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Distributed Ledger Technology selection for Digital Battery Passport: A BWM-TOPSIS approach ⋆

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Abstract: The growing demand for electric vehicles necessitates an efficient and sustainable life-cycle management of lithium-ion batteries. This work examines existent literature on digital battery passports, crucial for high-quality data for decision-making purposes, and distributed ledger technologies as transparent and efficient enablers. An hybrid BWM-TOPSIS approach is employed to rank various platforms for digital passport implementation in an automotive company. The analysis identifies Hedera as the most suitable ledger, followed by IOTA and EOS. Future research directions include empirical validation of the findings and exploring collaborative decision-making models to enhance the robustness of the selection process.

Keywords: Digital Battery Passport, Automotive, Sustainability, MCDM, Circular Economy

1. INTRODUCTION

The automotive sector significantly contributes to worldwide emissions of greenhouse gases, heavily influenced by both the final product and production processes (Kifor and Grigore, 2023). Fossil-fuel phase-out is driving sustainability choices towards the net-zero goal. Globally, the use of electric vehicles (EV) is growing, with Europe having the largest EV market share. In this context, lithium-ion batteries (LIBs) have emerged as the predominant storage technology. The European Union (EU) accounts for a 270 million-vehicle fleet and plans to phase fossil fuel-based vehicles out by 2030. China, South Korea, and Japan are leaders in the field of LIB production, and Europeans struggle to reach them. Therefore, Europe's reliance on external procurement of raw materials remains a significant concern (Anna et al., 2023).

EV batteries generally reach end-of-use when their energy capacity drops to 80% of the initial capacity within 5 to 10 years of service. Consequently, disposed LIBs could potentially ensure about 200 GWh (Shahjalal et al., 2022). Over the course of the next ten years, 100 million EV batteries are expected to be retired (Breiter et al., 2023). This poses severe waste management challenges but also a huge opportunity for Original Equipment Manufacturers (OEM) to build alternative revenue streams and diversify their business models. By embracing circular economy activities, OEMs, together with all stakeholders, can minimise waste and pollution, avoiding resource disposal (Islam and Iyer-Raniga, 2022).

LIB manufacturing is surging demand for mineral raw materials. Input materials procurement (i.e., nickel, cobalt, and lithium) raises serious concerns regarding sustainable extraction activities (Aguilar Esteva et al., 2021). The LIB supply chain is also subject to considerable disruption risk, largely due to the existence of single points of failure, such as dominant suppliers. These markets are likely to cause supply shortages in the near future (Ahuja et al., 2020). EV battery recovery could be a sustainable and viable model to shorten excessive lead times due to unreliable and complex supplies. Simultaneously, manufacturer-extended responsibility can lead to improved collection and recycling rates. To do so, new policies to increase accountability and transparency are required (Baars et al., 2020).

The Digital Product Passport (DPP) is a digital identity for individual products or batches aimed at tracking a product's life cycle. The DPP should include a series

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of information about the product: a unique identifier, product information and instructions, maintenance and disassembly, carbon footprint, recycling story, and certificates (Nowacki et al., 2023). New European regulations explicitly require the application of DPP to new batteries, or Digital Battery Passport (DBP), to enable better management and circularity (Berger et al., 2022). DBP implementation is mainly driven by circular economy initiatives to reduce an organisation's carbon footprint. Lack of data sharing means an impossibility to quantify and assess circular initiatives (Walden et al., 2021). Therefore, data collection and recording must be supported throughout the whole value chain. The information stored in DBPs must be immutable, and each participant has to be verified (Jansen et al., 2023). Antônio Rufino Júnior et al. (2022) demonstrate through a systematic review that the utilisation of Distributed Ledger Technology (DLT), such as blockchain, can foster sustainable behaviours across the entire battery value chain, enhancing life-cycle management from the manufacturer to the end user. The infrastructure of the DBP system remains undefined, indicating a significant opportunity for academic contribution in this domain (Nowacki et al., 2023).

This paper seeks to provide a step further in the investigation of DBP system architecture. Given the proliferation of DLT platforms in recent years, it is crucial to develop a decision-making tool to address the requirements of DBP systems. Multi-criteria decision-making (MCDM) tools have been extensively tested in literature addressing various fields. As MCDM deals with the assessment of relevant decision criteria and the ranking of alternatives, this study provides several different contributions:

- Conducting a thorough literature review to identify DBP requirements and the final characteristics of the system.
- Collecting major DLT platforms, focusing on their specific features and performances.
- Identification of the most suitable DLT platform candidate to function as a DBP for LIBs.

This paper is organised as follows: Section 2 delineates the background of LIBs DBP, DLT features and types, and the main applications of MCDM for DLT selection. Section 3 describes the MCDM tool exploited for selecting the optimal platform. Lastly, Section 4 discusses the results and concludes the paper.

2. BACKGROUND

2.1 Digital Battery Passport

Circular capabilities require a comprehensive perspective on the product life cycle. Consequently, a digital product identity emerges from this need (Nowacki et al., 2023). The Proposal for Ecodesign for Sustainable Products Regulation is a first glimpse at the product passport concept. Here, EU asks for a tracking record on an array of products (Becker, 2022).

In the context of EV batteries, the EU Sustainable Batteries Regulation sets sustainability, safety, and labelling standards, as well as end-of-life management for batteries. It also introduces a digital record system for industrial and EV batteries exceeding 2 kWh, mandating data collection from various stakeholders (i.e., cell producers, module producers, battery producers, automotive OEMs, and companies involved in battery service, refurbishing, and repurposing). Jansen et al. (2023) provide a solid overview of current DBP requirements. The authors identify eight categories characterised by sub-requirements. As suggested by Nowacki et al. (2023), the integration of DBP and DLT (coupled with the Internet of Things) can lead to data security, transparency, and traceability of products among value chains. DLT are keen to operate in complex environments where multiple stakeholders have contrasting interests (Antônio Rufino Júnior et al., 2022). Moreover, blockchain-based smart contracts can guarantee intellectual property protection while managing sustainability issues across the supply chain, which usually requires multiple data sources and specific regulatory and governing policies (Alqarni et al., 2023).

2.2 Distributed Ledger Technologies

The extensive exploration of DLT has led to the development of a variety of platforms across multiple domains. Blockchain and DLT are often used interchangeably in recent literature, although blockchain is actually a subdomain of DLT (Maple and Jackson, 2019). In the field of supply chain management, DLT can facilitate traceability and transparency, while achieving cybersecurity resilience and trust among stakeholders (Moosavi et al., 2021).

Since the number of DLT platforms is increasing, choosing the most appropriate one with regard to the use case and business involved can lead to sustainable and efficient exploitation. The criteria and their sub-criteria used for evaluating DLT platforms are based on a list derived from the literature, as detailed in Table 1. We found that the 13 sub-criteria can be divided into five clusters, translating system requirements from Jansen et al. (2023) in the context of DLT: Performance, Reliability, Flexibility, Sustainability, and Accessibility.

Performance criteria regarding technological capabilities involve the extent to which a network can be extended. A highly efficient system is more likely to be adopted in different scenarios. *Transaction per Second* is related to the throughput performance, how many transactions per unit of time (i.e., seconds) can be performed by the DLT platform. *Transaction Latency*, the time from submission to finalisation, shows the efficiency of adding pieces of information to the ledger. *Block size* indicates the maximum allowed block size.

Reliability cluster reflects the ability of the system to safeguard consistency and integrity. *51% attacks* is a metric to assess the network's vulnerability to attacks by powerful participants. While *Fault-tolerance* is the maximum percentage of faulty (or misleading) nodes allowed in the network in order to securely run the consensus protocol.

Flexibility features encompass several crucial aspects that determine the fundamental structure and operational capabilities of these systems. *Governance* denotes the typology of DLT considered (i.e., private, consortium, and public) with increasing levels of decentralisation. *Upgradability* means the ease with which new features can be added or unforeseen errors rectified in a system. *Scalability*

Table 1. Evaluation criteria for DLT evaluation

	Criteria	Sub-criteria	Type	Source
c_{11}	Performance	Transaction per Second	Quantitative	(Kubler et al., 2023)
c_{12}		Transaction Latency	Quantitative	(Filatovas et al., 2022)
c_{13}		Block size	Quantitative	(Chowdhury et al., 2019; Bonab et al., 2023)
c_{21}	Reliability	51% attacks	Qualitative	(Filatovas et al., 2022)
c_{22}		Fault-tolerance	Quantitative	(Filatovas et al., 2022)
c_{31}	Flexibility	Governance	Qualitative	(Chowdhury et al., 2019)
c_{32}		Upgradability	Qualitative	(Chowdhury et al., 2019)
c_{33}		Scalability	Quantitative	(Erol et al., 2023)
c_{41}	Sustainability	Energy Consumption	Qualitative	(Chowdhury et al., 2019)
c_{42}		Hardware dependency	Qualitative	(Kuo et al., 2019)
c_{51}	Accessibility	Platform Maturity	Qualitative	(Farshidi et al., 2020; Kubler et al., 2023)
c_{52}		Ease of Use	Qualitative	(Büyüközkan and Tüfekçi, 2021)
c_{53}		Suitability	Qualitative	(Chowdhury et al., 2019)

is the capability of a DLT system to manage an increasing workload.

Sustainability criteria refer to the degree to which a platform fits with environmental impact reduction goals by examining the systems cooperating for operations. *Energy Consumption* is an assessment of electrical energy consumption by the consensus algorithm during mining. *Hardware Dependency* indicates whether specific hardware requirements are needed for processing new blocks.

Accessibility cluster considers the operational features of the platform, taking into account usability and public acceptance. *Platform Maturity* measures the extent to which is recognised by the general population and businesses. *Ease of Use* is critical since DLT should offer simplicity in management. *Suitability* denotes whether a system is suitable for various data types, sizes, and/or volumes.

2.3 Decision models for platform selection

Many studies have employed the MCDM methods to address DLT platform selection. Gopalakrishnan et al. (2019) deploy an optimisation model to examine the trade-off between the costs associated with platform implementation and the security level, utilising utility theory and applying it to a food supply chain case study. Büyüközkan and Tüfekçi (2021) employ VIKOR technique for group decision-making in selecting an enterprise blockchain platform, an analysis performed by three decision-makers from banking, retail, and IT partners. Filatovas et al. (2022) present a framework incorporating multiple MCDM methods (namely, AHP, SAW, TOPSIS, and VIKOR) to select the optimal consensus protocol, exemplified through a case study on a bike rental application. Bonab et al. (2023) uses an integrated spherical fuzzy BWM-MARCOS approach to compare blockchain platforms. Erol et al. (2023) aim to guide the healthcare sector in selecting the most appropriate platform for data management, employing the rough Analytic Hierarchy Process (AHP) and the rough Consistency Protocol (CP). Görçün et al. (2023) combine Fermatean fuzzy sets with FUCOM and MAIRCA methods. Kubler et al. (2023) develop a platform for general-purpose DLT selection employing a hybrid AHP-TOPSIS approach. This hybrid method is also utilised by Soundararajan and Shenbagaraman (2023), incorporating a fuzzy approach. This literature review shows how platform selection methodologies do not address the specific use case of battery passports. Therefore, a hybrid method based on the Best-Worst Method (BWM) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), two affirmed methodologies widely used in the literature, is proposed.

3. CASE STUDY AND RESULTS

3.1 Scenario and Steps

The decision-making process is exemplified by a case study of an automotive company developing an in-house DLT system to meet DBP requirements for their LIBs. A sustainability expert with a master's degree in engineering and over five years of corporate sustainability experience in manufacturing collaborates with the technical office to lead the project's initial phase via a top-down approach. After defining criteria, the decision-maker gathers alternatives for evaluation. Table 2 lists the DLT platforms considered, including established and newer blockchains on public platforms, with data compiled from previously cited literature. The selected platforms are Ethereum (A_1), EOS (A_2), Cardano (A_3), Hyperledger Sawtooth (A_4), Corda (A_5), Multichain (A_6), IOTA (A_7), and Hedera (A_8).

3.2 Criteria Weighting - BWM

In the first step, the decision-maker selects the relative importance of each criterion using BWM. BWM fundamentally relies on comparing most and least favourable criteria against all other relevant criteria. Best-to-Others ($BtO = (a_{B1}, \ldots, a_{Bn})$) and Others-to-Worst ($OtW = (a_{1W}, \ldots, a_{nW})^T$) vectors are generated by determining preference order using numbers between 1 and 9. Table 3 shows the criteria comparison vectors. The optimal weights vector $(w_1^*, \ldots, w_n^*)$ is determined by solving a linear programming problem, as presented in Eq. 1-3. The objective function aims at minimising the maximum absolute difference differences $\left|\frac{w_B}{w_j} - a_{Bj}\right|$ and $\left|\frac{w_j}{w_W} - a_{jW}\right|$.

$$\min \max_j \left\{ \left|\frac{w_B}{w_j} - a_{Bj}\right|, \left|\frac{w_j}{w_W} - a_{jW}\right| \right\} \tag{1}$$

$$s.t. \quad \sum_j w_j = 1 \tag{2}$$

$$w_j \geq 0 \quad \forall\, j \tag{3}$$

The BWM is distinguished by its need for fewer data comparisons (compared with AHP or ANP, more tiring

Table 2. Collected data for different DLT platforms

Alternatives	Protocol		c_{11}	c_{12}	c_{13}	c_{21}	c_{22}	c_{31}	c_{32}	c_{33}	c_{41}	c_{42}	c_{51}	c_{52}	c_{53}
Ethereum	PoW	A_1	15-20	10	HL	V	50%	Pub	F	L	H	Yes	H	M	L
EOS	EOSIO	A_2	4000	1,5	HL	V	33%	Pri	F	H	L	No	M	M	H
Cardano	Ouroboros	A_3	2	20	SL	V	50%	Pub	F	L	M	No	L	H	L
Sawtooth	PoET	A_4	1000	124	SL	S	50%	Con	S	M	L	Yes	H	M	H
Corda	Notaries	A_5	170	2	SL	S	33%	Con	F	M	L	Yes	H	H	L
Multichain	PBFT	A_6	1000	20	SL	S	33%	Pri	S	H	L	No	M	M	L
IOTA	Tangle	A_7	1500	10	SL	S	50%	Pri	S	H	L	No	M	H	H
Hedera	Hashgraph	A_8	3000	3	SL	S	33%	Pub	S	H	L	Yes	L	H	L

Note: HL - Hard Limit (imposed by the network), SL - Soft Limit (imposed by the developer); V - Vulnerable, S - Safe; Pub - Public, Pri - Private, Con - Consortium; F - Fork, S - Seamless; L - Low, M - Medium, H - High

Table 3. Pairwise comparison vectors for Best and Worst criteria

	Selected	c_{10}	c_{20}	c_{30}	c_{40}	c_{50}
BtO	c_{20}	2	1	3	5	9
WtO^T	c_{50}	8	9	5	3	1

Table 4. BWM final criteria and sub-criteria weights

	Criteria	Sub-Criteria	Overall
c_{10}	0.253		
c_{11}		0.625	0.158
c_{12}		0.100	0.025
c_{13}		0.275	0.070
c_{20}	0.436		
c_{21}		0.500	0.218
c_{22}		0.500	0.218
c_{30}	0.169		
c_{31}		0.591	0.100
c_{32}		0.091	0.015
c_{33}		0.318	0.054
c_{40}	0.101		
c_{41}		0.500	0.051
c_{42}		0.500	0.051
c_{50}	0.041		
c_{51}		0.090	0.004
c_{52}		0.239	0.010
c_{53}		0.672	0.027

processes). It offers three principal advantages: the ease of use helps the decision-makers to pinpoint its priorities, comparison vectors derived significantly mitigate biases, great efficiency in data usage and time expenditure. Detailed step-by-step guide to BWM appears in Rezaei (2015).

3.3 Alternatives Ranking - TOPSIS

Upon collecting the necessary data for each alternative and establishing the decision matrix $(x_{ij})_{n\times m}$, encompassing m alternatives and n criteria (as listed in Table 2). The TOPSIS algorithm initially vector normalises the decision matrix (Eq. 4), then it multiply each alternative of the new $(f_{ij})_{n\times m}$ matrix by its corresponding BWM-based weight criterion generating the $(t_{ij})_{n\times m}$.

$$f_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}} \quad (4)$$

For each criterion, the positive-ideal solutions are denoted as Z^+ and the negative-ideal solutions as Z^-. In the context of benefit criteria (I^+), the maximum value corresponds to Z^+ and the minimum to Z^-, whereas for cost criteria (I^-), this relationship is reversed, with the maximum value being Z^- and the minimum Z^+ (Eq. 5-6).

$$Z^+ = (t_j^+)_n = \{\max t_{ij} | j \in I^+; \min t_{ij} | j \in I^-\} \quad (5)$$

$$Z^- = (t_j^-)_n = \{\min t_{ij} | j \in I^+; \max t_{ij} | j \in I^-\} \quad (6)$$

Then, TOPSIS calculates the degree of separation of each alternative from both the positive-ideal and negative-ideal solutions, as delineated in Eq 7-8.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (t_{ij} - t_j^+)^2} \qquad \forall i = 1, \ldots, m \quad (7)$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (t_{ij} - t_j^-)^2} \qquad \forall i = 1, \ldots, m \quad (8)$$

The last step of decision making process is the relative closeness calculation rc_i from positive ideal solution (Eq. 9). The top ranking alternative (i.e., maximum relative closeness value) will be the best one.

$$rc_i = \frac{d_i^-}{d_i^+ + d_i^-} \qquad \forall i = 1, \ldots, m \quad (9)$$

The positive-ideal, negative-ideal solution, and relative closeness of each alternative are presented in Table 5, as well as the final ranking. Hedera (A_8), IOTA (A_7), and EOS (A_2) are the top three ranked alternatives. Hedera is a public DLT which is characterised by high throughput, low latency, and enhanced security features from is consensus algorithm (asynchronous Byzantine Fault Tolerance).

Table 5. Final ranked alternatives

	A1	A2	A3	A4	A5	A6	A7	A8
d_i^+	0.16	0.09	0.15	0.09	0.11	0.09	0.07	0.05
d_i^-	0.03	0.13	0.05	0.18	0.11	0.11	0.12	0.13
rc_i	0.18	0.57	0.25	0.55	0.48	0.53	0.61	0.71
Rank	8	3	7	4	6	5	2	1

3.4 Sensitivity Analysis

The study uses a three-phase sensitivity analysis. Initially, the rank-reversal issue is assessed. Removing an alternative during the decision-making process may result in significant variations in the outcome. Thus, seven scenarios are generated, where the worst alternative is removed at each iteration and the deviations in the ranking results are analysed until no alternative remains. As Figure 1 shows, the second, third, and fourth scenarios cause relevant misalignment, but the best alternative persists.

Secondly, subjective criteria are characterised by decision-maker uncertainty and could lead to inconsistencies in

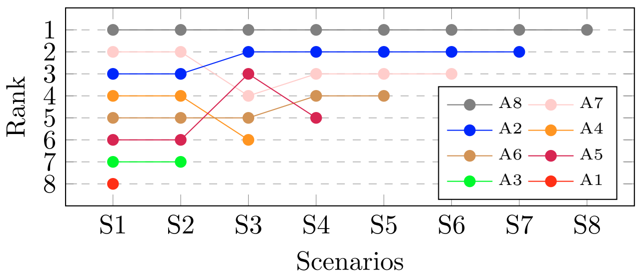

Fig. 1. Results of rank reversal issue

the ranking. The effect of changes in criterion weights on ranking results should be assessed. Here, the weight of the most important criterion is reduced (5%, 10%, 25%, 50%, 75% ,90%) and then the model is proved to be usable and applicable by adding proportionally to the other criteria so that the sum of all the criteria obtained equals 1. Results are depicted in Figure 2. Figure 2 shows how A4, A6, A5,

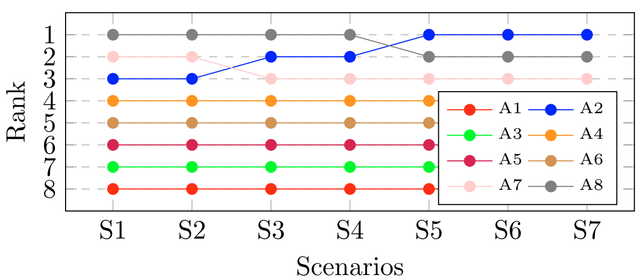

Fig. 2. Results of using different criteria weights

A3, and A1 exhibit stable rankings across all scenarios, suggesting a less sensitive nature compared to different criteria weights. Nonetheless, A2, A7, and A8 fluctuate in the top ranks. Notably, there is a significant shift in the ranking of A2, which takes the lead from S5. A8 and A7 drop to second and third place respectively. The first three alternatives could become debatable under certain conditions.

Thirdly, a comparative analysis is performed with five other MCDM methods: Complex PRoportional Assessment (COPRAS), Simple Additive Weight (SAW), Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE II), and VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR). Figure 3 presents the final rankings for each method. The plot

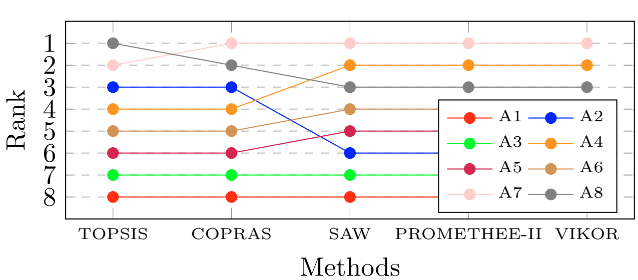

Fig. 3. Results of different MCDM methods

reveals clear preferences and variations in the ranking of alternatives across different MCDM methods, as depicted in Table 6 which reports the Spearman Correlation Coefficients (SCC) for each pair. A8 ranks as the best in TOPSIS and second in COPRAS, but drops to third in other methods. A7 is considered best consistently in every tested method except TOPSIS. This suggests that methods can be considered in two clusters: TOPSIS-COPRAS, which presents a single swap for first and second places (SCC 0.976), and SAW-PROMETHEEII-VIKOR, which have consistent rankings (perfectly correlated).

Table 6. SCC for different ranks from different MCDM methods

	TOPSIS	COPRAS	SAW	PRO-II	VIKOR
TOPSIS	1.000	0.976	0.762	0.762	0.762
COPRAS	0.976	1.000	0.810	0.810	0.810
SAW	0.762	0.810	1.000	1.000	1.000
PRO-II	0.762	0.810	1.000	1.000	1.000
VIKOR	0.762	0.810	1.000	1.000	1.000

4. CONCLUSIONS

This paper presents an analysis to find the best-fit DLT platform for developing a DBP for the automotive supply chain. An MCDM approach was employed to rank a series of DLT platforms for DBP implementation in EV batteries. The adoption of DLT in supply chain management offers an interesting solution for automakers to enhance the life-cycle management and resource efficiency. The implemented BWM-TOPSIS hybrid approach analytically assessed the decision-making process, considering a range of criteria including performance, reliability, flexibility, sustainability, and accessibility. The contributions of this work are twofold: firstly, it advances the literature on DBP infrastructure development within LIBs management; secondly, providing a first ranking for an efficiently tailored platform for battery passports. Following the decision-maker's criteria weights, the TOPSIS ranking has identified Hedera as the most suitable platform, followed by IOTA and EOS. Despite its contributions, this study faces limitations due to DBP system requirements and criteria selection from existing literature only, it does not address ambiguity in the data and the expert's opinions, and it finds inconsistencies in mid-ranked alternatives during sensitivity analysis. Future research is encouraged to validate these findings through empirical studies. Additionally, collaborative decision-making approaches and methods for coping with data and linguistic uncertainty should be explored.

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