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Industrial Engineering and Operations Management

XXVI IJCIEOM, Rio de Janeiro, Brazil, July 8–11, 2020

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Challenge and Trends for Sustainability in the 21st Century

Springer

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Preface

The XXVI International Conference on Industrial Engineering and Operations Management (IJCIEOM) occurs in turbulent and pandemic times. It will take place at the campus of the Pontifical Catholic University of Rio de Janeiro in the first semester of 2021. We joined IJCIEOM 2020–2021 in one Conference and decided to publish the Proceedings for 2020 well in advance. The presence and persistence of our peers, writing, and submitting first quality papers on the varied subjects covered by the Conference is a clear demonstration of the vigor and relevance of our field.

IJCIEOM 2020–2021 embraces the theme of "Challenge and Trends for Sustainability in the 21st Century", looking ahead to bridge theory and practice of economic, social, and environmental sustainability. This Conference aims to enhance the connection between academia and industry and to gather researchers and practitioners specializing in operation management, industrial engineering, engineering management, and other related disciplines from around the world.

All papers went through a double-blind review process from renowned academics of Industrial Engineering and Operations Management (IE&OM). This joint Conference is a result of combined efforts from ABEPRO (Associação Brasileira de Engenharia de Produção), ADINGOR (Asociación para el Desarrollo de la Ingeniería de Organización), IISE (Institute of Industrial and Systems Engineers), AIM (European Academy for Industrial Management), and ASEM (American Society for Engineering Management). The Conference honors the highest academic standards from our field of research and offers studies and results of relevance for management practice and future research.

The Proceeding assembles 52 papers from several tracks, including Operations and Process Management, Quality Management, Logistics and Supply Chain Management, Product Development, Knowledge and Information Management, Strategy and Organizational Engineering, Sustainability, Global Operations, Production Engineering Education, Healthcare Operations Management, and Disaster Management.

The topics included in the different tracks give an excellent overview of the actual contribution of our field to bridge theory and practice. Not only because of the varied scientific methods applied, ranging from optimization, markovian chains, inventory models, data envelopment analysis (DEA), multicriteria decision-making, structural equation modeling, neural networks, and bibliometric reviews to empirical research using survey and case study data, but also because of the rigor and relevance of the themes.

Operations and process management covers optimizing water use in university settings, inventory and shop floor management, military social protection systems, production planning and control in Industry 4.0, a study of times and movements in a shipyard, economics and cultural influence of manufacturing strategy, practices and performance, energy efficiency in smart manufacturing, and process mining using neural networks.

Logistics and supply chain management embraces a bibliometric analysis of suppliers, EPQ inventory models under advanced-cash-credit payment, implications of sustainability in logistics, small enterprises management roadmap, vehicle routing problem considering cargo theft probability, an application of the SCOR process to porcelain export, social and environmental risks in supply chains, risk management in wind power, and omnichannel retailing.

Quality management focuses on indicators for monitoring the regulatory compliance of equipment in industrial plants in the oil and gas sector, use of DMAIC and Lean Six Sigma in an automotive factory, statistical process control, service quality scales, the importance of measurement uncertainty analysis on statistical quality control charts, variance modified control carts, and Lean Office application to public buildings. Under the product development track, pricing scenarios of sustainable product-service systems discuss its application in the agricultural sector, from the farmers' viewpoint.

The production strategy area applies multicriteria analysis to Navy warship selection, offers an integrated model of organizational diagnostics, analyzes the competitive advantages arising from industrial clusters, uses logistic regression model for predicting cost performance in new product development, performance measurement systems, proposes a model for organizational performance assessments, and analyzes the success factors for civil construction projects management.

Knowledge and information management brings valuable discussions on scorecard applied to the organizational performance of distributed generation in electric utilities, on information and data quality states model in information systems, cost information systems applied to the public sector, data reconciliation and parameter estimation applied to a heat exchange process, and a data mining application in a higher education institution. The track on work and human factors shed light on occupational accidents among construction workers, purchase systems for people with reduced mobility, and competence management under Industry 4.0.

Sustainability, the central theme of the Conference, contributes papers in varied areas. Several articles cover environmental sustainability, as the psychological factors affecting the use of plastic cups, use of eggshell in circular economies, a data enveloping analysis (DEA) of the efficiency of environmental sanitation in Brazil, and an analysis of greenhouse gases and atmospheric pollutant emissions by helicopters in the oil and gas industry. The track also offers an inventory model with the inclusion of environmental parameter in stochastic EPQ with partial backorders. The sustainability track also included several papers on circular economy for lubricating oils in Brazil, and for devising strategies toward a transition to the circular economy. The sustainability track brought equally discussions on renewable energy, a historical review of the electricity sector in Brazil, cleaner services production, Sustainable Supply Chain Management in the food industry, extraction of oil of soursop (Annona muricata) and marolo (Annona crassiflora Mart) seeds, using different solvents and processes. It equally offers discussions on life cycle assessment (LCA) for photovoltaic solar energy, psychological aspects of buying green, energy management audit based on international standards, and introduced the discussion about local-level sustainability indicators, assessment of CO^2 emission in the soil-cement brick industry, and the circular economy for lubricating oils.

The track on production engineering education proposes measurement of the effectiveness of a Scrum Training Session. The healthcare track opens the discussion about the application of lean management and explores a multiple case study on patient demand forecast in emergency departments. The track of Global Operations offers a hybrid modeling for multicriteria evaluation of drones for use in naval warfare.

Finally and equally relevant was the track on disaster management, covering the selection of distribution centers, pedestrian evacuation plans for fire situations at a university, humanitarian relief for poverty zones, and a disaster response assessment applied to the case of the civil defence of the State of Rio de Janeiro, Brazil.

We hope the readers will enjoy the Proceedings organized within this book as much as we enjoyed preparing it for publication.

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Selecting Distribution Centers in Disaster Management by Network Analysis and Composition of Probabilistic Preferences

Luiz Octávio Gavião, Annibal Parracho Sant'Anna, Gilson Brito Alves Lima, Pauli Adriano de Almada Garcia, and Alessandro Mello de Sousa

Abstract Disaster management operations require adequate and rapid planning to efficiently serve the affected populations. In this context, an Area of Operations must be dimensioned with the main locations capable of receiving logistic facilities. These locations need to be connected by networks capable of ensuring the flow of critical supplies. The objective of this article is to identify the most influential nodes in a disaster management supply chain, by network analysis and a multicriteria decision aid method. Network analysis provides measures that indicate the most influential nodes in the network. These measures, called centralities, are selected through Principal Component Analysis (PCA). The nodes and their centrality evaluations configure a decision matrix to be modelled by the Composition of Probabilistic Preferences (CPP). CPP is an alternative to other MCDA methods used in this type of problem, such as TOPSIS, by exploring its non-linearity to highlight the best nodes in the network. The R software and specific packages were used to compute results. An undirected and weighted network of 12 nodes was used to test the model. Two nodes identified the best access to the affected area and suggested the best location to establish the distribution center or other logistics facilities.

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1 Introduction

The flow of critical supplies to populations affected by disasters is a key issue in humanitarian logistics [1–3]. Any delay in the arrival of medicines, blood plasma, water, food, personnel, among other emergency items impacts rescue. In this context, the road network that links possible points of the humanitarian supply chain is essential to guarantee the flow of personnel and material for assistance [4–7]. These points may receive command posts, logistical support areas, distribution centers or field hospitals to set up the disaster management support network [8, 9]. In this case, the identification of the most suitable points can assist in planning and, consequently, in the efficient execution of logistical support [10].

Network analysis provides a methodology and related metrics for mapping relationships between members of a group, characterizing the individual entities as nodes connected by ties to create networks [11]. The method is adaptable and highly useful in humanitarian research, quantifying patterns of community structure and collaboration among humanitarian organizations [12]. In this context, some early studies have associated network analysis with emergency response simulations [13, 14], with the Indonesian response after the Sumatran earthquake and tsunami [15], and with the 2015 Nepal/Gorkha earthquake [16].

Network analysis is especially useful to select nodes in a humanitarian supply chain. There are mathematical indicators that reflect the relative importance of each node. These measures are called centralities, which remain the most widely studied metrics in network analysis to date [11, 12]. However, the centrality results may not have the same importance for different nodes. Centrality measures are computed by different equations and represent different meanings in the network [11].

Several studies have used centrality measures with multicriteria methods to rank the most influential nodes [17–21]. The literature reveals that the Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) is one of the most used multicriteria decision aid method (MCDA) methods for this purpose. However, the Composition of Probabilistic Preferences (CPP) is an alternative to other methods used in this type of problem, by exploring its non-linearity to highlight the best nodes in the network.

In this context, as the first objective here is to identify the most influential nodes in disaster management supply chains, after choosing the set of centralities by Principal Component Analysis (PCA), the nodes are selected by CPP. The major insight extracted from the paper is the PCA-CPP association, which consists of a new methodological application to humanitarian supply chains.

The article consists of five sections. After the introduction, a brief review of CPP is presented in Sect. 2. Then, the steps of the proposed method are set out in Sect. 3. A numerical application illustrates the proposal in Sect. 4. Finally, a conclusion ends the research in Sect. 5.

2 The Composition of Probabilistic Preferences

CPP is a MCDA method, used in the most diverse areas of knowledge [22–25]. Among its various features, CPP can be applied to order alternatives evaluated under multiple criteria. Even though there are several other methods that would also be used to achieve the same objective, a special feature differentiates CPP from other multi-criteria methods; CPP normalizes evaluations by a non-linear algorithm, overvaluing the highest assessments and depreciating the lowest ones [22]. Figure 1 shows this characteristic, by comparing TOPSIS with CPP. For that, we explored a sample of data in arithmetic progression between 1 and 10, in the abscissa axis. The results are plotted on the ordinate axis. The slopes between the TOPSIS evaluations are uniform. On the other hand, CPP overvalues the best performances; the slope between 9 and 10 is higher and more inclined than the others.

CPP is computed in three steps. In the first one, the evaluations are randomized under a probability distribution. Then, Eqs. (1) and (2) are applied. The probabilities of the i-th alternative being higher (M_{ij}) and lower (m_{ij}) than the others are calculated for each criterion j. A random vector "X" symbolizes the alternatives of the problem. The functions related to the i-th alternative are indexed by "i" and the others by "$-i$". The F_X, f_X and D_{X_i} notations denote, respectively, the cumulative distribution function (cdf), the probability density function (pdf) and the domain of the random variable "X" [26].

$$M_{ij} = \int_{D_{X_i}} \left[\prod F_{X_{-i}}(x_{-i})\right] f_{X_i}(x_i)dx_i \tag{1}$$

$$m_{ij} = \int_{D_{X_i}} \left[\prod \left(1 - F_{X_{-i}}(x_{-i})\right)\right] f_{X_i}(x_i)dx_i \tag{2}$$

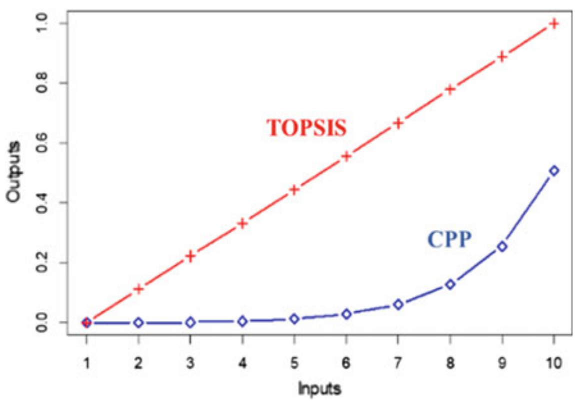

Fig. 1 Non linearity of CPP

Finally, the probabilities M_{ij} and m_{ij} are composed by four points of view for decision making: progressive, conservative, pessimistic and optimistic. The progressive point of view uses the probabilities M_{ij}, symbolizing the search for greater gains in the problem. The conservative point of view uses the probabilities m_{ij}, to avoid losses by increasing the distance to the worst results. The pessimistic point of view considers the progressive-conservative axis under all criteria, while the optimistic point of view is content to achieve results under at least one criterion. For the problem of choosing the best nodes in the network, the progressive-pessimistic (PP) and progressive-optimistic (PO) points of view are those that make sense for decision making in a disaster management context, due to the search for the best node centralities.

3 Method

The proposed model is developed in six steps, as shown in Fig. 2.

In Step 1, it is necessary to configure the Area of Operations (AO). This area should include, within its limits, the region affected by the disaster and the regions capable of receiving logistical facilities for the coordination of humanitarian assistance.

In Step 2, the main locations, large highways and paved or unpaved roads must also be raised. At the end of this stage, a undirected and weighted network of nodes (locations) and arcs (connections) must graphically translate the trafficability of the AO.

In Step 3, weights are established to qualify the connections between the locations of the AO. Among the criteria to be considered, it is suggested to evaluate the distances between the nodes, the quality of the road according to its characteristics and the degree of damage that the disaster caused to the conditions of use of the road. In this context, the best arc is the one that connects the shortest distances, with the best roads, with the least damage caused by the emergency.

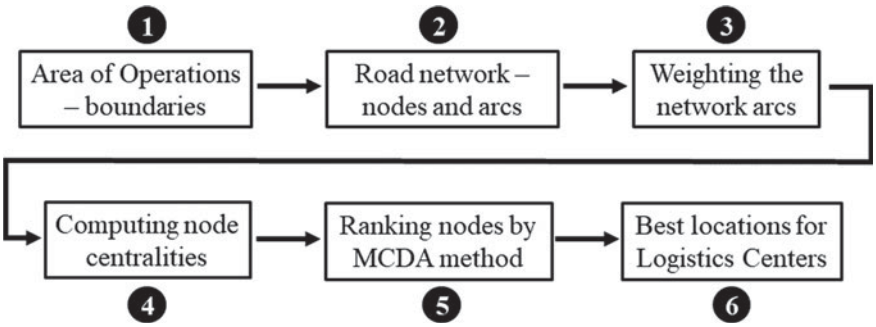

Fig. 2 Methodological steps

In Step 4, centrality measures of each node in the network are calculated. These measures identify the most important vertices within a network. The literature indicates that there are more than 50 types of centrality measures [27]. However, depending on the network features, some measures do not discriminate the nodes well. Thus, it is suggested to reduce the dimensionality of the problem by selecting the best results, with the use of PCA, for example.

In Step 5, after selecting the main centrality measures, a decision matrix is composed by the network nodes and their most relevant centrality measures. This matrix is the initial database for applying a MCDA to rank the nodes. If there is more than one rank for the same node, it is possible to merge the results using the Borda method [28].

In Step 6, results are analyzed to identify the best places to establish distribution centers and other logistical facilities that will support humanitarian assistance operations.

4 Application

4.1 Sample and Database

To illustrate the application of the proposed model, a network of localities and roads was created around a region affected by an environmental disaster, called “ground zero”. The network was configured by 12 locations, four of which show the last mile (I, J, K and L), providing direct support to the affected population, in addition to eight further locations, considered relevant by planning teams. Possible connections between locations are indicated by non-directional arcs in Fig. 3. Crash signs in red simulate problems in accessibility after disaster.

The arcs were weighted based on three assessments: road class, accessibility and distance between nodes. The road class was scored from 1 to 7, according to the table used in DNIT [29], which uses seven classifications for highways, which are adapted here to indicate the quality of the connection between the nodes. The accessibility of the road after disaster was scored from 0 to 1, varying from terrible to excellent conditions. The distance between the nodes was also evaluated between 0 and 1, which are equivalent to very long and very short distances, respectively. The products of these three variables provided the weights of the network’s adjacency matrix, as shown in Table 1. This matrix is the initial database for calculating the centralities of the network nodes. Null values indicate the absence of connection between the nodes.

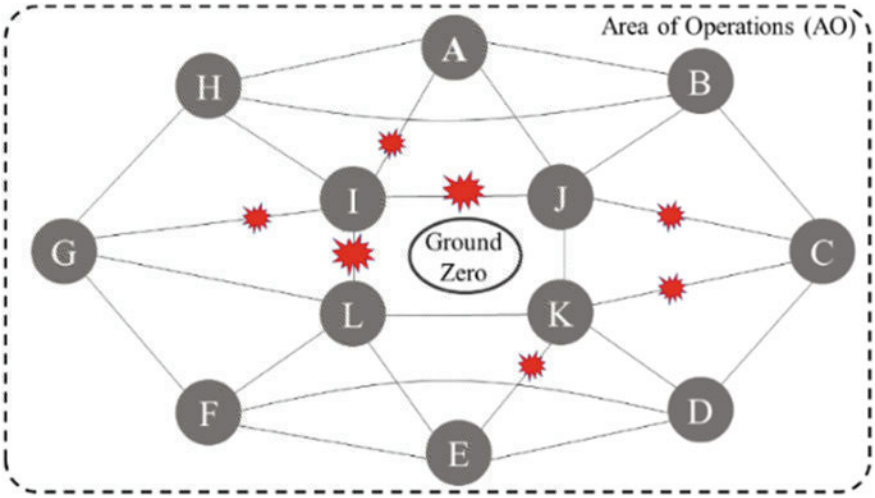

Fig. 3 Undirected and weighted network

Table 1 Adjacency matrix

Nodes	A	B	C	D	E	F	G	H	I	J	K	L
A	0	3.6	0	0	0	0	0	2.7	1.2	2	0	0
B	3.6	0	2.7	0	0	0	0	0	0	2	0	0
C	0	2.7	0	2.7	0	0	0	0	0	0.8	1.4	0
D	0	0	2.7	0	1.8	0	0	0	0	0	1	0
E	0	0	0	1.8	0	3.6	0	0	0	0	0.8	2
F	0	0	0	0	3.6	0	2.7	0	0	0	0	2
G	0	0	0	0	0	2.7	0	3.6	1	0	0	1
H	2.7	0	0	0	0	0	3.6	0	2	0	0	0
I	1.2	0	0	0	0	0	1	2	0	0.2	0	0.2
J	2	2	1.6	0	0	0	0	0	0.2	0	2	0
K	0	0	1.4	2	0.8	0	0	0	0	2	0	1
L	0	0	0	0	3	2	3	0	0.2	0	1	0

4.2 Results and Analysis

All calculations of the proposed model were performed using the R software. Centralities were computed by the R package CINNA. The functions '*calculate_centralities*' and '*pca_centralities*' returned 47 different measures of centrality of the nodes, according to Fig. 4 [27].

The best contributions to centrality measures are indicated by the red arrow in Fig. 4. The bars show that five measures differ significantly from the others. In

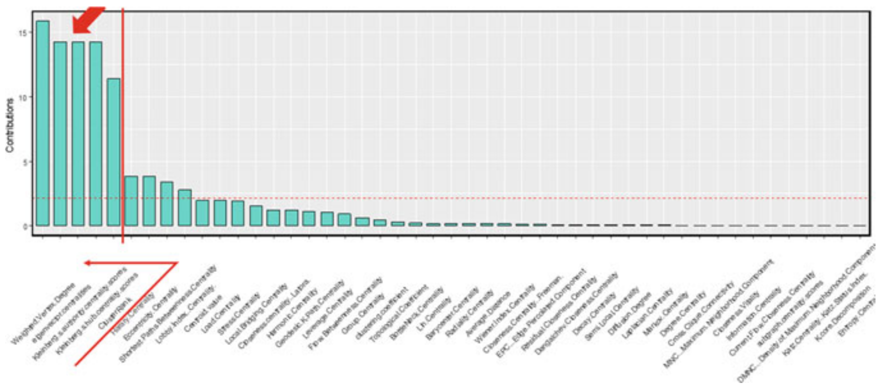

Fig. 4 PCA of centrality measures

practice, this indicates that their values are more discriminatory than the other indices. Thus, these best measures were exported to configure the decision matrix in Table 2.

Then, the CPP method was applied to the decision matrix, to select the most influential nodes in the network. The R package CPP was used to compute results [30]. After randomizing the variables with '*CPP.Axes.Beta*' function, the probabilities of each node centrality being higher than the others were calculated and shown in Table 3.

Table 4 shows the results of the compositions by PP and PO axes, with their respective rankings. The Borda ordinal MCDA method was also used to obtain the final ranking from the CPP progressive points of view [28]. Nodes F, G, H and L

Table 2 Centralities

	Weighted vertex degree	Eigenvector centralities	Kleinberg's authority centrality	Kleinberg's hub centrality	Cluster rank
A	9.5	0.6648324	0.6648324	0.6648324	10
B	8.3	0.5743593	0.5743593	0.5743593	10.666667
C	8.4	0.5222619	0.5222619	0.5222619	10
D	6.5	0.47874	0.47874	0.47874	10.666667
E	9.2	0.8851833	0.8851833	0.8851833	10
F	8.3	0.9234976	0.9234976	0.9234976	10.666667
G	10.3	1	1	1	10
H	8.3	0.7383063	0.7383063	0.7383063	10.666667
I	4.6	0.4225498	0.4225498	0.4225498	10.4
J	7.8	0.5254835	0.5254835	0.5254835	10.4
K	7.2	0.5214308	0.5214308	0.5214308	10.4
L	9.2	0.9593598	0.9593598	0.9593598	10.4

Table 3 Probabilities of maximizing the centralities

	Weighted vertex degree	Eigenvector centralities	Kleinberg's authority centrality	Kleinberg's hub centrality	Cluster rank
A	5.38E−02	7.47E−08	7.47E−08	7.47E−08	1.44E−22
B	3.99E−04	1.03E−10	1.03E−10	1.03E−10	2.50E−01
C	6.34E−04	1.10E−12	1.10E−12	1.10E−12	1.44E−22
D	1.06E−08	1.33E−14	1.33E−14	1.33E−14	2.50E−01
E	1.77E−02	8.65E−03	8.65E−03	8.65E−03	1.44E−22
F	3.99E−04	4.12E−02	4.12E−02	4.12E−02	2.50E−01
G	9.09E−01	7.86E−01	7.86E−01	7.86E−01	1.44E−22
H	3.99E−04	6.57E−06	6.57E−06	6.57E−06	2.50E−01
I	4.38E−17	8.93E−18	8.93E−18	8.93E−18	9.78E−08
J	3.33E−05	1.49E−12	1.49E−12	1.49E−12	9.78E−08
K	1.11E−06	1.02E−12	1.02E−12	1.02E−12	9.78E−08
L	1.77E−02	1.64E−01	1.64E−01	1.64E−01	9.78E−08

Table 4 CPP results and borda ranking

Vertices	CPP-PP	Rank	CPP-PO	Rank	Borda
A	3.217E−45	7	5.375E−02	7	14
B	1.086E−34	6	2.503E−01	5	11
C	1.221E−61	11	6.340E−04	9	20
D	6.239E−51	10	2.500E−01	6	16
E	1.650E−30	5	4.301E−02	8	13
F	6.962E−09	1	3.391E−01	3	4
G	6.348E−23	4	9.991E−01	1	5
H	2.825E−20	3	2.503E−01	4	7
I	3.046E−75	12	9.775E−08	12	24
J	1.077E−47	8	3.341E−05	10	18
K	1.151E−49	9	1.208E−06	11	20
L	7.631E−12	2	4.258E−01	2	4

received the lowest Borda sums. These nodes indicate the most favorable region for the establishment of distribution centers in the supply chain. They also show the best zone to access ground zero to provide the disaster relief.

The validity of the decision support models can be evaluated by calculating the degree of decision makers' satisfaction [31]. Other option to validate a MCDA model is to check its ability to mimic the real system, using statistical methods to compare model and real system outputs [32]. However, the application of the proposed model was not based on a real case. The nodes F, G, H and L form a coherent solution to the hypothetical problem, as it identifies a sector of approach to ground zero with lesser access limitations, which is visually evident in Fig. 3. Here it is assumed that the stakeholders involved in the disaster response would accept this result as the most favorable region to support the humanitarian supply chain.

5 Conclusion

Disaster management operations require adequate and rapid planning to efficiently serve the affected populations. In this context, an AO must be dimensioned with the main locations capable of receiving command and control, logistic facilities, distribution centers, storage facilities and others. These locations need to be connected by networks capable of ensuring the flow of critical supplies.

This article identified the most influential nodes in disaster management supply chains, using Network Analysis and CPP. The R software and specific packages were used to compute results. CPP is an alternative to other MCDA methods used in this type of problem, such as TOPSIS, by exploring its non-linearity to highlight the best nodes in the network.

Some options for further research are visualized. The establishment of the weights of the arches requires the subjectivity of specialists, being used here three variables considered most important in the analyzed literature. However, other variables can be considered, in order to improve the accuracy of these weights. We also see the possibility of applying the model to other types of networks in disaster management, such as airports and ports, or even interconnecting the different types of nodes.

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Development of Indicators for Monitoring the Regulatory Compliance of Static Equipment in Industrial Plants—an Empirical Study in the Oil and Gas Sector

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Abstract Safety management depends on systematic anticipation, monitoring and development of organizational performance. In this sense, this article aims to develop a set of regulatory compliance indicators based on a Regulatory Standard 13 (NR-13) to propose a tool for monitoring the conformity of static equipment and thus improve the safety of industrial plants. To do this, a mixed-method approach using interviews, focus groups and Multi-criteria decision making (MCDM) model was applied. The results show seven Key performance indicators (KPIs) composed by 14 metrics permeating inspections related to: Coverage, Control Instruments and Devices, Documentary Requirements, Ergonomic Aspects, Operation Safety, Safety inspection and Pendencies. Thus, the proposition of a standardized procedural systematic based on a set of KPIs represents an important contribution towards the automation of legal compliance verification, making it possible to understand the criticality of the verification of certain equipment, reducing the time and cost of processes (efficiency) and increasing plant compliance and quality (effectiveness).

Keywords KPIs · Regulatory compliance · MCDM · NR-13 · Oil & gas

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1 Introduction

The Oil & Gas (O&G) industry contains a characteristic convergence of several dangerous elements that have the potential for both occupational accidents and major disasters. The great challenge of industrial safety is being able to anticipate vulnerabilities, rather than acting reactively [1]. Serious accidents in industrial activities can lead to catastrophic damage such as damage to the company's reputation and fatalities, which highlights the importance of prevention and control tools [2–4]. Therefore, organizations and safety-critical systems must be able to proactively assess and manage the safety of their activities [5]. Safety, however, is a difficult phenomenon to describe, measure, confirm and manage [6]. Safety management depends on systematic anticipation, monitoring and development of organizational performance. In this sense, performance measurement is important for continuous improvement and for identifying and resolving priorities. Performance indicators are a set of measures used to measure the impact on process performance [7].

Currently, several indicators play a key role in providing information about the current performance of the organizational process. An indicator can be considered any measure—quantitative or qualitative—that seeks to produce information on an issue of interest. Indicators can play a key role in providing information on organizational performance, motivating people to work with quality and increasing the organizational safety potential [8].

In addition, the industry is experiencing the fourth revolution (Industry 4.0) that acts as a driving force for improving productivity, the efficiency of socio-technical systems, and the adoption of information and communication technologies (ICT) in a dynamic environment [9–11] consisting of several alternatives and multiple conflicting goals. Considering the complex interactions with industrial systems [6], the need for practical mathematical models associated with technological and analytical solutions to assist managers and decision makers is urgent, and can be important tools for strategic and operational decision making in the real world [12–14]. There is an increasing need for adequate analytical tools and qualified professionals capable of making the right decisions in the presence of multiple criteria, incomplete data, multiple decision agents and even uncertainties [15]. To that end, Multi-criteria decision making (MCDM) has been used to support people and organizations to make more satisfactory decisions under the influence of a variety of criteria [16].

2 Objectives

This research aims to develop indicators for monitoring the regulatory compliance of static equipment in industrial plants. The development of indicators that can compose a system for measuring legal compliance in line with Regulatory Standard 13 (NR-13) and with the organization's safety objectives and documents (checklists for each type of equipment) seeks to obtain a reliable tool for equipment comparison, identification of critical points that may compromise the conformity of operations, as well as the quality performance of processes and the safety, risk and health of workers.

3 Methods

The development of legal conformity assessment indicators involved five steps (see Fig. 1):

In the first step, there was a systematic and structured analysis of the standard and checklists (LVs) for the creation of parameters that will compose a set of metrics. First, the standard was interpreted, through manual coding, an analytical process in which these qualitative data (standard premises) are categorized to facilitate the interpretative analysis of the content. Logically, NR-13 was divided into five categories: coverage, general provisions, pressure vessels, boilers and pipes. Within these categories there are subcategories and the aim is to synthesize the content of the standard in the form of parameters and variables, as well as to understand the dependency relationship between them. Then, the NR-13 checklists of a large company operating in the O & G sector (named in this work as company X) were analyzed. In this analysis, we sought to understand the verification procedures used in the field, to compare the items of the LVs with the interpretation of the NR-13, as well as to obtain the crossing of the information of the LVs and the preliminary list of parameters, in order to complement this list, adding other parameters, thus adjusting the relationships between variables. During the analysis of the LVs, there was also the verification of the automated items. For that, colors were used in Excel spreadsheet to demarcate the difficulty level of automating the items. After completing the survey of parameters, meetings took place in order to define criticality and verify which variables would be feasible to be obtained.

After the survey and adjustment of the automated and critical parameters and the verification of the origin and access of this information, the second step of creating metrics and indicators began. Metrics are the raw variables defined based on the parameters that are being synthesized, while the indicators represent the measures that can be calculated in order to evaluate performance (in percentage). Thus, the indicators are composed of metrics. The empirical knowledge of the consultants of the digital engineering area of a R&D group that is exploring the subject in the

Fig. 1 Research steps

Tecgraf Institute at PUC-Rio was used as a basis and the consensus obtained through internal meetings involving consultants and researchers.

Then, the third step (verification and grouping of metrics) counted on the participation of five professionals from the company X, specialists in inspection of static equipment (pressure vessels, boilers, pipes and tanks) according to NR-13, in which through an interview protocol it was possible to collect information and perform analyzes for the development of legal compliance indicators, in addition to validating the metrics created in internal meetings with Tecgraf consultants. The interviews had an average duration of eight hours and consisted of: description of the research objectives and presentation of the metrics and indicators tables.

The interview protocol consisted of: verifying the agreement or disagreement of specialists in relation to the concept and purpose (validation) of the metrics composed by non-conformity verification parameters; select nine main metrics for each type of equipment and order them in terms of priority, that is, from the most important (1) to the least important (9); and group the metrics according to their gravity (G), urgency (U) and tendency (T)—GUT (grouping by dimension) with a scale of increasing importance from 1 (minimum) to 10 (maximum) for each dimension [17]. The concepts of the GUT matrix were adapted for research, seeking to evaluate the relationship of the metrics with potential non-conformities to be verified/evaluated in the process of verifying the legal compliance of static equipment. In this sense, G indicated the severity effects/impacts that the metric can cause on the quality of the verification of the legal compliance of the projects, U indicated the need to implement the metric for the use of the project equipment; and T indicated the frequency of a recurring pending metric to happen.

Based on the results of the interviews, a multicriteria analysis was performed, considering the three criteria (dimensions G, U and T) and multidecisor, grouping the responses of the five experts interviewed. In addition to this, a multidecisor analysis was also performed for each criterion. To calculate the GUT and each dimension, the TOPSIS method (Technique for Order of Preference by Similarity to Ideal Solution) was used, which is commonly applied to ranking problems. As [18], the TOPSIS technique for ordering preference by similarity for the ideal solution was first developed by [19], in order to solve a decision-making problem with multiple attributes and this provided the principle of commitment in which the chosen alternative should be the one with the shortest distance from the Positive Ideal Solution (PIS) and the one with the greatest distance from the Negative Ideal Solution (NIS). Thus, the TOPSIS method was chosen, as according to [20], it is adequate to model precisely known quantitative criteria values, the data collection process is less complex and requires less judgments. According to [21], the idea of the TOPSIS method can be expressed in the following stages:

Stage 1: Determination of the objectives in order to develop the decision matrix (Performance Matrix—PM) with m alternatives and n criteria, whereas the intersection between each alternative and criterion is given by x_{ij}, thus obtaining the matrix $\left(X_{ij}\right)_{ij}$;

$$PM = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

Stage 2: Normalize the performance matrix for $R^* = \left(r_{ij}\right)$. In this research we use the vectoral normalization method, according to $r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$

Stage 3: Matrix weighting: it is required to develop a set of values regarding the relative importance of different alternatives. Hence, it is developed a set of values w_k to each criterion. This weighting factor may be ad hoc reflex from relative importance, according to the formulation below;

$$V_{ij} = \left(w_{ij}\right)_{m_x n} = \left(w_j r_{ij}\right)_{m_x n} \tag{2}$$

In which w_j is the scale value for the criterion j, and $\sum_{i=1}^{n} w_j = 1$.

Stage 4: Identify and compute the ideal alternative (PIS);

Stage 5: Identify and compute the anti-ideal alternative (NIS);

Stage 6: Obtain distance measures based on the Euclid distance, thus developing an ideal distance measure for the ideal point $\left(D_i^+\right)$ and for the anti-ideal point $\left(D_i^-\right)$, given as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - s_{ij}^+\right)^2}, for \;\; i = 1, 2, \ldots, m \tag{3}$$

$$D_i^- = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - s_{ij}^-\right)^2}, for \;\; i = 1, 2, \ldots, m \tag{4}$$

Stage 7: Determine the R index, defined below:

$$R_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{5}$$

Stage 8: Obtain the ranking order according to the maximization of the values calculated in the step 7.

Then, in the fourth step (prioritization of metrics), the following criteria were used: the order (ranking) generated from the GUT multicriteria and multidecisor analysis, the frequency of the selected metrics from the ranking of metrics considered most important in the interviews, and the emphasis given to the metrics for the discussion (consensus) of focus groups, involving consultants and researchers. Thus, to prioritize the metrics, we sought to offer a more comprehensive point of view [22] based on the use of a mixed methodology (qualitative and quantitative) [23] balanced by three