A Blockchain-based Life Cycle Assessment (LCA) Framework for Building Materials Selection

Nesrine Gaaliche and Mohammad Abou Elseoud

1 Introduction

Life Cycle Assessment (LCA) originated in the United States in the late 1960s as part of the National Environmental Policy Act. In real estate it is a global analysis of the environmental impact of products used in the building throughout their life cycle. It analyzes the phases of raw material supply, production, transport, use and disposal. LCA has several advantages, essentially for any building project. According to the United Nations program, buildings and construction contribute nearly 40% of carbon emissions.

Given the complexity of the construction process, from sourcing raw materials to the final finishing touches, LCA was once a time-consuming

N. Gaaliche (✉)
School of Engineering, Bahrain Polytechnic, Isa Town, Bahrain
e-mail: nessrine.gaaliche1@gmail.com

Unit of Mechanical Production Engineering and Materials—National School of Engineers of Sfax, University of Sfax, Sfax, Tunisia

M. A. Elseoud
University of Bahrain, Zallaq, Bahrain
e-mail: msayed@uob.edu.bh

A. Jreisat and M. Mili (eds.), *Blockchain in Real Estate*,
https://doi.org/10.1007/978-981-99-8533-3_5

and required process. However, thanks to the proliferation of assessment technologies such as software and scheduling tools, LCA no longer takes months.

LCA has several advantages essentially for any building project. According to the United Nations program, buildings and construction contribute nearly 40% of carbon emissions. As architects become increasingly invested in sustainable buildings, the most important outcome of an LCA is how well it can help select products that have confirmed a structure's environmental footprint. Using building product data, LCA provides valuable insight into a building's environmental weak points, which helps to solve potential problems such as carbon emissions, waste, or energy flows. Additionally, especially if a construction project is taking place in an environmentally vulnerable area, LCA can also help developers deal with issues such as habitat destruction or resource depletion. ACV can significantly reduce costs in the short and long term, in particular by allowing property developers to have an overview of all aspects of their projects. An important detail of a building as such is its energy consumption. If not systematically optimized, energy consumption can eat up a lot of resources during the construction process and beyond. By using a combination of product data, this assessment can also help developers, including comparing different products and materials with the same results in order to choose the most commendable option.

This method remains a comprehensive process that requires many different skills and an interdisciplinary approach. However, by harnessing the right technologies, it is possible to streamline communication between colleagues, in particular to improve the results and reduce the time required for this analysis.

This research develops a framework to guide the implementation of blockchain-based LCA. The blockchain is a distributed ledger maintained by a set of nodes. Users can interact with nodes in order to send transactions to the blockchain. A blockchain ledger takes the form of a collection of blocks containing transactions submitted by users, along with metadata about itself or the ledger. Each block is linked to the previous one by its hash value. In this sense, since modifying a block would alter this value as well as all the other hash values of the following blocks, it is theoretically impossible to alter the content of a block. New blocks are formed by a subset of nodes responsible for aggregating transactions into a block and validating it by implementing different cryptographic processes depending on the blockchain used, to ensure its validity when added to the blockchain.

The blockchain appeared during the creation of Bitcoin (Nakamoto, 2008), in order to allow users to exchange the cryptocurrency of the same name. Subsequently, many blockchains were able to emerge. Ethereum, the best known, is acclaimed (Wood et al., 2014) for its ability to deploy and interact with smart contracts, housed in the blockchain (Toufaily et al., 2021). Smart contracts for the blockchain allow not only to execute functions directly within it, but also to store states. They therefore benefit directly from the particular properties of the blockchain, which are integrity, decentralization, non-repudiation of transactions and transparency. This gives the blockchain an artificial trusted third-party status, where it is possible to trust the code and the power of the network unlike conventional trusted third parties who ensure the validity of transactions through their status, such as banks or governments.

These characteristics have attracted the attention of industrialists and academics, who see the blockchain as a means of revolutionizing the way of exchanging value between individuals as well as guaranteeing the veracity and integrity of the data stored in it. Indeed, the blockchain would be "a native digital medium for value, by which we could manage, store and exchange multiple goods [...] peer-to-peer and in a secure way" (Tapscott, 2016). As a result, there are many relevant use cases of blockchain in the literature in different sectors of activity, such as supply chain management (Cachin & Vukolic, 2017), finance (Ren et al., 2023), network control (Patil et al., 2023), decentralized digital identity (Shari & Malip, 2023) or health (Erol et al., 2023).

However, despite its potential, blockchain faces many barriers to adoption. According to a study carried out by PwC in 2018, companies face problems such as uncertain regulation on the subject, a lack of trust in other actors when participating in a project using blockchain, as well as the difficult management of the intellectual property of the data and goods recorded there. These problems are gradually being resolved thanks to the collaboration of the actors of the blockchain ecosystem and the competent legal and governmental authorities. Nevertheless, companies are still facing a technological barrier, for several reasons. They may encounter difficulties in recruiting collaborators specialized in blockchain, as the technology is still young. They may also find it difficult to integrate blockchain into their existing information systems and business processes, because there are not yet identified and proven best practices in business by software architects. In order to overcome this problem, studies have been carried out to assist the integration of the blockchain into software architectures. In this sense, a study proposes a collection of architectural models containing blockchain, as well as the different cases where these models are applicable (Xu et al., 2018).

But the main obstacle lies in the design of the blockchain solution as well as its implementation. At this point, developers may have several questions.

Which blockchain to use in a given context, knowing that there are many competing technologies with, for each, their own properties and characteristics? Maybe it is ultimately more reasonable to use a "proven" solution instead of a blockchain (database, microservices…)? Finally, how to configure the various parameters of the blockchain, which have an important impact on the satisfaction of the requirements (performance, resilience, security…) such as the consensus algorithm or the inter-block interval, often requiring the intervention of experts in the field to achieve a result that meets the requirements?

Many studies have been conducted to answer the first two questions and thus facilitate the choice of the blockchain solution, in particular through decision models through various questions. Another study presents a vademecum containing all the information necessary to understand blockchain from a technical point of view, as well as a decision model for blockchain applied to several example scenarios. The proposed recommender systems are often made up of a series of abstract questions, making it possible to answer questions such as "do I need a blockchain?" or "what type of blockchain to adopt?", but not to provide specific recommendations, or go into more detail by considering the choices between many blockchain parameters and properties. Users wishing to obtain a more precise recommendation should therefore turn to the latter. This type of study is relevant for people with good knowledge in the field of blockchain, but it will be difficult for uninitiated people to answer the questions of the decision model precisely. Moreover, many of these studies only focus on blockchain requirements, while users have requirements related to software quality (performance, security, reliability…). The links that connect blockchain attributes to software qualities as defined in engineering are often not very explicit and it is difficult to quantify the impact of a blockchain parameter on the software qualities of the final solution. Finally, when the number of technical attributes considered becomes large, it is impossible to make a choice taking them all into account, the computational complexity when using the model manually being too high.

To overcome these limitations, we introduce in this chapter an automated decision process that determines the most interesting alternative for a given case study. In it, the preferences or requirements of users regarding the software quality of the solution to be created will be used as input. These will be compared to the different characteristics of the alternatives considered by a multi-criteria decision-making aid method. These characteristics will be contained in the form of a knowledge base and defined using the existing literature (experiments, literature reviews …), the white papers of the blockchains considered as well as our own results of experiments. We also present an application of our decision process to a relevant use case in the field of supply chain management. This part will be an opportunity for us to validate the results of the decision process, through manual experiments confirming the decisions made by the process.

Section 2 presents the decision-making process. Section 3 applies our approach to building material selection problem. We present the work related to our study in Sect. 4, then we continue with a discussion of our results and our approach in Sect. 5. Section 6 concludes.

2 Construction of the Decision-making Process

In this section, we will present the inputs as well as the operation of the decision process to help the user choose the most suitable blockchain model.

2.1 Input

The accuracy of a multi-criteria decision support algorithm depends mainly on the input data. In this subsection, we present our approach to build a reliable and adapted knowledge base, as well as our method to elicit the weights that will be applied to each of the criteria for the execution of the decision process.

2.1.1 Alternatives and Attributes

To support our decision support process, we built a first version of the knowledge base containing a set of am blockchain alternatives and their respective attributes (Table 1). We have chosen this specific panel of blockchains because they are considered to be the most widely used blockchains by enterprise blockchain service providers.

Since the objective of our work is to help make decisions about which blockchain to use when selecting building materials without having any particular expertise on how to configure it, we have chosen a set of criteria that can be placed under the different macro-attributes proposed by the ISO 25010 standard, a standard defining the different macro-attributes to be considered in order to guarantee the quality of a system or software during its implementation. We have chosen the attributes that seem relevant to us in the considerations to have when choosing a blockchain, but also for the possibility of transcribing them in digital format. Therefore, our criteria are not specific to blockchain technology, but related to system quality. It is our decision process that will be responsible for translating these system quality attributes into blockchain attributes (such as inter-block interval, consensus algorithm, or block

Table 1 Alternatives and retained attributes

Attributes/ Alternatives	*Bitcoin*	*Ethereum*	*Ethereum*	*Hyperledger Fabric*	*Corda*
Algorithme de consensus	PoW[a]	PoW	PoW[b]	Raft	PBFT[c]
Efficient en	No	No	No	No	No
énergie:	No	No	No	No	No
Gas Emission	No	No	No	No	No
Liquid discharge					
Solid waste					
Tolerant of Byzantine faults	50.00%	50.00%	33.30%	0.00%	33.30%
Smart contracts	No	No	Yes	Yes	Yes
Cryptocurrencies	Yes	Yes	Yes	No	No
Storage element	Basic	Advanced	Advanced	Advanced	Advanced
Computational	No	Advanced	Advanced	Advanced	Advanced
element	Basic	Advanced	Advanced	Advanced	Advanced
Asset manager element	No	Advanced	Advanced	Advanced	Advanced
Software connector					
Learning curve	Low	Medium	Medium	Very High	Very High

[a] Proof-of-work (PoW)
[b] Proof-of-Authority (PoA)
[c] Practical Byzantine Fault Tolerance

size). Figure 1 presents a diagram showing the relationships between software quality attributes (chosen criteria for our decision process) and blockchain-specific attributes. The values entered for each attribute of alternatives in our knowledge base come from different sources: studies (such as that of Belotti et al. [2019], white papers [e.g. Nakamoto, 2008; Wood et al., 2014]), technical documentation and scientific literature (Rossi et al., 2019). Some of these values are approximate (marked by the symbol $\mp$), as they are subject to variation in the topology and configuration of the blockchain network as well as the technical characteristics of the nodes that make it up (CPU, RAM, etc.).

Their value is therefore constructed from known attributes, such as the consensus algorithm supported (an algorithm tolerant of Byzantine faults like the algorithm Bitcoin PoW will have lower transaction throughput than a fault-tolerant algorithm, like Raft used by Hyperledger Fabric). Nevertheless, these values can be fixed when the blockchain parameters are known. Our decision-making process having to take into account assets already present in the company (such as the technical infrastructure or the models of business processes), we rely on the performance of performance tests in order to be able to give a fixed value to the variable attributes in depending on the given context. This knowledge base will also vary over time. The values of the attributes of the different

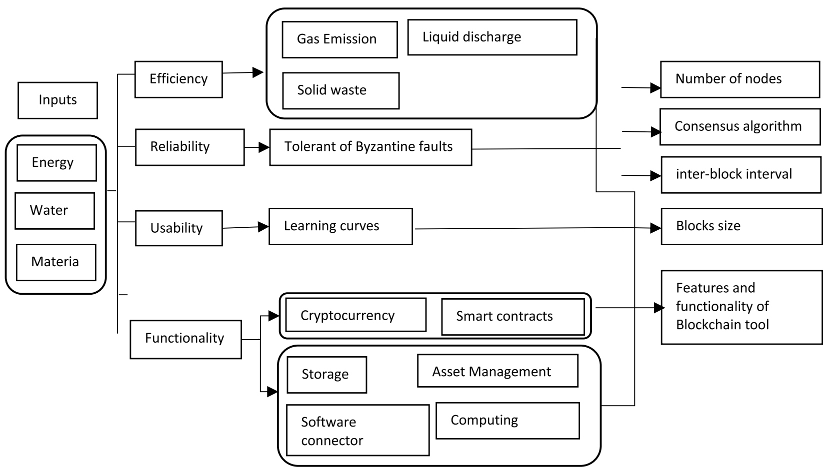

Fig. 1 Blockchain-based life cycle assessment system

Table 2 Likert scale combining labels and preference values

Linguistic variable preference value	pn
Extremely desirable	4
Quite desirable	3
Desirable	2
Low desirable	1
Indifferent	0

blockchains chosen will be modified if necessary (update of one of the elements of a blockchain). These variations can have an impact on the choice of the best alternative by our decision-making process, it will be necessary to evaluate the age of the knowledge base in order to determine if the recommendation is relevant at a given moment.

2.1.2 User-defined Weights and Conditions

In order to obtain a blockchain recommendation that meets the user's expectations, the automated decision-making process must take into account the user's requirements and preferences. When the user is prompted to enter their choices, they can mark a criterion as Required or Undesirable. During decision-making, an alternative whose attribute does not meet one of these two requirements would be automatically disqualified from the possible alternatives, regardless of its score obtained by the execution of the multi-criteria decision support algorithm.

The user can also indicate their preferences for attributes, through literal variables forming a Likert scale (Allen & Seaman, 2007) (Table 2). The choice of one of these variables makes it possible to obtain a preference value $p_n \in n$ for each of the criteria cn. In order to obtain the weights of each of the criteria ω_n in such a way that the sum of these weights is equal to 1, we must divide each of the preferences p_n for a criterion by the sum of the preferences.

2.2 Internal Logic

First, our decision process performs an initial filtering of alternatives based on user requirements. If a criterion marked as Required or Undesirable is not met by one of the alternatives, it is automatically eliminated, regardless of the score it could have obtained using the decision algorithm that follows. For a Required criterion that is not a Boolean, the user specifies an extremum value. For example, if a certain number of transactions per second is required, alternatives that do not meet the threshold value will be disqualified.

The automated decision process on the remaining alternatives is based on the use of a multi-criteria decision support algorithm called TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) (Lai et al., 1994). The TOPSIS algorithm is based on the fact that the most relevant alternative am for a given set of choices must be the closest possible to the positive ideal solution A+ and the farthest from the negative ideal solution A−.

The choice of this algorithm was guided by a study presenting a state of the art of studies on the choice of a multi-criteria decision support method (Kornyshova & Salinesi, 2007). This proposes a decision framework including different properties to pay attention to when choosing a multi-criteria decision aid method. We judged that the TOPSIS method was suitable for our decision-making process, in particular because it supports the multi-criteria analysis of many and varied attributes (which is the case when comparing two blockchains) while being simple to implement and precise in the decision. It also allows to take into account weights defined by a user, which is required given the modus operandi of our decision process. Several steps necessary for the execution of the TOPSIS method are detailed in the following.

Construction of the matrix—Let m alternatives a and n attributes c for each of them. Grouping these alternatives gives a matrix $X = \{x_{ij}\}$ for $\{i \in N|1 \leq i \leq m\}$ and $\{j \in N|1 \leq j \leq n\}$.

Matrix standardization and application of weights—standardization of criteria with different units and scales is necessary in order to be able to compare them with each other. It is also at this stage that we apply the weights coming from the user's preferences.

$$v_{ij} = r_{ij} \times \omega_j = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \times \omega_j \quad (1)$$

Calculation of the positive and negative ideal solutions and then measurement of the difference with each of the alternatives—By selecting the best and the worst performances of each of the criteria of the weighted normalized decision matrix, we can determine the positive A^+ and negative A^- ideal solutions in order to measure the gap of each of the alternatives with these two solutions that we will denote S^+ and S^-.

$$A^+ = \left(v_1^+, \ldots, v_j^+\right) \text{ and } A^- = (v_1^-, \ldots, v_j^-) \tag{2}$$

$$S_i^+ = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^+)^2} \text{ and } S_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^-)^2} \tag{3}$$

Calculation of the relative distance with the ideal solution—This last step makes it possible to give a score to each alternative, which represents its distance with the ideal solution. The ordering of these scores makes it possible to define the best possible alternative compared to the given alternatives as well as the preferences of the user.

$$C_i i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{4}$$

3 Application to a Supply Chain Management Case Study

In order to test the proposed automated decision-making process, we selected a study that proposes to introduce a blockchain system to a supply chain in order to allow data sharing between the different actors (Longo et al., 2019).

In this part, we will detail the scenario proposed by the cited study, then the different attributes required for the blockchain to be implemented which arise from this subject in order to perform our automated decision-making process. Finally, our results are validated using a performance testing tool implemented for this purpose.

3.1 Case: Building Material Selection

Our empirical study consists of a building material selection problem: Brick, Aluminum and Iron. We consider that there is real-time, transparent and reliable data sharing between suppliers of these building materials. Each material has specific features of energy efficiency, storage and supply contracting.

We propose the establishment of a blockchain making it possible to record data linked to the selection of building materials in the form of hash value. The saving of this value makes it possible to certify the consistency and reliability of the data transmitted between third parties, they can now trust each other.

3.2 Building Material Selection Requirements

To be able to recommend using our decision process, it is necessary to identify the quality attributes as well as the requirements and preferences regarding these attributes (Sect. 2). This subsection therefore discusses each of the system quality attributes proposed previously and explains the choice of the value of each of them.

Efficiency—The blockchain-based Life Cycle Assessment System needs to support energy efficiency including: Gas Emission, Liquid discharge and solid waste. Since these attributes are beneficial to the environment, we still chose to set them quite desirable.

Reliability—Since the materials have different features mainly with regard to their supply, it is essential to have a percentage of Byzantine fault tolerance, which indicates that the system is able to function correctly for a certain number of nodes that may have adverse behavior. We have chosen a percentage of at least 33.3%, which makes it possible to guarantee the good continuity of the blockchain network for a number of faulty nodes $f + 1 < \frac{n}{3}$, n is the number of total nodes constituting the network (Saberi et al., 2018).

Functionality—To meet the objectives of the defined subject, the blockchain must be able to take the form of a storage element to contain the data as well as to support the administration of these, de facto through contracts smart. These two attributes are therefore defined as Advanced and Required respectively. The other features are not necessary, they are marked Indifferent.

Usability—Finally, the last attribute chosen is the learning curve: in a context where the blockchain must save costs associated with the supply chain as well as support a low complexity application, using a technology in which it is easy to learn the mechanics can be an asset. We have chosen to mark it as Desirable.

3.3 Results

Performing the automated process eliminates the Ethereum, PoW alternative, as it does not allow smart contract support, as well as the Hyperledger Fabric alternative, as it does not tolerate Byzantine faults. We thus obtain two matrices, one containing the weights and the other the possible alternatives (resp. Ethereum-PoW, Ethereum-PoA, and Corda). Knowing that a weight of 0 for a given attribute makes it insignificant in the calculation of the score of each alternative (Table 3), we can simplify these matrices for the following values:

$$W = \begin{pmatrix} 0.15 \\ 0.85 \\ 0.3 \\ 0.2 \end{pmatrix}$$

$$A = \begin{pmatrix} 160 & 8 & 1 \\ 0 & 1 & 1 \\ 1 & 0.343 & 0.22 \\ 0.4 & 0.4 & 0.8 \end{pmatrix}$$

Table 3 Desired blockchain system requirements for the case study

Attributes	*Requirements*	*Required*	*Value Preferences*
Gas Emission,	None		Quite desirable
Liquid discharge and	None		Quite desirable
Solid waste	None		Quite desirable
Byzantine Fault Tolerant	Required	≥33.33%	Desirable
Smart contracts Cryptocurrencies	Required	Yes	Indifferent
Storage element Calculation element	None	Advanced	Indifferent
Asset manager element Software	Required		Indifferent
connector	None		Indifferent
	None		Indifferent
	None		Indifferent
Learning Curve	None		Desirable

Table 4 Result of the execution of the decision process

Alternative	*Score*
Ethereum, PoA	0.7472
Bitcoin, PoW	0.6836
Corda, PBFT	0.1258
Ethereum, PoW	Disqualified
Hyperledger Fabric, Raft	Disqualified

Our decision algorithm therefore considers the Ethereum-PoA alternative to be the best (Table 4). Indeed, its obtained score is the closest to 1 (positive ideal solution) of the three alternatives.[1]

4 Related Works

Our work is in line with studies carried out to facilitate the adoption of the blockchain by means of decision support between different types of blockchains, or by the decision between using a blockchain or not in a given context.

Sedlmeir et al. (2022) list the main properties of the blockchain (Transparency, integrity, trust…) and propose a decision model on the adoption of the blockchain or not depending on the answer to certain questions (such as: "Are there several third parties involved?" or "Are they trusted?") related to the given case study. They then apply their model to several example use cases. Although there is a study of the blockchain parameters to define the questions of the decision model, the result is of a very high level of abstraction (public, private, permissioned or no blockchain).

It therefore does not allow a precise decision to be made on the blockchain technology to be used as well as these parameters. Ray (2019) carry out a literature review on studies relating to decision models for blockchain in order to build their own model. The results of this one are a little more precise than the previous one, but still do not give a precise recommendation. The authors of (Labazova, 2019) also carried out a literature review while using a DSR (Design Science Research) approach to build their model. This has several levels of decision and takes into account blockchain properties, which allows a user to make a

[1] POA Clique: https://github.com/ethereum/EIPs/issues/225.

choice with increased precision in output compared to previous studies. Moreover, the authors show the dependencies between certain parameters (for example, confidentiality and transparency). However, the input parameters are mostly specific to the blockchain and condition the use of the model by an expert. Another interesting study presents a third approach to decision support by offering a complete detailed work of blockchain fundamentals in the first part of their study, as well as a decision model introducing opposing criteria (such as performance/costs), but also a series of questions to refine the choice ("When to use the blockchain?", "What to use?", "How to use this blockchain?") (Zheng et al., 2017). All these studies help to guide decision-making for a given blockchain project, but do not allow going into more detail (blockchain parameters) because of the limitations of decision models. The lack of automation and the manual resolution of questions does not allow to take into account a large number of input requirements.

Some studies have been conducted to address this issue. As an example, the authors of Tang et al. (2019) propose to use a multi-criteria decision support method called TOPSIS, which is the same as the one used in this study, in order to determine the best solution of public blockchain available from a set of input criteria. The approach is interesting in this context, but does not take into account other blockchains (private, permissioned). In addition, the blockchain technical criteria are grouped under the "basic technology", "applicability" and "transaction per second" criteria, the first being quantified via experts, the recommendations given as a result may therefore lack precision if one considers place from the point of view of the company wishing to start its project.

In Farshidi et al. (2020), the authors built a decision-making system for blockchain technologies based on previous work for other technologies. They carried out a survey of experts to determine the most relevant selection criteria, then filled out a knowledge base containing the values of these attributes chosen for a large set of blockchains (obtained with white papers, studies, performance …) in order to give recommendations via an inference engine. Their tool is very powerful and makes it possible to give precise recommendations, we want to go further by offering something more blockchain-oriented (taking into account specific business processes and architectural models) which is more accessible for non-blockchain experts, through a model that links blockchain and software quality attributes. Thus the user can enter more common requirements than those specific to blockchain technology.

5 Discussions

The prediction obtained, which is to use Ethereum-PoA, seems to us a relevant choice for several reasons. Indeed, all the features that we consider necessary for the proper implementation of the chosen case study are present, while ensuring an optimal cost of it (low learning difficulty and energy saving). However, the method remains sensitive to weight variations. If we had chosen a higher weight for transaction throughput, we might have had a different output result. Sensitivity studies can establish ranges, which serve to indicate how much a weight can vary without affecting the final result. There are also methods, such as that of the determination of weight by entropy, making it possible to limit the impact of criteria with high entropy by reducing their weight (Huang, 2008). Moreover, the Likert scale that we have chosen for the expression of preferences can lead to a bias depending on the perception of the differences between the different values proposed by the user. In order to make the result more reliable, other weighting systems could be considered (AHP).

For our second experiment implementing a performance test of the Ethereum-PoA blockchain, we found that it was no longer able to process 100% of incoming transactions from 400 transactions per second. The monitoring of the execution on each of the nodes shows that this incapacity appears when the CPU of the nodes is no longer able to support the load of transactions received by the Geth client. It is however possible to decrease the inter-block interval in order to increase performance, but too low a value could degrade the quality of the network (difficulty reaching a consensus between authority nodes) and increase the disk space required (each block comprising at least one header of non-zero size). Therefore, we have chosen to keep the default value, but studying the impact of a drop on stability could be profitable. Also, we found during our experiment that the curve faithfully represents the loss of transactions, but we believe that repeating the experiment for each measurement point several times and extending the time of each experiment could greatly refine the results.

6 Conclusion

In this study, we adapted a multi-criteria decision support method to design an automated decision process for blockchain. For this, we selected a relevant panel of blockchains as well as criteria relating to the quality of a system (ISO 25010 standard) to create a knowledge base, then we chose a list of terms allowing a user to submit his preferences and requirements for the criteria chosen for the decision. Finally, we validated our process on a supply chain management case study and showed that our tool is able to recommend a blockchain aligned with the user's needs. The implementation is in progress, and will be completed and made available in open access on GitHub in future work. This study is a first step to design a more extensive automated decision process, as it could take into account a larger number of inputs (system architecture topology, infrastructure, business processes…). This would allow us, using this information, to run a custom performance test (such as the one presented in Subsection 3.4) for each user before even running the decision algorithm, the goal being to extremely precisely set the values of the varying criteria (transaction rate, latency, etc.). Another avenue for improvement is the use of approaches based on fuzzy logic or Bayesian models which would take into account the subjective aspect of the decision criteria.

References

Allen, I. E., & Seaman, C. A. (2007). Likert scales and data analyses. *Quality Progress, 40*(7), 64–65.

Cachin, C., & Vukolic, M. (2017). Blockchains consensus protocols in the wild. arXiv preprint arXiv:1707.01873.

Erol, I., & Oztel, A., Searcy, C., & Medeni, İ. T. (2023). Selecting the most suitable blockchain platform: A case study on the healthcare industry using a novel rough MCDM framework. *Technological Forecasting and Social Change, 186*, 122132.

Farshidi, S., Jansen, S., España, S., & Verkleij, J. (2020). Decision support for blockchain platform selection: Three industry case studies. *IEEE Transactions on Engineering Management, 67*, 1109–1128.

Huang, J. (2008). Combining entropy weight and TOPSIS method for information system selection. In *2008 IEEE Conference on Cybernetics and Intelligent Systems* (pp. 1281–1284). IEEE.

Kornyshova, E., & Salinesi, C. (2007). MCDM techniques selection approaches: State of the art. In *2007 IEEE Symposium on Computational Intelligence in Multi-criteria Decision-making* (pp. 22–29). IEEE.

Labazova, O. (2019). Towards a framework for evaluation of Blockchain implementations. In *ICIS 2019 Proceedings*.

Lai, Y.-J., Liu, T.-Y., & Hwang, C.-L. (1994). Topsis for MODM. *European Journal of Operational Research, 76*(3), 486–500.

Longo, F., Nicoletti, L., Padovano, A., d'Atri, G., & Forte, M. (2019). Blockchain-enabled supply chain: An experimental study. *Computers & Industrial Engineering, 136*, 57–69.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system.** Szabo, N. (1997). Formalizing and securing relationships on public networks. *First Monday, 2*(9).

Patil, K., Divesh, O., Elisabeth, M. S., & Pankaj, P. C. (2023). Behavioral drivers of blockchain assimilation in supply chains—A social network theory perspective. *Technological Forecasting and Social Change, 192*, 122578.

Ray S. (2019). Blockchains versus traditional databases [online]. https://hackernoon.com/blockchains-versus-traditional-databases-c1a728159f79. Accessed 1 July 2019.

Ren, Y.-S., Ma, C. Q., Chen, X.-Q., Lei, Y. T., & Wang, Y.-R. (2023). Sustainable finance and blockchain: A systematic review and research agenda. *Research in International Business and Finance, 64*, 101871.

Rossi, M., Mueller-Bloch, C., Thatcher, J. B., & Beck, R. (2019). Blockchain research in information systems: Current trends and an inclusive future research agenda. *Journal of the Association for Information Systems, 20*(9), 1388–1403.

Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2018). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research, 57*(7), 2117–2135.

Sedlmeir, J., Lautenschlager, J., Fridgen, G., et al. (2022). The transparency challenge of blockchain in organizations. *Electron Markets, 32*, 1779–1794. https://doi.org/10.1007/s12525-022-00536-0

Shari, F. M., & Malip, A. (2023). Blockchain-based decentralized data dissemination scheme in smart transportation. *Journal of Systems Architecture, 134*, 102800.

Tang, H., Shi, Y., & Dong, P. (2019). Public blockchain evaluation using entropy and TOPSIS. *Expert Systems with Applications, 117*, 204–210.

Tapscott, D. (2016). *Blockchain revolution: How the technology behind bitcoin is changing money, business, and the world*. Penguin.

Toufaily, E., Zalan, T., & Dhaou, S. B. (2021). A framework of blockchain technology adoption: An investigation of challenges and expected value. *Information & Management, 58*(3), 103444. https://doi.org/10.1016/j.im.2021.103444

Wood, G., et al. (2014). Ethereum: A secure decentralised generalised transaction ledger. *Ethereum Project Yellow Paper, 151*(2014), 1–32.

Xu, X., Pautasso, C., Zhu, L., Lu, Q., & Weber, I. (2018). A pattern collection for blockchain-based applications. In *ACM International Conference Proceeding Series*.

Zheng, Z., Xie, S., Dai, H.-N., Chen, X., & Wang H. (2017). An overview of blockchain technology: Architecture, consensus, and future trends. In *IEEE BigData Congress*.