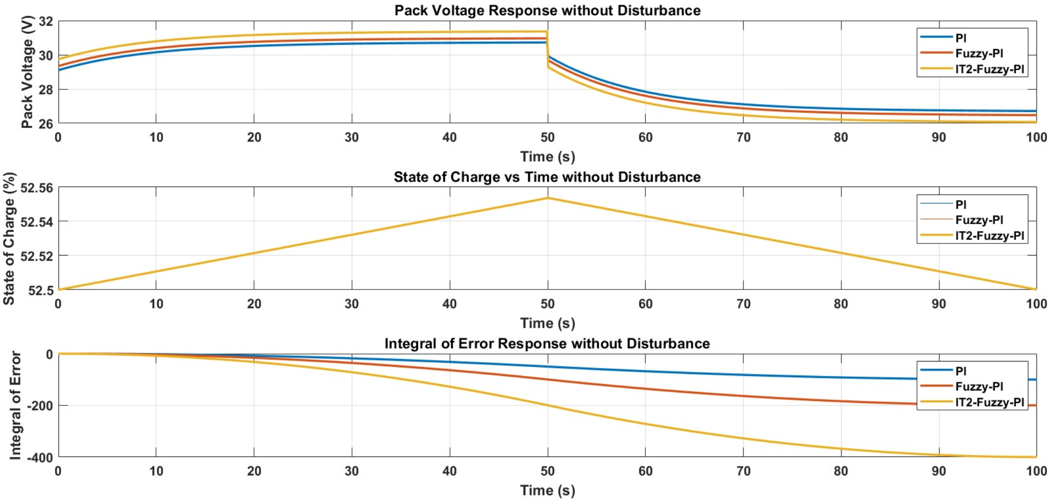

Fig. 9. Comparative servo response of three battery controllers including SoC and integral of error

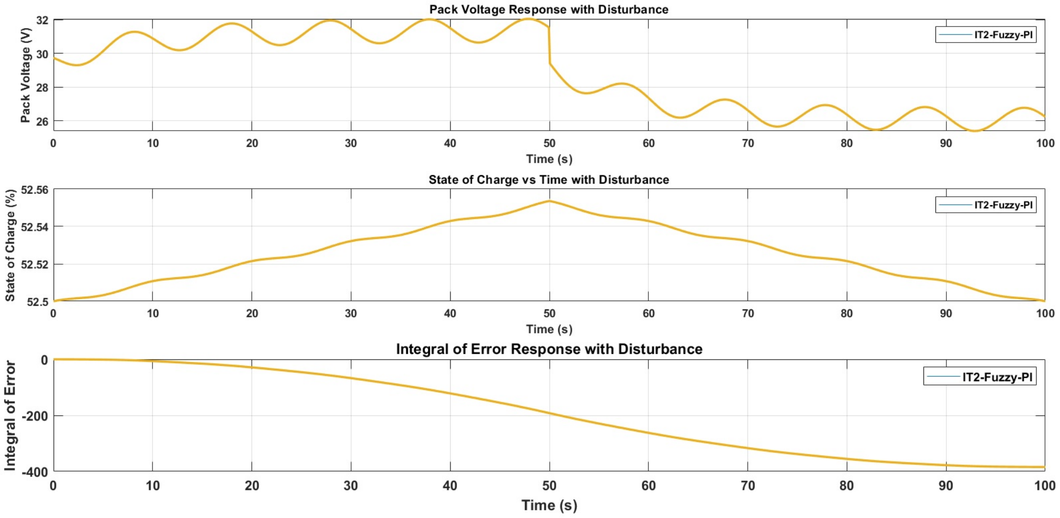

Fig. 10. Regulator response of IT2 fuzzy PI-based battery control including SoC and integral of error

charging. In steady-state conditions, the servo response of the interval type 2 fuzzy PI-enhanced battery controller in a battery management system achieves 31.36V, the fuzzy PI controller reaches 30.95V, and the PI controller attains 30.71V. Based on these values, the interval type 2 fuzzy PI-enhanced battery controller demonstrates superiority in maintaining optimal charging voltage.

The simulation results unequivocally indicated the superior recital of the interval type 2 fuzzy PI over both the PI and fuzzy PI controllers, as evidenced by its remarkable servo and regulatory responses. Figure 9 presented a comprehensive comparison of the responses from all three controllers, allowing for a direct visual assessment of their performance. In terms of servo response, which measures how quickly and accurately the controllers respond to changes in set points, the IT2 Fuzzy PI controller exhibited superior performance. It effectively tracked the desired set points, minimizing overshoot and settling time, and achieving faster and more precise responses compared to the other two controllers.

Furthermore, in terms of regulatory response shown in Fig. 10, which evaluates how well the controllers maintain the system within desired operational limits, the IT2 fuzzy PI controller again outperformed the other regulators. It demonstrated robust control, effectively minimizing deviations from the desired setpoints and maintaining stable battery operation over time.

Figures 9 and 10 also included the responses of the battery state of charge (SoC) and the integral of error for each controller. The IT2 fuzzy PI controller consistently maintained the SoC close to the desired setpoint, with minimal fluctuations and deviations. Additionally, it exhibited the lowest integral of error, indicating better overall control performance and reduced cumulative error.

These simulation results and discussions confirm that the IT2 fuzzy PI controller offers significant advantages in battery management for electric vehicles in indoor logistics environments. Its superior performance in both servo and regulatory responses demonstrates its effectiveness in accurately regulating the battery charging and discharging processes and maintaining stable battery operation.

Figure 11 represents the speed response of the BEU vehicles operating in an indoor logistics environment using an interval type 2 fuzzy PI-enhanced battery controller in a battery management system.

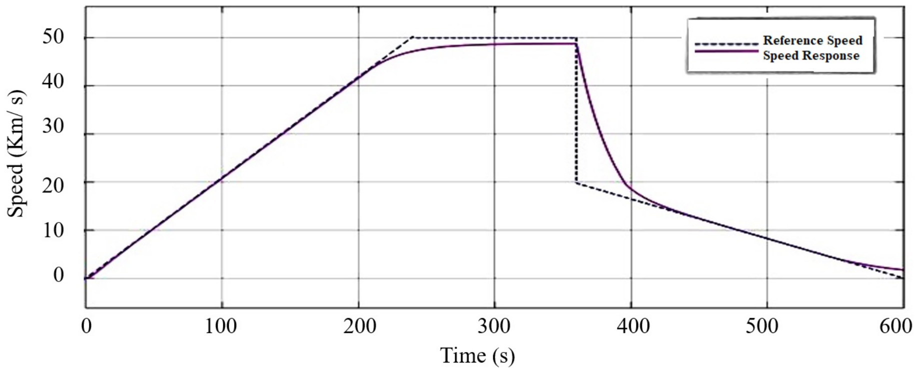

Fig. 11. Speed response of the battery utility electric vehicles operating in indoor logistics environment

8. CONCLUSIONS AND FUTURE SCOPE

In conclusion, the interval type 2 fuzzy PI-enhanced state space model presented in this work delivers an inclusive and effective approach for battery management in BEU vehicles operating in indoor logistics environments. By integrating interval type 2 fuzzy logic with the PI and state space modeling, the proposed model offers enhanced control performance, robustness to uncertainties, and accurate estimation of battery state variables. The model addresses the challenges of nonlinearities, uncertainties, and disturbances commonly encountered in battery systems. The outcomes of the simulation illustrate the model capacity to enhance battery charging and discharging processes, optimize energy efficiency, and ensure the long-term durability of the battery pack. Furthermore, the model contributes to the development of sustainable transportation practices by promoting efficient battery management and reducing the environmental impact of electric vehicles. Imminent exploration can emphasize the practical implementation besides validation of the model in real-world scenarios, as well as exploring advanced optimization techniques and adaptive control strategies. Overall, the interval type 2 fuzzy PI-enhanced state space model holds great promise for advancing battery management systems and optimizing the performance of battery electric utility vehicles in indoor logistics environments. In the future, the cyber-related issues while charging the EVs will give better opportunities for designing charging stations in a good way.

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