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Procedia Computer Science 214 (2022) 809–816

Procedia Computer Science

www.elsevier.com/locate/procedia

9th International Conference on Information Technology and Quantitative Management

Analysis of Data Normalization in Decision Making Process for ICU's Patients During the Pandemic

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Abstract

Multi Criteria Decision Making (MCDM) helps decision makers to select the best solution among the set of alternatives with respect to the criteria which have different scales. Selection of the best solution by comparison between alternatives in most MCDM problems needs the normalizing process that maps criteria into the same scale. Hence, using different normalization techniques produces a different ranking of alternatives and has influence effects on the final ranking. So, selecting a more suitable technique for the MCDM problem leads to more accurate ranking results. Considering the current pandemic and the importance of efficient usage of clinical staff and ICU's bed, using more proper normalization techniques assists decision makers to rank and prioritize ICU's patients with less error and facilitates resource allocation in ICU. This study introduces an assessment framework using different metrics to ensure a more proper normalization technique for the chosen MCDM method.

Keywords: Normalization; MCDM; Decision Making; Assessment Framework; Fuzzification; Metrics; Data Analyzing; ICU.

1. Introduction

The current pandemic situation caused by the SARS-CoV-2 virus and consequently by COVID-19 disease, has put Intensive Care Units (ICUs) in the spotlight and posed additional major challenges in terms of staff availability, capacity limits and economic efficiency. It has again been shown that the coverage of ICUs and their capacities are unevenly distributed between large centers and the periphery [1]. Therefore, during the pandemic crisis, cooperation and knowledge sharing became even more important to prevent or reduce the spread of disease among patients and

10.1016/j.procs.2022.11.245

health professionals, while maintaining healthcare quality for the patients receiving care. The ICU4Covid H2020 project [2] and its Cyber-Physical System for Telemedicine and Intensive Care (CPS4TIC) makes it possible to expand computer operations and transfer knowledge from the central ICU hubs to peripheral hospitals, while significantly reducing the risk of infection for staff. The CPS4TIC consists of a telemedical cockpit, telemedicine consoles in every peripheral hospital, a connector platform, and smart bedside hubs [3]. The CPS4TIC further establishes a seamless connector platform to securely connect ICU Hubs central and peripheral hospitals for real-time continuous patients monitoring; perform telemedical consultation based on synoptic data from different sources; and to enable storage, adaptation, and sharing prediction models between ICU Hubs, as presented in Figure 1. The CPS4TIC also enables enhanced data and information analytics resulting, e.g., in support the medical decision making or development of tailored treatment schemes for patient suffering from COVID-19 or similar infectious diseases. Data is collected from patients entirely covered by the routine clinical care of the hospitals. Most of the data is collected through the CPS4TIC's real-time connection to ICU devices and to existing Patient Data Management Systems (PDMS). CPS4TIC focus on the developing and rapid sharing of models for prediction, diagnosis and prognostics based on evidence and data and the expert clinicians' decisions.

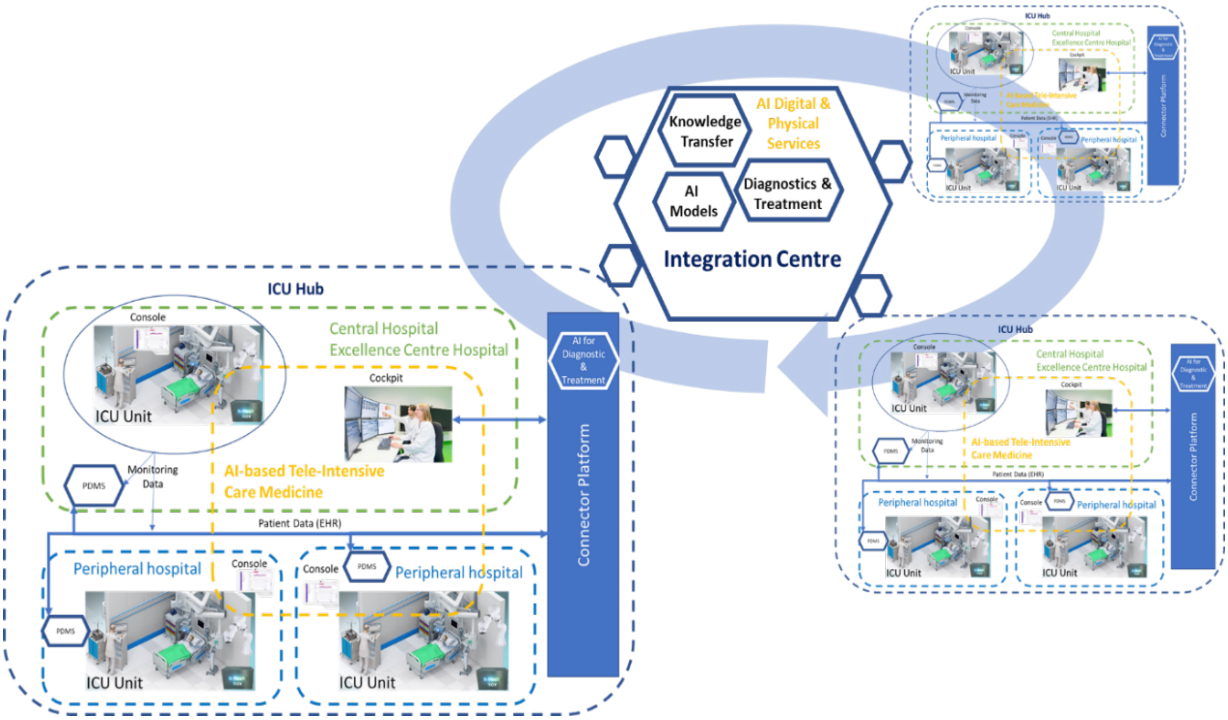

Figure 1. Interconnected ICU Hubs.

Figure 1 represents the collaboration between different CPS4TIC systems and shows the importance of Collaborative Network (CN) in dealing with rapid changes in information and communication systems [4]. In classic definition of the CN, partners share skills and resources to make optimal solutions and overcome their limitations [5]. Collaboration systems create the value through the joint efforts of partners/enterprises related to the data sets within complex scenario of Multi-Criteria Decision Making (MCDM) problems to rank alternatives among different criteria (quantitative or qualitative criteria) [5].

On the other hand, in presence of heterogonies data from sensors, the normalizing process is widely used in producing dimensionless data, especially with MCDM problems. Most MCDM methods need the preparation of the normalized decision matrices to convert criteria values into the same scales. Some MCDM methods like PROMETHEE and VIKOR can rank alternatives without normalization while some others like TOPSIS require the usage of the normalizing process [6]. Several normalization techniques are identified in the literature [7], however, there is no consensus which normalization technique is more fit for the well-known MCDM methods. The normalization process keeps approximately the same magnitude of criteria and applying different normalization techniques leads to the different ranking of alternatives. In the case of using unsuitable normalization techniques with the MCDM methods, the best solution may be overlooked. So, in order to avoid deviation from the best final solution, the selection of a more proper normalization technique is essential [8]. There are some study about evaluating normalization techniques and checked the suitability of the techniques for classification and MCDM problems [9]–[12]. Although related approaches can be found in the literature, there is a lack of a comprehensive assessment framework that manages the process of choosing the best normalization technique for MCDM decision problems which is the main motivation for this research.

The main aim of this study is to develop an assessment framework to evaluate different normalization techniques, using several metrics, and to recommend the more appropriate techniques for decision makers to handle MCDM problems related to the data sets from ICUs and guarantee the most efficient decision about the patients and their treatments. It builds upon the findings of [8] by presenting the implementation design view of the MCDM assessment framework and validates it using a real example from the ongoing ICU4Covid H2020 project), analyzing the effect of normalization techniques on ICU, and helping to improve regarding the recent pandemic. Moreover, this paper introduces and explains the new ICU Hub that is developing in ICU4Covid. Due to the limited pages, the authors will elaborate on the ICU Hub in the extended version of the paper.

2. Multiple Criteria Decision Making (MCDM)

Decision making get considerable attentions due to the its ability to solve variety of decision problems from simple tasks to the complex one. MCDM methods are powerful tools for solving decision problems in different area such as manufacturing, health care, management, energy, supply chain, and etc. The main goal of MCDM methods is to help decision makers to evaluate real-word situations based on qualitative/quantitative criteria/objectives in certain/uncertain/ risky environments, namely to find the most suitable course of action/choice/strategy/policy among several available options [13]. Decision makers' goals, preferences, alternatives and outcomes could be represented by the components of any MCDM problem, as alternative, criteria, weight, and decision matrix [14]–[16]. There are many different MCDM methods proposed in the literature [15], [17], [18] can be classified into two main categories Compensatory and Non-Compensatory methods. The Non-compensatory category can be sub-divided in three MCDM methods: Dominance, MaxMin, and MaxMax. Compensatory methods can be sub-divided in further three sub-classes: Scoring, Ordering, and Comparative methods. And the compensatory sub-class includes: (1) Weighted Average, Weighted Product, and Weighted Aggregated Sum Product Assessment Method (WASPAS) methods which belong to the Scoring sub-class; (2) TOPSIS, VIKOR, and Lexicographic methods, which belong to Ranking sub-class; and (3) AHP and ELECTRE, which belong to the Comparative sub-class. The main advantages of using compensatory methods is their ability to allow trade-offs between good and bad performance of different criteria, through compensation between those two types of criteria [19]. Most well-known MCDM methods belong to this high-level compensatory category, so, the focus of this research is on compensatory methods and from each sub-class (scoring, raking and comparative) at least one MCDM method is chosen to evaluate their most adequate normalization procedure. In summary, the chosen MCDM methods to be studied in this research work are: Sum Weighted Average (which is often known as Simple Additive Weighting (SAW) method), TOPSIS, AHP, and ELECTRE. For more details about the TOPSIS method please see [18], [20].

Numerous normalization techniques have been introduced in the literature and used with MCDM methods to convert heterogeneous input data to the dimensionless form [7]. The normalizing process enables decision makers to compare alternatives with respect to the criteria that have different units/scales by mapping the decision matrix into the interval [0-1]. Jahan and Edwards [7] listed thirty-one normalization techniques and classified them in four categories and presented formula for both benefit and cost criteria and discussed some pros and cons of each technique. For this research work we selected at least one normalization technique from each category. Further, the chosen techniques are also well-known in the literature and widely used by decision makers in decision problems. Table 1 shows the six selected normalization techniques for our comparison study. We classified the chosen normalization techniques into three categories: (i) Linear, (ii) Semi linear, and (iii) Non-Linear.

Table 1. Normalization techniques [7].

Number	Normalization technique (NT)	Condition of use	Formula
N1	Linear: Max	Benefit criteria	$n_{ij}^{+} = \frac{r_{ij}}{r_{max}}$
		Cost criteria	$n_{ij}^{-} = 1 - \frac{r_{ij}}{r_{max}}$
N2	Linear: Max-Min	Benefit criteria	$n_{ij}^{+} = \frac{r_{ij} - r_{min}}{r_{max} - r_{min}}$
		Cost criteria	$n_{ij}^{-} = \frac{r_{max} - r_{ij}}{r_{max} - r_{min}}$
N3	Linear: sum	Benefit criteria	$n_{ij}^{+} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$
		Cost criteria	$n_{ij}^{-} = \frac{1/r_{ij}}{\sum_{i=1}^{m} 1/r_{ij}}$
N4	Semi-linear: Vector	Benefit criteria	$n_{ij}^{+} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$
		Cost criteria	$n_{ij}^{-} = 1 - \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$
N5	Non-linear: Logarithmic	Benefit criteria	$n_{ij}^{+} = \frac{\ln (r_{ij})}{\ln (\prod_{i=1}^{m} r_{ij})}$
		Cost criteria	$n_{ij}^{-} = \frac{1 - \frac{\ln (r_{ij})}{\ln (\prod_{i=1}^{m} r_{ij})}}{m-1}$
N6	Non-linear: Fuzzification – (membership functions)	Benefit & Cost criteria	E.g. trapezoidal: $f(x,a,b,c,d) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ \frac{d-x}{d-c} & c \leq x \leq d \\ 0 & d \leq x \end{cases}$

3. Assessment Framework

As mentioned before, several normalization techniques are applied with MCDM methods for producing dimensionless and comparable input data. Different normalization techniques produce different ranking of alternatives in MCDM problems. So, there is needed to select a more proper technique to reach the best ranking of alternatives.

Some research papers investigated on assessing different normalization techniques in MCDM problems. For instance Chakraborty and Yeh [11] used Ranking Consistency Index (RCI) to show similarity/dissimilarity of four normalization techniques namely Vector, Max-Min, Max, and Sum with SAW (Simple Additive Weighting) method. Celen [10] analyzed the impact of vector, max-min, max and sum techniques using consistency index (Spearman correlation) with TOPSIS method to rank banks performance in Turkey and suggested Vector technique as the best one for the case study. Baghla and Bansal [21] elaborated the effects of Max, Max-Min, and Vector normalization techniques with VIKOR method and showed that Vector has better performance considering the simulation results in their study. Mathew et al. [22] analyzed the behavior of six normalization techniques with weighted aggregated sum product assessment (WASPAS) method using Spearman correlation and results showed up Max-Min technique one giving the best results in their case study.

There are some other papers that explore the comparison of different normalization techniques in MCDM problem but there is a lack of assessment framework that is consisted of several metrics. So, this section focuses on the proposal of a framework that offers a novel assessment tool to recommend which normalization technique is more suitable for usage with well-known MCDM methods.

As Figure 2 shows, decision makers should follow four steps to compare the results of different normalization techniques using the proposed assessment framework. In the first step, the type of criteria will be determined, then normalization techniques will be candidate in second step, and in the third step different metrics will implement to analyze the effect of normalization techniques on ranking of alternatives in MCDM problem. Finally, in the last step, the most proper technique will recommend by the assessment framework.

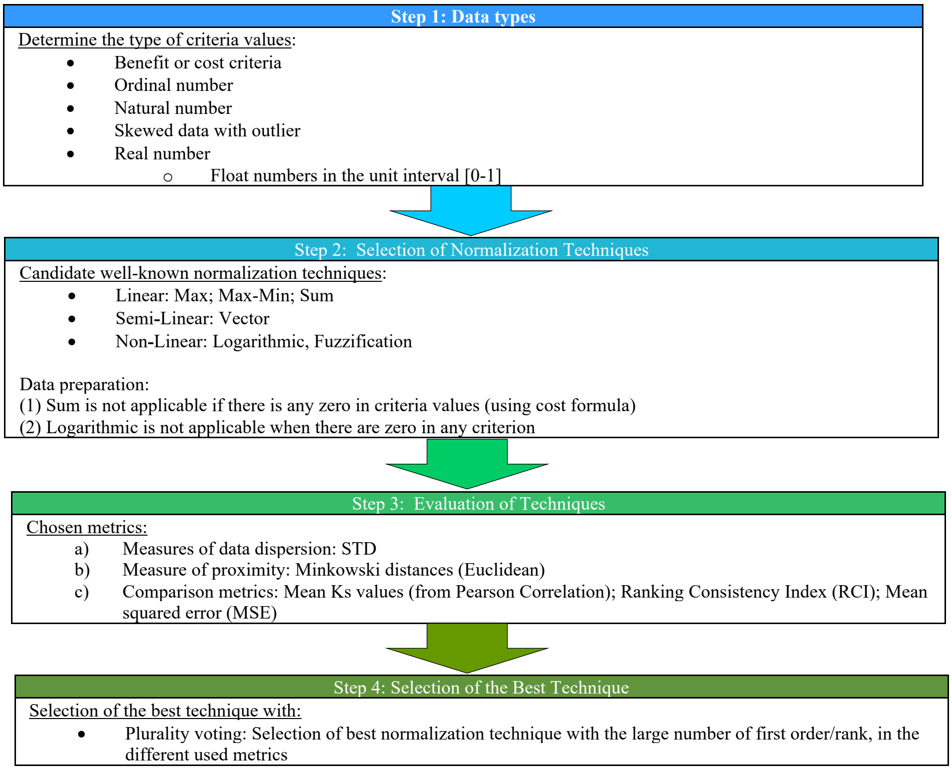

Figure 2. Different steps of the proposed assessment framework.

3.1. Implementation Design of the Assessment Framework

This section presents the implementation design of the final assessment framework for the future automatic tool that can help decision makers to select the best normalization technique for decision problems, in a user-friendly manner within the minimum human intervention (Figure 3). For simplicity purposes, those MCDM methods and normalization techniques which depend on human/expert intervention are not shown in this model. For instance, the AHP MCDM method is removed because it needs expert's intervention to determine comparison matrices and when there are more than 7-9 criteria and/or alternatives it is too cumbersome to be used. From the normalization techniques, Fuzzification has the drawback of requiring the definition of appropriate membership functions to represent the input criteria, by analysts or experts [23], which is a cumbersome manual process. Therefore, to have a fully automatic evaluation process using the conceptual framework, the AHP method and Fuzzification normalization technique are removed from the implemented model.

Figure 3 depicts the decision-making process that the decision makers should follow. Initially, the decision maker defines the decision matrix which contains the values of alternatives with respect to the desired criteria. For each criterion, he/she should assign weights and indicate cost (the lower values the better) or benefit (the higher values the better) criteria. Then it must be chosen which normalization techniques could be used in the decision problem, paying attention to the existence of zero values in the decision matrix, which causes the elimination of the Logarithmic and Sum techniques. Also, the existence of decimal numbers causes the elimination of logarithmic technique if it produces negative normalized values. Then decision maker selects which MCDM methods he/she wishes to use among TOPSIS, SAW, and ELECTRE methods for aggregation/ ranking alternatives. Finally, the design model proceeds to the metrics calculation of the assessment framework: RCI, STD, MSE, Mean ks, and Euclidean. In the end, the process will recommend the best normalization technique to the decision maker using plurality voting for the related decision problem.

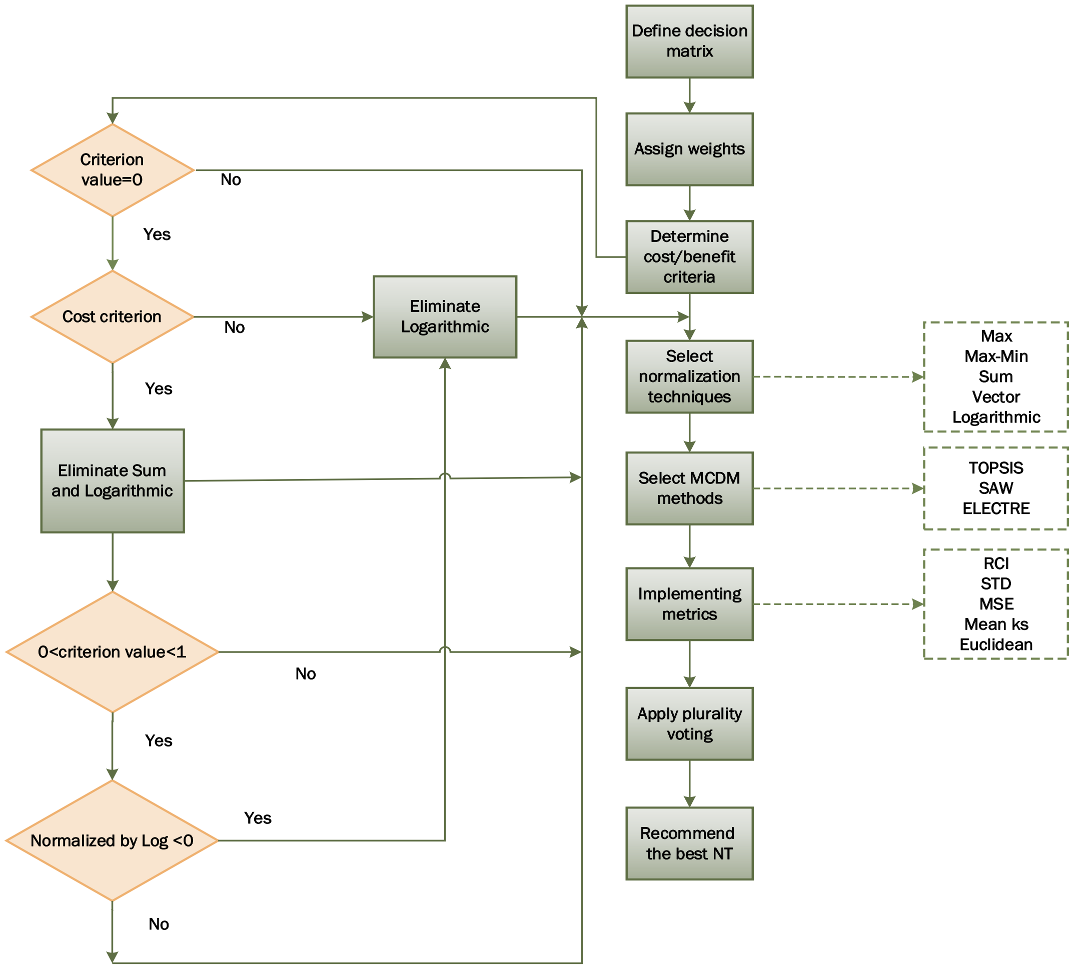

Figure 3. Implementation design of the proposed assessment framework.

4. Illustrative Example from a Real-World Scenario

To show the applicability of the proposed assessment framework on the collected data from CPS4TIC's real-time connection to ICU devices, we used the illustrative example that consists of physical measurements of 6 patients namely: blood pressure (systolic) (C1), oxygen level (C2), body temperature (C3), and age (C4). Six patients are as the alternatives (A1, A2, …, A6) and four physical measurements as criteria (C1, C2, C3, and C4) in which C3 and C4 are the cost criteria (the lower value the better). Also, weights are assumed equal for all criteria. In this real-world example, the data are collected from ICU patients which are hospitalized in central or peripheral hospitals and will transfer to the cockpit using the connector platform for medical decision making and performing telemedical consultations (Figure 1). So, using suitable normalization techniques can improve the accuracy of ICU hub's actions in prioritizing patients to get faster treatment based on the deterioration of the patient's condition.

We tested Max, Max-Min, Sum, Vector, and Logarithmic normalization techniques with Simple Additive Weighting (SAW) method. More details about SAW method is available in [18]. It should be noticed that we only focus on one time data set from CPS4TIC to better explain the effect of the different normalization techniques on this kind of problems. The input data for the illustrative example are shown in Table 2.

Table 2. Decision matrix for input data

	C1	C2	C3	C4
A1	14.85	93	37.8	80
A2	14.5	92	37.5	56
A3	16.9	91	38	80
A4	11.8	96	37	44
A5	13.9	98	39	80
A6	12.8	93	37	63

After determination of the normalized decision matrix, SAW method implemented and alternatives' values and ranking results for the illustrative example were calculated (Table 3).

Table 3. Alternatives' values, and ranking results with SAW method.

	Max	**Rank**	**Max-Min**	**Rank**	**Sum**	**Rank**	**Vector**	**Rank**	**Logarithmic**	**Rank**
A1	0.4646	5	0.2995	4	0.2362	5	0.4765	5	0.2464	3
A2	0.5338	2	0.4740	3	0.2550	2	0.5181	2	0.2477	2
A3	0.4886	4	0.2500	5	0.2434	3	0.4907	4	0.2491	1
A4	0.5448	1	0.7500	1	0.2654	1	0.5245	1	0.2450	5
A5	0.4556	6	0.2029	6	0.2336	6	0.4712	6	0.2453	4
A6	0.4925	3	0.5171	2	0.2416	4	0.4935	3	0.2444	6

As Table 3 shows, different normalization techniques produce different ranking results, but which ranking result is more reliable and accurate. To answer this question, we applied the proposed assessment framework that includes several metrics as RCI, STD, MSE, Mean ks, and Euclidean. Table 4 represents the results of used metrics and their ordering results.

Table 4. Results of implementing the used metrics from the assessment framework.

	Euclidean	**Rank ↑**	**STD**	**Rank ↑**	**RCI**	**Rank ↑**	**MSE**	**Rank ↓**	**Mean ks**	**Rank ↑**	**Plurality voting (PV)**
Max	0.1973	2	0.0360	2	9.75	1	2	2	0.7168	1	2
Max-Min	1.1269	1	0.2057	1	5.5	4	3.25	4	0.5324	4	2
Sum	0.0664	4	0.0121	4	8.75	3	1.9167	1	0.7030	3	1
Vector	0.1182	3	0.0216	3	9.25	2	2.25	3	0.7161	2	0
Logarithmic	0.0098	5	0.2029	6	0.2336	6	0.4712	6	0.2453	4	0

As Table 4 is shown, each metrics produce different ordering for each normalization technique. So, we used plurality voting (Step 4) that works as an aggregation method to determine a single result from different used metrics. For the related illustrative example, Max and Max-Min are recommended as the best techniques to prioritize ICU's patients due to the highest PV value that two times being in the first order with respect to the used metrics. So, based on this result, patient A4 has the first priority to use the medical treatment in ICU.

5. Conclusion

This study elaborated on the novel assessment framework that could improve decision makers' decisions by recommending more suitable normalization techniques. On the other hand, the importance of efficient decisions in ICU during the pandemic motivated us to consider the applicability and usage of the proposed framework to rank ICU's patients and allocate resources (doctors, nurses, ICU beds, etc.) in a more accurate manner.

Several metrics are used in the assessment framework to evaluate five normalization techniques (Max, Max-Min, Sum, Vector, and Logarithmic) and recommend more proper techniques for the problem at hand using SAW, TOPSIS, and ELECTRE from MCDM methods. The real world example in this study analyzed the effect of mentioned normalization techniques with SAW method and the results showed Max and Max-Min techniques are more suitable for the ranking of ICU's patients due to having higher PV values than other used techniques. This work is the preliminary study of analyzing the effect of normalization techniques on decision problems that contain data from CPS4TIC. So, examination of the other MCDM methods (TOPSIS, MOORA, etc.) is considered as a future study. Moreover, the extension of the framework's application to big data (especially data from CPS4TIC real-time connection to ICU devices) is planned for future work. Besides, the collaboration between different parts of ICU hubs is another topic for further research in the concept of CN and its role in the fast changing environment due to the pandemic.

Acknowledgements

This work has received founding by the Center of Technology and Systems (CTS), the Portuguese Foundation for Science and Technology (FCT) through the Strategic Program UIDB/00066/2020, and the from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101016000.

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