

# A Hybrid Decision-Making Model Based on the Plithogenic Set Theory for Distributed Ledger Technology Selection in Electric Vehicle Digital Battery Passport Systems

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Received: 11 February 2026 | Revised: 6 March 2026 and 17 March 2026 | Accepted: 18 March 2026

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## ABSTRACT

The accelerating adoption of Electric Vehicles (EVs) has intensified the need for efficient and sustainable life-cycle management of Lithium-Ion Batteries (LIBs). However, the complexity of battery supply chains, data fragmentation, and varying technological characteristics among distributed ledger platforms create significant uncertainty in selecting an appropriate infrastructure for implementing Digital Battery Passports (DBP). This study proposes a structured decision-support model to evaluate and differentiate among Distributed Ledger Technologies (DLT) under an uncertain decision environment. The proposed framework integrates the plithogenic set theory to capture expert uncertainty and inconsistency, the Best-Worst Method (BWM) to determine the relative importance of evaluation criteria, and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank alternative platforms. The model is applied to assess eight leading DLT platforms for DBP implementation in the automotive context. The results indicate that Hedera is the most suitable platform, achieving the highest TOPSIS closeness coefficient (0.8223), followed by IOTA and EOS. The findings confirm that incorporating contradiction-aware uncertainty modeling into a hybrid MCDM framework enhances the robustness and transparency of DLT platform selection for DBP-oriented applications.

*Keywords-digital battery passport; MCDM method; plithogenic set; electric vehicles*

## I. INTRODUCTION

The automotive industry significantly contributes to global greenhouse gas emissions, driving the transition toward sustainable solutions, particularly Electric Vehicles (EVs) [1]. In this context, Lithium-Ion Batteries (LIBs) are the dominant energy storage technology. However, the rapid growth of the EV fleet has introduced great challenges related to raw material extraction, supply chain disruption risks, and especially end-of-life battery management [2]. It is projected that in the coming decade, hundreds of millions of EV batteries will be retired, creating an urgent need for effective life-cycle management solutions aligned with circular economy principles. The European Union has proposed a regulatory framework for sustainable battery development, in which the Digital Battery Passport (DBP) is considered a key instrument to ensure transparency, traceability, and data management across the value chain [3]. DBP requires the collection and storage of information from multiple stakeholders, including cell manufacturers, battery assemblers, OEMs, recyclers, and reuse operators. The integration of DBP with Distributed Ledger Technology (DLT), such as blockchain, is widely recognized for its strong potential to enhance security, transparency, and data traceability in multi-stakeholder environments

characterized by diverse and sometimes conflicting interests [4]. However, the diversity of available DLT platforms, combined with complex evaluation criteria (e.g., performance, scalability, cost, security, sustainability), makes selecting an appropriate platform for DBP implementation challenging and highly uncertain. Therefore, a decision-support tool capable of handling ambiguity in expert assessments and providing an objective ranking of alternatives is essential, particularly in contexts where evaluation criteria may be conflicting and interdependent [5]. Multi-Criteria Decision Making (MCDM) methods have been proven to be effective tools for addressing complex selection problems involving both qualitative and quantitative criteria [6–8]. MCDM enables the integration of expert opinions, the quantification of criteria importance, and the establishment of a systematic ranking mechanism based on well-defined mathematical principles [9, 10]. Numerous studies have applied MCDM in areas such as energy systems [11], sustainable supply chains [12], technology selection, and blockchain system evaluation [13]. Methods such as Analytic Hierarchy Process (AHP) [14], Analytic Network Process (ANP) [15], ViseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [16], and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [17] have been

widely employed to select renewable energy technologies, optimize logistics strategies, and assess digital technology platforms under uncertain environments. Hybrid MCDM models (combining criteria-weighting techniques with alternative-ranking methods) have been highly regarded for enhancing the consistency and reliability of results. Authors in [18] integrated four MCDM techniques (TOPSIS, PROMETHEE, ELECTRE, and Data Envelopment Analysis (DEA)) to rank alternatives for optimal solar site selection in Punjab, India. In [19], locations for tank crossings over frozen water obstacles were selected using a hybrid fuzzy AHP – Einstein Weighted Arithmetic Average (EWAA) – Combined Compromise Solution (CoCoSo) model.

Although hybrid MCDM models have been widely applied, an important methodological limitation remains in many decision-making settings: expert judgments are frequently uncertain and mutually inconsistent, and the aggregation of such judgments is often handled using deterministic averaging or conventional fuzzy operators that do not explicitly account for the degree of contradiction among linguistic evaluations. This issue is particularly relevant for DBP implementation, where platform selection must reconcile heterogeneous stakeholder priorities (e.g., throughput and latency versus governance and upgradability, sustainability constraints, and operational accessibility) and where platform information may be incomplete or rapidly evolving. Therefore, beyond determining criteria weights and computing rankings, a DBP-focused evaluation model should incorporate an aggregation mechanism capable of capturing both uncertainty and disagreement in expert inputs. To address this gap, the present study introduces plithogenic set-based aggregation into a hybrid Best–Worst Method (BWM)–TOPSIS pipeline. By using contradiction-aware operators to adjust aggregation results according to the contradiction degree between attribute values and the dominant value, the proposed framework produces an aggregated decision matrix that better reflects real-world expert disagreement, thereby improving the robustness and transparency of DLT platform selection for EV DBP systems.

## II. METHOD

The plithogenic set theory is a generalized framework that extends crisp sets, fuzzy sets, intuitionistic fuzzy sets, and neutrosophic sets. It is developed to effectively address problems involving multiple attributes and the existence of contradiction levels among evaluation values. A plithogenic set can be represented as:

$$P = (U, A, V, d, c) \quad (1)$$

where  $U$  is the universe of elements,  $A = \{\alpha_1, \alpha_2, \dots, \alpha_m\}$  is the set of attributes with  $m \geq 1$ ,  $V = \{v_1, v_2, \dots, v_n\}$  is the set of possible attribute values with  $n \geq 1$ ,  $d(x, v)$  denotes the appurtenance (membership) degree of element  $x \in U$  with respect to the attribute value  $v \in V$ , and  $c(v_i, v_D)$  represents the contradiction degree between the attribute value  $v_i$  and the dominant value  $v_D$ , where  $c(v_i, v_D) \in [0, 1]$ . A value of  $c(v_i, v_D) = 0$  indicates no contradiction, whereas  $c(v_i, v_D) = 1$  indicates complete contradiction. This contradiction degree allows flexible adjustment of aggregation operators under

uncertainty. Given two plithogenic sets,  $\tilde{a} = (a_{i1}, a_{i2}, a_{i3})$  and  $\tilde{b} = (b_{i1}, b_{i2}, b_{i3})$ , with  $1 \leq i \leq n$ , the plithogenic intersection is defined as:

$$\tilde{a} \wedge_p \tilde{b} = \left( a_{i1} \wedge_F b_{i1}, \frac{1}{2}(a_{i2} \wedge_F b_{i2}) + \frac{1}{2}(a_{i2} \vee_F b_{i2}), a_{i3} \vee_F b_{i3} \right) \quad (2)$$

where the basic operators  $\wedge_F$  and  $\vee_F$  are adjusted according to the contradiction degree:

$$a \wedge_p b = [1 - c(v_i, v_D)] t_{norm}(a, b) + c(v_i, v_D) t_{conorm}(a, b) \quad (3)$$

$$a \vee_p b = [1 - c(v_i, v_D)] t_{conorm}(a, b) + c(v_i, v_D) t_{norm}(a, b) \quad (4)$$

where  $t_{norm}$  denotes the T-norm operator and  $t_{conorm}$  denotes the T-conorm operator. In many practical applications, these operators are commonly chosen in algebraic form as:

$$t_{norm}(a, b) = ab \quad (5)$$

$$t_{conorm}(a, b) = a + b - ab \quad (6)$$

The plithogenic union is defined similarly:

$$\tilde{a} \vee_p \tilde{b} = \left( a_{i1} \vee_F b_{i1}, \frac{1}{2}(a_{i2} \wedge_F b_{i2}) + \frac{1}{2}(a_{i2} \vee_F b_{i2}), a_{i3} \wedge_F b_{i3} \right) \quad (7)$$

Beyond the intersection and union operations, the plithogenic theory also extends to implication and equivalence operators, which are constructed based on the combination of T-norm, T-conorm, and the contradiction degree. When the contradiction degree approaches zero, plithogenic operators converge to classical operators; conversely, when the contradiction degree is high, the aggregation result is adjusted to reflect the level of disagreement among attribute values. Through this contradiction-based adjustment mechanism, plithogenic sets are capable of simultaneously modeling uncertainty and conflict in input information, thereby enhancing the accuracy of aggregation and evaluation processes. This feature is particularly valuable in MCDM problems, where expert opinions may differ, and criteria may exhibit conflicting characteristics. Integrating plithogenic sets into decision-making models improves flexibility, reliability, and the ability of the evaluation system to realistically reflect complex assessment environments. Authors in [20] proposed that BWM is an MCDM approach to determine criteria weights in an efficient and consistent manner. Compared with traditional pairwise comparison methods such as AHP, BWM requires fewer comparisons while improving the consistency of expert judgments.

Assume there is a set of criteria  $C = \{c_1, c_2, \dots, c_n\}$ . The objective of BWM is to determine the weight vector  $w = (w_1, w_2, \dots, w_n)$ , subject to the following conditions:

$$w_j \geq 0, \sum_{j=1}^n w_j \quad (8)$$

Step 1: Identify the best and worst criteria. The decision-maker selects the best criterion, denoted as  $c_B$ , and the worst criterion, denoted as  $c_W$ .

Step 2: Construct the Best-to-Others (B-O) comparison vector. The decision-maker determines the preference of the best criterion over each of the other criteria using a scale (typically from 1 to 9):

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}) \tag{9}$$

where  $a_{Bj}$  represents the preference of criterion  $c_B$  over criterion  $c_j$ , and  $a_{BB} = 1$ .

Step 3: Construct the Others-to-Worst (O-W) comparison vector. The decision-maker determines the preference of each criterion relative to the worst criterion:

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW}) \tag{10}$$

where  $a_{jW}$  represents the preference of criterion  $c_j$  over the worst criterion  $c_W$ , and  $a_{WW} = 1$ .

Step 4: Optimization model. The optimal weights are determined by minimizing the maximum deviation between the weight ratios and the corresponding comparison values:

$$\frac{w_B}{w_j} \approx a_{Bj} \tag{11}$$

$$\frac{w_j}{w_W} \approx a_{jW} \tag{12}$$

The problem can be formulated as the following min-max model:

$$\min_{w, \xi} \xi \tag{13}$$

subject to:

$$| \frac{w_B}{w_j} - a_{Bj} | \leq \xi, \forall j \tag{14}$$

$$| \frac{w_j}{w_W} - a_{jW} | \leq \xi, \forall j \tag{15}$$

$$\sum_{j=1}^n w_j = 1 \tag{16}$$

where  $w_j \geq 0, \forall j$  and  $\xi$  represents the maximum deviation. The above problem can be transformed into a linear programming model and solved using standard optimization techniques. After obtaining the optimal weights, the consistency of the evaluation is measured by the Consistency Ratio (CR). The optimal value  $\xi^*$  is compared with corresponding reference values to assess the rationality of the pairwise comparisons. A smaller CR indicates a higher level of consistency in the expert judgments. The core principle of TOPSIS assumes that the optimal alternative should have the shortest distance to the Positive Ideal Solution (PIS) and simultaneously the greatest distance from the Negative Ideal Solution (NIS). This method enables the ranking of alternatives according to their proximity to the best solution and their remoteness from the worst solution within the criteria space. Given a decision matrix  $D = [x_{ij}]$ , the method first normalizes the data to eliminate scale differences among criteria. The normalized values are then multiplied by their respective weights to obtain the weighted normalized matrix. Next, the PIS and NIS are determined by selecting the best and worst performance values for each criterion, depending on whether the criterion is of benefit or cost type. The Euclidean distances

of each alternative from the PIS and NIS are calculated, and a closeness coefficient is computed as:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{17}$$

where  $D_i^+$  and  $D_i^-$  denote the distances to the positive and negative ideal solutions, respectively. Alternatives are ranked in descending order of  $CC_i$ , with higher values indicating better performance.

TOPSIS is particularly suitable for complex decision environments due to its computational simplicity, intuitive ranking logic, and compatibility with various weighting methods. The implementation steps of TOPSIS are illustrated in Figure 1. This study proposes an integrated MCDM framework that combines the plithogenic set theory, the BWM, and TOPSIS to enhance the accuracy and reliability of the evaluation process under uncertainty. In this model, plithogenic sets are used to aggregate expert opinions while considering the degree of contradiction among evaluations; BWM determines the optimal weights of the criteria; and TOPSIS ranks the alternatives based on their proximity to the ideal solution. The implementation procedure consists of the following main steps. First, define the set of criteria  $C = \{c_1, c_2, \dots, c_n\}$  and the set of alternatives  $A = \{a_1, a_2, \dots, a_m\}$  for the decision problem. At the same time, select a group of experts  $DM = \{d_1, d_2, \dots, d_k\}$  to conduct the evaluation. Next, determine the weights of the criteria using the BWM approach. Experts identify the most important and least important criteria, then perform pairwise comparisons to construct the B-O and O-W vectors. A min-max optimization model is solved to obtain the optimal weight vector subject to normalization constraints. After obtaining the criteria weights, the alternatives are evaluated using TOPSIS. Each expert constructs a decision matrix based on a triangular neutrosophic scale to capture the degrees of membership, indeterminacy, and non-membership of each alternative with respect to each criterion. These individual decision matrices are then aggregated into a collective matrix using plithogenic operators, where the degree of contradiction among attribute values is incorporated to adjust the aggregation results. Subsequently, the aggregated decision matrix is normalized and multiplied by the criteria weights to obtain the weighted normalized matrix. From this matrix, the positive and negative ideal solutions are identified based on whether each criterion is of benefit or cost type. Finally, the Euclidean distances of each alternative to the positive and negative ideal solutions are computed. The closeness coefficient is then calculated for each alternative and used as the basis for ranking. The alternative with the highest closeness coefficient is considered the optimal solution.

### III. RESULTS AND DISCUSSION

To quantify expert evaluations under uncertainty, this study employs a seven-level triangular neutrosophic scale to represent the degree of occurrence of each criterion.

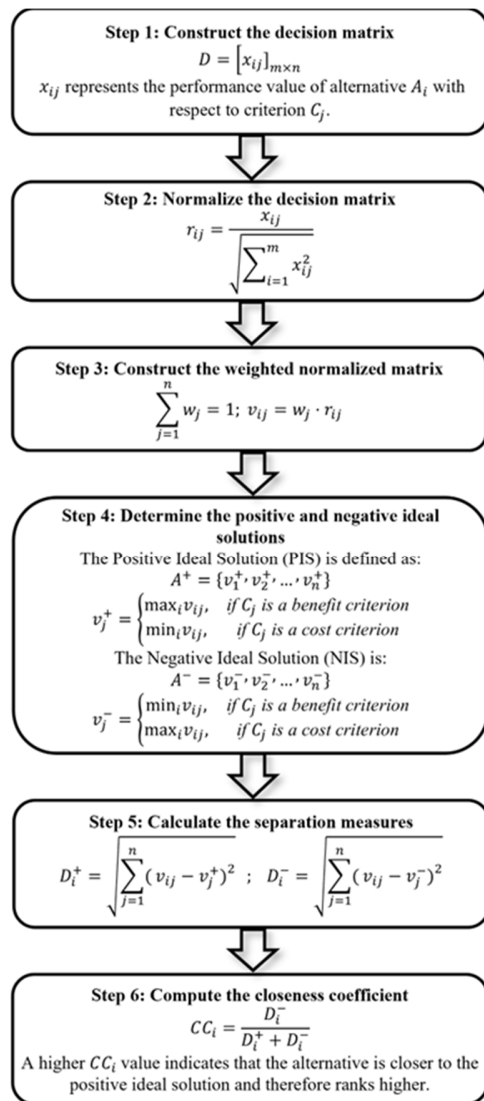


Fig. 1. Implementation steps of TOPSIS.

Each linguistic level is expressed as a triangular neutrosophic number in the form  $((l, m, u), \alpha, \theta, \beta)$ , where  $(l, m, u)$  denotes the triangular membership values, and  $\alpha, \theta, \beta$  represent the degrees of truth (determination), indeterminacy, and falsity (non-membership), respectively. The triangular neutrosophic evaluation scale is presented in Table I. In the proposed framework, the contradiction degree  $c(v, v_d) \in [0,1]$  is used to regulate the aggregation between an evaluated linguistic value  $v$  and the dominant value  $v_d$  of the corresponding attribute, as required by plithogenic operators. In this study, the dominant value  $v_d$  for each criterion is taken as the central (most representative) linguistic level on the adopted seven-level triangular neutrosophic scale (Table I), and the contradiction degree is computed by a normalized ordinal distance on that scale. Let the linguistic terms be indexed in increasing order  $\{N, VW, W, E, S, VS, A\}$  with indices  $1, \dots, 7$ . For a given expert evaluation  $v$  with index  $r(v)$  and dominant value  $v_d$  with index  $r(v_d)$ , the contradiction degree is defined as:  $c(v, v_d) = |r(v) - r(v_d)|/6$ , so that  $c = 0$  indicates no

contradiction (identical linguistic level) and  $c = 1$  indicates maximum contradiction (opposite ends of the scale). These contradiction degrees are then used to form the contradiction-adjusted (plithogenic) aggregation operators in (3)–(4), which interpolate between the selected T-norm and T-conorm: when  $c$  is small, the aggregation behaves closer to the T-norm (more conservative conjunction), whereas larger  $c$  shifts the operator toward the T-conorm (more permissive disjunction), thereby explicitly reflecting the intensity of disagreement among linguistic evaluations. In this work, the algebraic forms of T-norm and T-conorm in (5)–(6) are adopted.

TABLE I. TRIANGULAR NEUTROSOPHIC EVALUATION SCALE

Category	$l$	$m$	$u$	$\alpha$	$\theta$	$\beta$
Nothing (N)	0.10	0.15	0.25	0.1	0.2	0.15
Very weak (VW)	0.15	0.25	0.35	0.6	0.2	0.3
Weak (W)	0.35	0.40	0.50	0.6	0.1	0.2
Equally (E)	0.60	0.65	0.70	0.8	0.1	0.1
Strong (S)	0.65	0.70	0.80	0.9	0.2	0.1
Very strong (VS)	0.85	0.90	0.90	0.7	0.2	0.2
Absolute (A)	0.90	0.95	0.95	0.9	0.1	0.1

The selection of an appropriate DLT platform for implementing the DBP system requires a comprehensive set of evaluation criteria that reflect technical capability, operational reliability, flexibility, sustainability, and practical accessibility. Based on a review of the literature and the system requirements of DBP, the criteria were categorized into five main groups: Performance, Reliability, Flexibility, Sustainability, and Accessibility (Table II).

TABLE II. EVALUATION CRITERIA

Symbol	Criteria	Sub-criteria	Source
C11	Performance	Transaction per s	[21]
C12		Transaction latency	[22]
C13		Block size	[23, 24]
C21	Reliability	51% attacks	[22]
C22		Fault-tolerance	[22]
C31	Flexibility	Governance	[23]
C32		Upgradability	[23]
C33		Scalability	[25]
C41	Sustainability	Energy consumption	[23]
C42		Hardware dependency	[26]
C51	Accessibility	Platform maturity	[27], [21]
C52		Ease of use	[28]
C53		Suitability	[23]

After establishing the criteria system and sub-criteria, the next step is to determine the weight of each criterion using the BWM. Table III presents the B–O and O–W comparison vectors.

In this study, DLT platforms were selected based on their popularity, industrial applicability, and ability to meet DBP system requirements. The alternatives include widely deployed public blockchain platforms as well as enterprise-oriented distributed ledger solutions. Specifically, eight platforms were analyzed: Ethereum (A1), EOS (A2), Cardano (A3), Hyperledger Sawtooth (A4), Corda (A5), Multichain (A6), IOTA (A7), and Hedera (A8). These platforms represent diverse technological architectures and consensus mechanisms, ranging from traditional public blockchains to enterprise-

focused distributed ledger solutions and Directed Acyclic Graph (DAG)-based technologies. The selection of these alternatives ensures diversity in governance models, levels of decentralization, technical performance, and sustainability characteristics, thereby providing a comprehensive basis for comparison during the evaluation and ranking process. In addition, three experts evaluated each DLT platform against the established criteria and sub-criteria. The assessments were expressed using linguistic scales and subsequently encoded into triangular neutrosophic numbers to capture both the degree of reliability and uncertainty in expert judgments (Tables IV-VI).

TABLE III. CRITERIA WEIGHTS

Pairwise comparison vectors	B-O	O-W	Overall
Selected	C21	C51	-
C11	3	7	0.10523
C12	7	2	0.04509
C13	5	4	0.06314
C21	1	9	0.26079
C22	2	6	0.15785
C31	5	4	0.06314
C32	8	1	0.03946
C33	6	2	0.05262
C41	6	3	0.05262
C42	6	3	0.05262
C51	9	1	0.22877
C52	8	2	0.03946
C53	7	2	0.04510

TABLE IV. EVALUATION MATRIX OF EXPERT 1

Criteria	A1	A2	A3	A4	A5	A6	A7	A8
C11	W	A	VW	S	E	S	VS	A
C12	S	A	E	W	VS	E	S	VS
C13	W	VS	S	S	S	S	S	S
C21	W	A	W	E	VS	VS	VS	VS
C22	N	S	VS	E	S	S	VS	VS
C31	E	S	E	E	VS	S	S	S
C32	W	VS	W	E	W	VS	VS	VS
C33	W	S	W	S	E	S	S	VS
C41	W	VS	S	VS	VS	VS	VS	VS
C42	W	VS	VS	W	W	VS	VS	W
C51	W	S	W	S	S	S	S	VS
C52	VW	S	S	S	S	S	S	S
C53	W	S	W	S	W	W	S	S

TABLE V. EVALUATION MATRIX OF EXPERT 2

Criteria	A1	A2	A3	A4	A5	A6	A7	A8
C11	W	VS	VW	E	E	S	VS	A
C12	S	A	E	VW	VS	E	S	VS
C13	W	VS	S	S	S	S	S	S
C21	W	VS	W	VS	VS	VS	VS	VS
C22	VS	S	VS	VS	S	S	VS	VS
C31	W	S	W	S	S	S	S	S
C32	W	E	W	VS	W	VS	VS	VS
C33	W	S	W	S	E	S	S	VS
C41	VW	VS	S	E	VS	VS	VS	VS
C42	W	VS	VS	W	W	VS	VS	W
C51	N	VS	W	E	S	S	S	VS
C52	W	A	S	E	S	S	S	S
C53	W	S	W	E	W	W	S	S

TABLE VI. EVALUATION MATRIX OF EXPERT 3

Criteria	A1	A2	A3	A4	A5	A6	A7	A8
C11	W	A	VW	S	E	S	VS	A
C12	S	A	E	W	VS	E	S	VS
C13	W	VS	S	S	S	S	S	S
C21	W	VS	W	VS	VS	VS	VS	VS
C22	VS	S	VS	VS	S	S	VS	VS
C31	E	S	E	VS	VS	S	S	S
C32	W	S	W	W	W	VS	VS	VS
C33	W	S	W	S	E	S	S	VS
C41	W	VS	S	VS	VS	VS	VS	VS
C42	W	VS	VS	W	W	VS	VS	W
C51	W	S	W	S	S	S	S	VS
C52	E	A	S	S	S	S	S	S
C53	W	S	W	S	W	W	S	S

The study aggregates the individual expert evaluation matrices into a single collective decision matrix using the plithogenic aggregation operator. Subsequently, the aggregated decision matrix is de-neutrosophicated into crisp values using:

$$S(a) = \frac{1}{8}(a_1 + b_1 + c_1)(2 + \alpha - \theta - \beta) \tag{18}$$

All computations were implemented in Python 3.12, using NumPy for vectorized matrix operations and distance calculations.

The computational pipeline is: (i) map linguistic labels to triangular neutrosophic numbers (Table I); (ii) compute contradiction degrees using the normalized ordinal-distance rule above; (iii) perform contradiction-adjusted plithogenic aggregation to obtain a collective matrix; (iv) apply de-neutrosophication (18) to generate crisp values; (v) normalize and weight the matrix using BWM-derived weights (Table III); (vi) compute PIS/NIS, Euclidean distances to ideal solutions (Table VII), closeness coefficients, and final ranking (Figure 2). This implementation ensures the transparency and reproducibility of the proposed method while preserving the interpretability of the ranking mechanism. The closeness coefficient  $CC_i$  is computed for each alternative from its distances to the positive and negative ideal solutions (Table VII). The resulting values are:  $CC_{A1} = 0.2129$ ,  $CC_{A2} = 0.7425$ ,  $CC_{A3} = 0.2980$ ,  $CC_{A4} = 0.7225$ ,  $CC_{A5} = 0.7041$ ,  $CC_{A6} = 0.7224$ ,  $CC_{A7} = 0.7608$ , and  $CC_{A8} = 0.8223$ . Accordingly, the final ranking is  $A8 > A7 > A2 > A4 > A6 > A5 > A3 > A1$ . The results indicate that Hedera (A8) ranks first due to its comprehensive suitability for DBP implementation, particularly in terms of high performance, low latency, scalability, and platform maturity, which align well with the large-scale data processing and transparency requirements of the battery value chain. IOTA (A7) ranks second, benefiting from its Tangle architecture, strong scalability, and low transaction cost and energy consumption; however, its level of industrial readiness remains slightly lower than Hedera's. EOS (A2) ranks third, mainly due to its high throughput and low latency, although limitations in governance structure and adaptability to complex industrial ecosystems prevent it from achieving a higher position. The mid-ranked group (including A4, A6, and A5) demonstrates strengths in specific aspects, such as privacy and consortium-based governance, but lacks overall balance to fully meet the requirements of a large-scale, multi-stakeholder DBP system.

Cardano (A3) and Ethereum (A1) occupy the lowest positions; Ethereum is constrained by performance and energy consumption issues, while Cardano has yet to demonstrate clear practical advantages for industrial DBP deployment. Recent works on platform selection commonly rely on conventional hybrid MCDM structures, in which a weighting method (BWM, AHP, entropy) is combined with a ranking technique (e.g., TOPSIS, TODIM) [4, 29]. While these models have demonstrated practical effectiveness, they typically aggregate expert judgments using deterministic operators (e.g., arithmetic mean) or fuzzy operators that do not explicitly represent the degree of contradiction among linguistic evaluations. This limitation is particularly relevant in DBP-oriented applications, where multiple stakeholders (manufacturers, OEMs, recyclers, regulators, and service providers) may hold diverging priorities, and where platform characteristics are frequently reported with uncertainty or incomplete evidence. In this context, the main methodological novelty of the present study lies in introducing plithogenic aggregation prior to TOPSIS ranking. Specifically, the contradiction-aware mechanism adjusts the aggregation behavior according to the contradiction degree between attribute values and the dominant value, thereby capturing disagreement intensity among experts rather than smoothing it out by simple averaging. Consequently, the aggregated decision matrix becomes more representative of real-world uncertainty and inconsistency in expert opinions, which improves transparency in how the final ranking is derived. Compared with DBP-related BWM–TOPSIS selection studies, the proposed Plithogenic framework adds a dedicated uncertainty-and-contradiction handling layer, while retaining the interpretability and computational simplicity of TOPSIS.

TABLE VII. DISTANCES TO THE POSITIVE AND NEGATIVE IDEAL SOLUTIONS

Alternatives	$D_i^+$	$D_i^-$
A1	0.07672372	0.02075653
A2	0.02562052	0.07388027
A3	0.07564378	0.03211728
A4	0.02444422	0.06363346
A5	0.02865936	0.06818301
A6	0.02669723	0.06948722
A7	0.02305572	0.07332029
A8	0.01717414	0.07946855

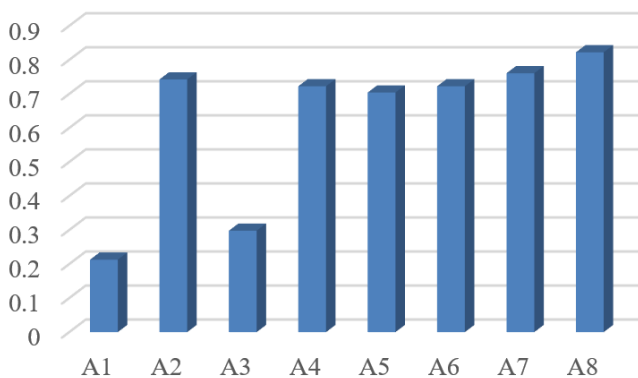


Fig. 2. Ranking of alternatives.

#### IV. CONCLUSIONS

This study proposed a hybrid framework integrating plithogenic sets, Best–Worst Method (BWM), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to support the selection of Distributed Ledger Technology (DLT) platforms for Digital Battery Passport (DBP) implementation in the electric-vehicle sector. The main methodological contribution of the study lies in the introduction of plithogenic aggregation as a contradiction-aware layer for combining expert judgments before ranking. Unlike conventional hybrid Multi-Criteria Decision Making (MCDM) approaches that commonly rely on arithmetic averaging or standard fuzzy aggregation, the proposed framework explicitly incorporates the degree of contradiction among linguistic evaluations, thereby providing a more realistic representation of uncertainty and disagreement in expert assessments. The framework was applied to evaluate eight candidate DLT platforms under a multi-criteria structure covering performance, reliability, flexibility, sustainability, and accessibility. The results show that Hedera (A8) is the most suitable platform for DBP implementation, followed by IOTA (A7) and EOS (A2). This ranking indicates that platforms offering a balanced combination of scalability, low latency, energy efficiency, and implementation maturity are more appropriate for the multi-stakeholder and data-intensive requirements of DBP systems. The proposed framework demonstrates a clear ability to distinguish between platform groups, effectively supporting strategic decision-making, while overcoming a key limitation of previous methods (the lack of contradiction handling in the evaluation process [4]). The study is limited by the number of participating experts and the reliance on expert judgment and secondary information. Future work will expand the expert panel, incorporate empirical and operational data from DBP-oriented deployments, and conduct robustness and sensitivity analyses to test ranking stability, following recent practices in hybrid MCDM and blockchain/DLT evaluation research.

#### DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests.

#### ACKNOWLEDGMENT

This research was supported by Electric Power University.

#### DATA AVAILABILITY

The dataset used in this study is publicly available at [30].

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