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Critical Success Factors of the Reliability-Centred Maintenance Implementation in the Oil and Gas Industry

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Received: 5 August 2020; Accepted: 18 September 2020; Published: 23 September 2020

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Abstract: Reliability-Centred Maintenance (RCM) is a strategic process to improve the maintenance planning of companies which contributes to sustainable production. This method has been applied by numerous industries to achieve an efficient maintenance process, but many have not fully completed their goals. The reason for this failure is that RCM implementation is complex, and organisations need to have adequate preparations before they implement it. In the pre-implementation phase, it is necessary to know the number of Critical Success Factors (CSFs) as a critical measure for implementing the RCM method successfully. Therefore, it is important for practitioners to apply a symmetric mechanism involving fuzzy systems to achieve the desired RCM implementation. There are a limited number of studies that have observed these factors regarding the characteristics of oil and gas companies, especially in the pre-implementation phase. Addressing RCM pre-implementation issues is of high importance from the economic perspective of sustainability for oil and gas organisations. The objective of this study is to investigate significant items in RCM pre-implementation through a combination of quantitative and qualitative analyses. The Nominal Group Technique (NGT) method is applied by gaining the opinion of experts to determine the factors and prioritising them using mathematical modelling. A group of related experts from the oil and gas industry were initially interviewed and surveyed to determine the critical success factors. These identified factors were then analysed using quantitative analysis to identify the important degrees and scored using Fuzzy Analytic Network Process (FANP). Fifteen major factors affecting the criticality of successful RCM implementation have been identified and prioritised, based on their weights. The model proposed in this study could be used as a guideline for assessing CSFs in other countries. To apply the proposed model in different contexts, it needs to be modified according to the needs, policies, and perspectives of each country.

Keywords: reliability centred maintenance (RCM); critical success factors (CSFs); nominal group technique (NGT); fuzzy analytic network process (FANP); oil and gas industry

1. Introduction

Managers are now looking for various maintenance disciplines to rationalise the achievement of their business in the face of ongoing challenges to improve plant reliability at a lower cost [1]. In this regard, Reliability Centred Maintenance (RCM) is defined as a systematic methodology for the optimisation and development of the maintenance requirements of a physical resource [2]. It has been recently found to be the most efficient strategy in comparison with the existing supervision of maintenance strategies [2]. This method has been successfully applied for more than 30 y in several industries, such as aircraft, military forces, nuclear power, and oil and gas companies [3]. Research has confirmed that the RCM method is imperative to reduce maintenance costs and improve the effectiveness of the maintenance systems [4]. It enables the organisation to minimise maintenance duration and create a safe environment, which has been an issue of concern to manufacturers [5]. An application of the RCM method is imperative for organisations to optimise their maintenance activities and to develop a cost-effective method for managing their maintenance procedures [6]. Wang et al. [7] concluded that the system operates under a performance-based contract. RCM helps service providers to increase profits and improve system performance at lower costs. Similar to them, Ma et al. [8] confirmed the maintenance cost is minimised via RCM implementation in their case study, namely, a warm standby cooling system.

Especially in the oil and gas industry, there is an ongoing emphasis on cost management, where prices are very flexible and vulnerable to changes in supply and demand [9]. Oil and gas plants produce a wide range of products used as chemicals and fuels, so, maintenance activities within them remarkably affect their productivity. The use of RCM can help organisations develop a systematic maintenance program, meeting these requirements in a cost-effective manner [9].

The RCM methods have a close link to sustainability [10]. An organisation that strives towards effective sustainability requires effective RCM practices and technologies [11]. However, the organisation still faces difficulty and even failure during the RCM implementation. Plucknette [12] stated that based on the survey of more than 250 companies, over 85% of the RCM analysis had not been completely implemented. While the fundamental notion of the RCM method is simple, its implementation is tremendously complicated [13].

An organisation should have effective preparations before they transform their conventional maintenance systems towards RCM [14]. One of the essential processes in the pre-implementation phase is considering several Critical Success Factors (CSFs), used as an important measure to implement the RCM methods successfully. Practitioners often ignore this preparation phase. This problem also emerged in Iranian manufacturing organisations. Numbers of companies in Iran have considered the vital role of the RCM to enhance the effectivity and efficiency of the equipment and machinery [15]. This approach has not been applied effectively in Iranian oil industries as it needs proper preparation for planning [16]. RCM implementation is complex, and organisations need to have adequate preparations before they implement the RCM methods. In the pre-implementation phase, the number of CSFs, as a key measure to implement the RCM methods successfully, is necessary. The practitioners often skip this pre-implementation phase. As a result, the majority of the manufacturing companies face many problems during the implementation process since they do not have a sufficient preparation plan.

There are a small number of RCM researches that aimed to identify and prioritise the critical factors for implementing RCM regarding the characteristics of oil and gas organisations [16]. The majority of them focused on the implementation process without considering the important processes in the pre-implementation phase. To fill this gap, this study is conducted to identify the CSFs which are imperative to be addressed by oil and gas organisations using symmetric mechanism involving fuzzy systems to achieve the desired RCM implementation. It is done using the Nominal Group Technique (NGT) and Fuzzy Analytic Network Process (FANP). The Analytic Network Process (ANP) is generally used to rank the decisions without creating assumptions about the unidirectional hierarchy relationship between decision levels. As ANP lacks a comprehensive consideration of human intelligence in modelling, fuzzy models have been applied as they have better compatibility with linguistic explanations and are often ambiguous for making long-term predictions and for making real-world decisions [17]. Fuzzy logic has been widely applied in numerous fields such as optimisation, systems engineering, and image processing [18].

The structure of this paper is organised as follows. Section 2 provides an analysis of related studies, which culminates with the identification of the knowledge gap. Section 3 explains the research process of the present study. Section 4 presents the data analysis and discussion of the research findings. Section 5 concludes the study and recommends the numbers of potential research directions.

2. Literature Review

A concept that has changed in the Prognostics and Health Management (PHM) implementation from seeking the remaining useful life to determining extendable useful life [19]. Research in RCM area has been rapidly growing these years because of increasing challenges and expectations of maintenance [14]. The topic in the RCM area includes RCM implementation, optimisation of the method, integration between the RCM with other techniques, risk reduction, and evaluation of the RCM failures [2]. This study categorised the topics into three phases: RCM pre-implementation, implementation and post-implementation, as shown in Figure 1.

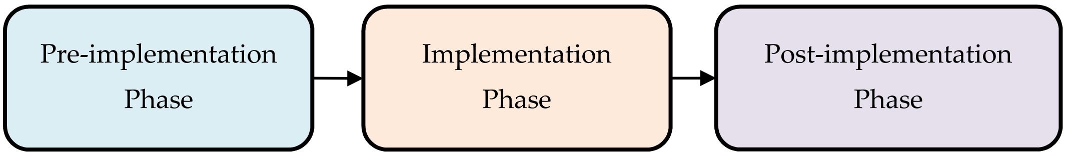

Figure 1. Reliability Centred Maintenance (RCM) implementation phases.

Tang et al. [14] mentioned that the screening phase is one of the critical steps of the RCM implementation, which is named as the pre-implementation phase, as provided in Figure 1. This phase of RCM focuses on assessing and providing the necessary preparations before RCM implementation. There is rarely a systematic operation method to identify the CSFs of RCM pre-implementation. In their research, Tang et al. [14] presented a framework for the identification of the maintenance of significant items through a mixture of quantitative and qualitative analysis.

In the power system industry, Afzali et al. [20] presented new weighted importance (WI) reliability index model. They proposed an applicable method to rank the components of the RCM distribution system for RCM at two different levels. First, the sample feeder substation feeder is ranked for the RCM action. The sample feeder component is then rated for the RCM action. In another study, Alvarez-Alvarado and Jayaweer [21] found RCM as a popular method in that industry. They proposed an innovative smart maintenance model through three main concepts, namely Markov chains to describe the reliability of component, Fuzzy logic to determine the operational risk of component, and maintenance exertion degree to define the impact of maintenance over the component failure rate. In electric power distribution systems, Piasson et al. [22] proposed a model to optimise the RCM implementation by reducing the maintenance costs and increasing the index of systems reliability. They evaluated the reliability indices of the components using a fuzzy inference system and proposed a Non-Dominated Sorting Genetic Algorithm II (NSGA-II) algorithm to resolve multi-objective models that provide an optimised Pareto frontier. Yssaad and Abene [23] optimised the application of RCM using reliability, availability, and maintainability studies to advance the power distribution systems.

Zakikhani et al. [13] developed a framework for maintenance scheduling for the external corrosion of gas transmission pipelines using the RCM planning technique. This framework is designed based on the pipeline reliability outline obtained from the Monte Carlo simulation. They discovered that the maintenance method developed only relied on the consideration of reliability, cost, and condition levels as the criteria for maintenance decisions and discounted the significance of continues action and accessibility.

Rahmati et al. [15] proposed a new stochastic RCM procedure in a new multi-objective joint maintenance and production planning problem. They used four multi-objective simulation-based optimisation algorithms to resolve the issues as they belong to the Non-deterministic Polynomial-time Hardness (NP-Hard) class of optimisation problems. These four multi-objective simulations are the multi-objective biogeography based optimisation algorithm, the Pareto envelope-based selection algorithm, a new version of the Non-Dominated Sorting Genetic Algorithm (NSGAIII), and multi-objective evolutionary algorithm based on decomposition. A new combined visualisation method using the Gant chart is also projected to discuss the entire RCM scheme in a systematic manner.

Piechnicki et al. [24] designed a conceptual framework that adapts tacit and explicit information from maintenance functions. Their study generates a new knowledge base that is used to analyse and improve decisions on implementing customised RCM models. They used multi-criteria decision making analysis techniques to support decisions in the RCM implementation stage. Data-driven prognostic approaches are also studied for equipment maintenance [25].

Tang et al. [14] developed a framework to identify the critical maintenance items in RCM using qualitative and quantitative analysis to advance the effectiveness and efficiency of the maintenance policy. They used the multiple risk matrix, Failure Mode and Effects Analysis (FMEA), Analytic Hierarchy Process (AHP), and Fuzzy Borda Count methods to do their research. Reliability-based maintenance modelling was also employed to enhance the rolling stock objectives of manufacturers [26]. Similarly, Yavuz [27] confirmed the effectiveness of the RCM approach in the food industry.

Regarding the characteristics of oil and gas organisations, there are few scientific maintenance studies which are explicitly conducted to improve the reliability of the refinery unit [28]. Petrochemical industries are classified as high-risk companies, and the application of suitable maintenance strategies is imperative to reduce costs, to improve quality, minimise equipment downtime, and increase productivity [29]. The components of refinery equipment are explosive, flammable, and toxic, so it is necessary to carry out an effective maintenance plan to ensure safety and reliability [28]. The oil and gas industry has still an essential role in the economic growth of most developing countries [30], and the success or failure of maintenance programs may depend on adequate identification and consideration of CSFs.

The literature review confirmed that, when paired with RCM policy, maintenance tasks in the oil and gas industry will perform in an efficient, reliable, cost-effective, and safe manner [9]. There is a variety of research in the RCM subject [31]; however, there are fewer studies that concern the preliminary implementation of the RCM, such as the determination of important factors of success, particularly in oil and gas companies. These factors are the core elements of a maintenance plan that it views as the most important task before the RCM implementation. Practitioners in organisations need to evaluate these factors to accomplish successful RCM implementation and reduce failure risks. This knowledge gap motivates the present study to identify numbers of CSFs as a key measure to achieve successful implementation of the RCM. The identification uses the Fuzzy Analytic Network Process (FANP) to address the uncertainty and imprecision in the prioritisation process.

3. Materials and Methods

A Nominal Group Technique (NGT), which involves qualitative and quantitative analysis [32], is applied to collect and analyse the data. This technique is chosen because it is a structured technique for group brainstorming, that encourages contributions from everyone and facilitates quick agreement on the relative importance of issues [33]. The experts should make their decision using the votes and opinions of everyone.

There are two main phases of our research methodology: (i) Determining the success factors of the RCM implementation, and, (ii) Prioritising them. A schematic overview of the research method in this study is provided in Figure 2. A nominal group technique is adopted to refine the factors and make pairwise comparisons, and the fuzzy ANP method is used to evaluate the relative importance and prioritise the identified success factors.

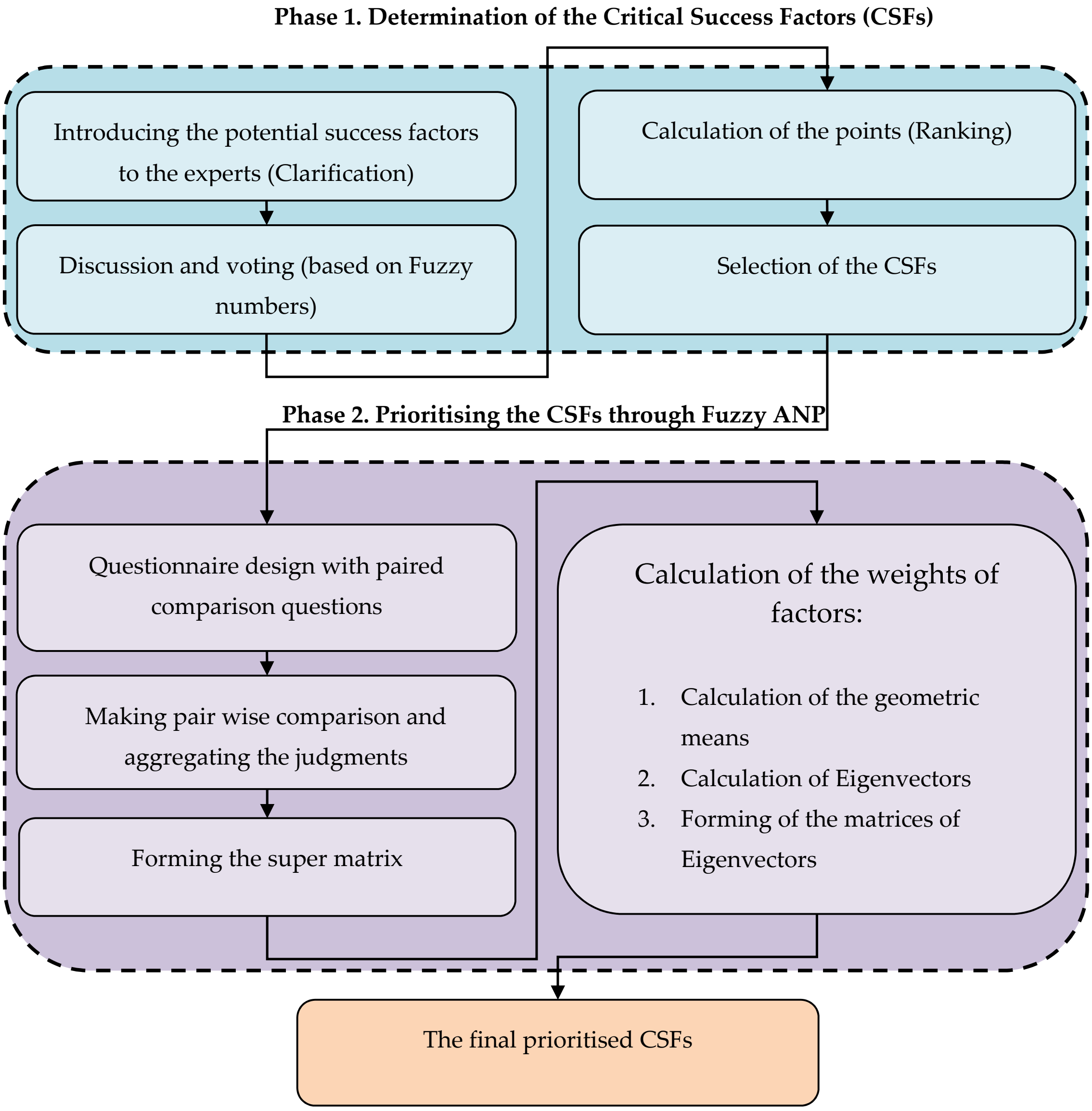

Figure 2. Research flow of the study

As shown in Figure 2, a preliminary list of success factors, consisting of 20 items, was identified based on a review of the literature and surveys. These success factors are then introduced to the RCM team, which includes ten experts and managers from technical and engineering departments, the strategic planning and development deputy, the support and logistics deputy, and the human resources, deputy. This team has been selected at the discretion of the managers of Persian Gulf Star Oil Company. It involves people who have been responsible for the maintenance of company and repair program.

The initial factors were validated, modified and scored by team members through discussion and voting, which resulted in 15 CSFs. These CSFs were then prioritised using fuzzy ANP, as shown in phase 2. The Analytic Network Process (ANP) is an extension of the analytical hierarchy process which allows analysis of complex systems. As there are limitations in the determination of success factors, to make better decisions in this process, the weights of factors are determined by using fuzzy ANP. In FANP, the importance weights of criteria can be evaluated using linguistic values represented by fuzzy numbers. This technique enables one to overcome uncertainties and inaccuracies in the priority setting process.

In phase 2, a questionnaire for paired comparisons is developed. The RCM team members filled in the surveys and the aggregated pairwise comparison matrices are calculated based on their responses. To obtain the final priorities in a system that is affected by internal dependence, local priority vectors are entered in proportion to the columns of the matrix, which is known as the supermatrix. Based on this matrix, the weights of factors were calculated, through four steps and the critical factors influencing the success of RCM pre-implementation are prioritised.

4. Results

According to Figure 2, this study was completed in two main phases, namely, determination of the CSFs and prioritising them through the formation of the supermatrix and calculation of the weight of factors using FANP. The calculations are made, and the results obtained from the various stages of the research are presented in this section.

4.1. Determination of the Critical Success Factors

The determination of the CSFs was done via discussions with a group of experts through the NGT. The descriptive statistics related to the identified factors are summarised in Table 1. These values were calculated based on the analysis of the data gathered by the questionnaires.

Table 1. The descriptive statistics

Symbol	Sum	Mean	Mode	Max	Min	Standard Error	Variance	Skewness	Kurtosis
F1	78	7.8	7	9	7	0.75	0.56	0.41	−1.07
F2	43	4.3	4	6	3	0.90	0.81	0.23	−0.35
F3	81	8.1	8	9	7	0.70	0.49	−0.17	−0.73
F4	79	7.9	7	10	7	1.04	1.09	0.86	−0.52
F5	65	6.5	6	8	5	0.81	0.65	0.00	0.11
F6	81	8.1	8	10	7	0.94	0.89	0.61	−0.16
F7	61	6.1	7	7	5	0.83	0.69	−0.22	−1.73
F8	59	5.9	6	8	5	0.94	0.89	1.08	0.91
F9	43	4.3	4	5	3	0.64	0.41	−0.43	−0.28
F10	77	7.7	7	10	6	1.10	1.21	0.73	0.51
F11	71	7.1	7	8	6	0.70	0.49	−0.17	−0.73
F12	83	8.3	9	10	7	1.00	1.01	−0.04	−1.24
F13	47	4.7	5	6	3	0.90	0.81	−0.23	−0.35
F14	55	5.5	6	7	3	1.20	1.45	−0.82	0.25
F15	61	6.1	5	8	5	1.04	1.09	0.39	−1.24
F16	63	6.3	5	8	5	1.19	1.41	0.14	−1.77
F17	37	3.7	2	7	2	1.79	3.21	1.16	0.17
F18	52	5.2	5	6	4	0.60	0.36	−0.13	0.18
F19	39	3.9	2	9	1	2.62	6.89	0.92	−0.67
F20	69	6.9	7	10	5	1.58	2.49	0.56	−0.04

Sum: Summation function; Mean: The average of the numbers; Mode: The number that appears most frequently in a data set; Max: Maximum function; Min: Minimum function.

The symbols, F1 to F10, are related to the "Items", introduced in Table 2. Small values of skewness and kurtosis indicate that in most cases, the data have a normal distribution [34]. The items were scored using linguistic values represented by fuzzy numbers. The linguistic scales and their fuzzy levels in this study are developed in the following Table 3.

Table 2. The scored items for successful implementation of RCM.

No.	Status of Item	Score	Items	Symbol
1	Accepted	78	Skilled human resources	F1
2	Rejected	43	Needs assessment for CMMS (Computerized Maintenance Management System)	F2
3	Accepted	81	Sufficient budget	F3
4	Accepted	79	Awareness of the need for improved maintenance programs in the organisation	F4
5	Accepted	65	Technical knowledge and using the best way to select critical equipment for RCM analysis	F5
6	Accepted	81	Sufficient time	F6
7	Accepted	61	Training	F7
8	Accepted	59	RCM knowledge among managers	F8
9	Rejected	43	Shortage of the main parts of the equipment	F9
10	Accepted	77	Understand the need to establish an RCM strategy	F10
11	Accepted	71	Paying attention to maintenance strategies to reduce costs	F11
12	Accepted	83	Motivation among staff	F12
13	Rejected	47	Economic sanctions	F13
14	Accepted	55	Teamwork	F14
15	Accepted	61	RCM knowledge among staffs	F15
16	Accepted	63	Accessibility to machinery information	F16
17	Rejected	37	Safety and environmental issues	F17
18	Accepted	52	Capability to change the design of equipment	F18
19	Rejected	39	Responsiveness of the top management	F19
20	Accepted	69	Staffs' commitment	F20

Table 3. The linguistic scales for relative importance.

Code	Linguistic Scale	Triangular Fuzzy Scale
1	Complete equal importance	(1,1,1)
2	Nearly equal importance	(0.5,1,1.5)
3	Low importance	(1,1.5,2)
4	High importance	(1.5,2,2.5)
5	Very high importance	(2,2.5,3)
6	Completely high importance	(2.5,3,3.5)

The calculated values of the scores related to all 20 factors are given in Table 2. Those that scored less than 50 points were eliminated, while the items receiving more than 50 points are considered as the CSFs.

As provided in Table 2, fifteen success factors scored more than 50, and five factors had a score of less than 50. The final fifteen CFSs for pre-implementation of RCM are listed as follows:

1. Skilled human resources
2. Sufficient budget
3. Awareness of the need for improved maintenance programs in the organisation
4. Technical knowledge and using the best way to select critical equipment for RCM analysis
5. Sufficient time
6. Training
7. RCM knowledge among managers
8. Understand the need to establish an RCM strategy
9. Paying attention to maintenance strategies to reduce costs
10. Motivation among staffs
11. Teamwork

12. RCM knowledge among staff
13. Accessibility to machinery information
14. Capability to change the design of equipment
15. Staffs' commitment

4.2. Prioritising the CSFs through Fuzzy ANP

A questionnaire with paired comparison questions was designed, validated, and distributed among the experts to rank the identified CSFs. The pairwise comparisons matrix based on the collected data was formed. A summary of the supermatrix analysis for obtaining the weights of factors was derived, based on the work of Gogus and Boucher [35]. Each of the local priority vectors was entered as a part of the matrix column, known as supermatrix. This partitioned matrix represents the effect of the element to the left of the matrix on the element at the top of the matrix. The supermatrix serves as a unifying framework [36]. Its general form is shown in Figure 3.

$$
\begin{array}{ccc}
 & & \begin{array}{cccccccccccccc} C_1 & & & & \cdots & C_k & & & & \cdots & C_n & & & \\ e_{11} & e_{12} & \cdots & e_{1m_1} & \cdots & e_{k1} & e_{k2} & \cdots & e_{km_k} & \cdots & e_{n1} & e_{n2} & \cdots & e_{nm}\end{array} \\
W = & \begin{array}{cc} C_1 & \begin{array}{c} e_{11}\\ e_{12}\\ \vdots \\ e_{1m_1}\end{array} \\ \vdots & \vdots \\ C_k & \begin{array}{c} e_{k1}\\ e_{k2}\\ \vdots\\ e_{km_k}\end{array} \\ \vdots & \vdots \\ C_n & \begin{array}{c} e_{n1}\\ e_{n2}\\ \vdots\\ e_{nm}\end{array}\end{array} & \begin{bmatrix} w_{11} & \cdots & w_{1k} & \cdots & w_{1n} \\ \vdots & & \vdots & & \vdots \\ w_{k1} & \cdots & w_{kk} & \cdots & w_{kn} \\ \vdots & & \vdots & & \vdots \\ w_{n1} & \cdots & w_{nk1} & \cdots & w_{nn}\end{bmatrix}
\end{array}
$$

Figure 3. A generalised supermatrix (adopted from Asan et al. [36]).

In Figure 3, C_m means the mth cluster with n_m elements symbolised as e_{m1}, e_{m2}, ..., e_{mn}, where e_{mn} represents the nth element in the mth cluster. W_{ij} is a block matrix consisting of principal eigenvectors representing the influence of the elements in the ith cluster on the elements in the jth cluster.

4.2.1. Calculation of the Geometric Means

The geometric means of the paired wise comparisons are presented in Table 4. They were obtained via calculation of the square root of multiplying of the high and low limits of triangular numbers, namely, $A^g = \sqrt{a_{iju}.a_{ijl}}$.

The weight vectors of each matrix should be calculated using $w^m = [w_i^m]$ and $w^g = [w_i^g]$ by considering the Equations (1) and (2), which are developed in this study.

$$w_i^m = \frac{1}{n}\sum_{j=1}^{n} \frac{a_{ijm}}{\sum\limits_{i=1}^{n} a_{ijm}} \tag{1}$$

$$w_i^g = \frac{1}{n}\sum_{j=1}^{n} \frac{\sqrt{a_{iju}.a_{ijl}}}{\sum\limits_{i=1}^{n} \sqrt{a_{iju}.a_{ijl}}} \tag{2}$$

For this matrix, the Consistency Ratios (CR) obtained were 0.037 and 0.096, which are less than 0.1, meaning the matrix is compatible.

4.2.2. Calculation of the Eigenvectors

The Eigenvectors were calculated using the logarithmic method of the least squares, which is shown in Equation (3).

$$w_k^s = \frac{\left(\prod\limits_{j=1}^{n} a_{kj}^s\right)^{\frac{1}{n}}}{\sum\limits_{i=1}^{n}\left(\prod\limits_{j=1}^{n} a_{ij}^m\right)^{\frac{1}{n}}}, \quad s \in \{l,\ m,\ u\} \tag{3}$$

$$\widetilde{w}_k = (w_k^l,\ w_k^m,\ w_k^u) \quad k = 1,2,3,\ldots,n$$

The values of Eigenvectors are presented in the last row of Table 3.

4.2.3. Forming of the Matrices of Eigenvectors

Based on the Eigenvectors values, the Principal Eigenvectors matrix is calculated in this study and presented in Table 5.

Table 4 contains Eigenvectors that show internal dependencies between factors. If there is no relationship between the two elements, the value of (0,0,0) is considered.

4.2.4. Calculation of the Final Weights

For calculating the final weight of items for each surface (W_i^*), the following formulas were applied.

$$W_i^* = W_{ii} \times W_{i(i-1)} \times W_{i-1}^* \tag{4}$$

$$W_i^* = I \times W_{i(i-1)} \times W_{i-1}^* \tag{5}$$

According to Equations (4) and (5), the final weights were calculated, and the results are shown in Table 6.

Table 4. The geometric means of pairwise comparisons and Eigenvectors

	F1	F3	F4	F5	F6	F7	F8	F10	F11	F12	F14	F15	F16	F18	F20	Eigenvector
F1	(1,1,1)	(0.5,0.667,1)	(0.4,0.5,0.667)	(0.4,0.5,0.667)	(1,1.5,2)	(0.5,1,1.5)	(1,1.5,2)	(0.5,1,1.5)	(0.5,1,1.5)	(1,1.5,2)	(1.5,2,2.5)	(1,1.5,2)	(0.5,1,1.5)	(1.5,2,2.5)	(0.5,1,1.5)	(0.046,0.07,0.096)
F3	(1,1.5,2)	(1,1,1)	(0.5,0.667,1)	(0.5,0.667,1)	(1.5,2,2.5)	(0.5,1,1.5)	(0.5,1,1.5)	(0.5,1,1.5)	(1,1.5,2)	(1.5,2,2.5)	(0.5,1,1.5)	(0.5,1,1.5)	(0.5,1,1.5)	(1,1.5,2)	(0.5,1,1.5)	(0.045,0.073,0.102)
F4	(1.5,2,2.5)	(1,1.5,2)	(1,1,1)	(1,1.5,2)	(1.5,2,2.5)	(1.5,2,2.5)	(1,1.5,2)	(1,1.5,2)	(1.5,2,2.5)	(2,2.5,3)	(1,1.5,2)	(0.5,1,1.5)	(1,1.5,2)	(2,2.5,3)	(0.5,1,1.5)	(0.072,0.104,0.134)
F5	(1.5,2,2.5)	(1,1.5,2)	(0.5,0.667,1)	(1,1,1)	(0.5,1,1.5)	(1,1.5,2)	(1.5,2,2.5)	(1.5,2,2.5)	(1.5,2,2.5)	(2,2.5,3)	(1,1.5,2)	(1,1.5,2)	(0.5,1,1.5)	(2,2.5,3)	(1,1.5,2)	(0.069,0.098,0.128)
F6	(0.5,0.667,1)	(0.4,0.5,0.667)	(0.4,0.5,0.667)	(0.667,1,2)	(1,1,1)	(0.4,0.5,0.667)	(1,1.5,2)	(0.5,0.667,1)	(0.5,0.667,1)	(0.667,1,2)	(1,1.5,2)	(0.4,0.5,0.667)	(0.333,0.4,0.5)	(2,2.5,3)	(0.667,1,2)	(0.04,0.053,0.075)
F7	(0.667,1,2)	(0.667,1,2)	(0.4,0.5,0.667)	(0.5,0.667,1)	(1.5,2,2.5)	(1,1,1)	(0.5,1,1.5)	(0.5,1,1.5)	(0.5,0.667,1)	(1,1.5,2)	(1.5,2,2.5)	(1.5,2,2.5)	(1,1.5,2)	(2,2.5,3)	(1,1.5,2)	(0.055,0.078,0.109)
F8	(0.5,0.667,1)	(0.667,1,2)	(0.5,0.667,1)	(0.4,0.5,0.667)	(0.5,0.667,1)	(0.667,1,2)	(1,1,1)	(0.4,0.5,0.667)	(0.667,1,2)	(0.5,0.667,1)	(1,1.5,2)	(0.667,1,2)	(0.5,1,1.5)	(0.5,1,1.5)	(0.5,1,1.5)	(0.037,0.055,0.084)
F10	(0.667,1,2)	(0.667,1,2)	(0.5,0.667,1)	(0.4,0.5,0.667)	(1,1.5,2)	(0.667,1,2)	(1.5,2,2.5)	(1,1,1)	(1,1.5,2)	(0.5,1,1.5)	(0.5,1,1.5)	(0.5,0.667,1)	(0.5,1,1.5)	(0.5,1,1.5)	(0.5,0.667,1)	(0.042,0.063,0.094)
F11	(0.667,1,2)	(0.5,0.667,1)	(0.4,0.5,0.667)	(0.4,0.5,0.667)	(1,1.5,2)	(1,1.5,2)	(0.5,1,1.5)	(0.5,0.667,1)	(1,1,1)	(0.5,1,1.5)	(0.5,0.667,1)	(0.5,0.667,1)	(1,1.5,2)	(0.5,1,1.5)	(0.5,0.667,1)	(0.039,0.056,0.08)
F12	(0.5,0.667,1)	(0.4,0.5,0.667)	(0.333,0.4,0.5)	(0.333,0.4,0.5)	(0.5,1,1.5)	(0.5,0.667,1)	(1,1.5,2)	(0.667,1,2)	(0.667,1,2)	(1,1,1)	(1,1.5,2)	(1,1.5,2)	(1,1.5,2)	(1,1.5,2)	(1.5,2,2.5)	(0.045,0.062,0.087)
F14	(0.4,0.5,0.667)	(0.667,1,2)	(0.5,0.667,1)	(0.5,0.667,1)	(0.5,0.667,1)	(0.4,0.5,0.667)	(0.5,0.667,1)	(0.667,1,2)	(1,1.5,2)	(0.5,0.667,1)	(1,1,1)	(0.5,1,1.5)	(0.5,1,1.5)	(0.5,0.667,1)	(0.4,0.5,0.667)	(0.035,0.049,0.073)
F15	(0.5,0.667,1)	(0.667,1,2)	(0.667,1,2)	(0.5,0.667,1)	(1.5,2,2.5)	(0.4,0.5,0.667)	(0.5,1,1.5)	(1,1.5,2)	(1,1.5,2)	(0.5,0.667,1)	(0.667,1,2)	(1,1,1)	(1,1.5,2)	(1,1.5,2)	(0.5,1,1.5)	(0.046,0.067,0.098)
F16	(0.667,1,2)	(0.667,1,2)	(0.5,0.667,1)	(0.667,1,2)	(2,2.5,3)	(0.5,0.667,1)	(0.667,1,2)	(0.667,1,2)	(0.5,0.667,1)	(0.5,0.667,1)	(0.667,1,2)	(0.5,0.667,1)	(1,1,1)	(0.5,0.667,1)	(0.4,0.5,0.667)	(0.041,0.056,0.09)
F18	(0.4,0.5,0.667)	(0.5,0.667,1)	(0.333,0.4,0.5)	(0.333,0.4,0.5)	(0.333,0.4,0.5)	(0.333,0.4,0.5)	(0.667,1,2)	(0.667,1,2)	(0.667,1,2)	(0.5,0.667,1)	(1,1.5,2)	(0.5,0.667,1)	(1,1.5,2)	(1,1,1)	(0.5,0.667,1)	(0.035,0.046,0.066)
F20	(0.667,1,2)	(0.667,1,2)	(0.667,1,2)	(0.5,0.667,1)	(0.5,1,1.5)	(0.5,0.667,1)	(0.667,1,2)	(1,1.5,2)	(1,1.5,2)	(0.4,0.5,0.667)	(1.5,2,2.5)	(0.667,1,2)	(1.5,2,2.5)	(1,1.5,2)	(1,1,1)	(0.049,0.07,0.106)

Table 5. The Principal Eigenvectors matrix

	F1	F3	F4	F5	F6	F7	F8	F10	F11	F12	F14	F15	F16	F18	F20
F1	(0.5,0.5,0.5)	(0,0,0)	(0.102,0.124,0.163)	(0.072,0.099,0.134)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F3	(0,0,0)	(0.5,0.5,0.5)	(0.129,0.163,0.205)	(0.102,0.134,0.171)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F4	(0.245,0.3,0.346)	(0.245,0.3,0.346)	(0.5,0.5,0.5)	(0.134,0.176,0.215)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F5	(0.173,0.2,0.245)	(0.173,0.2,0.245)	(0.163,0.213,0.258)	(0.5,0.5,0.5)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F6	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,1)	(0.245,0.3,0.346)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F7	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0.5,0.5,0.5)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F8	(0,0,0)	(0,0,0)	(0,0,0)	(0.073,0.092,0.13)	(0,0,0)	(0,0,0)	(1,1,1)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F10	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,1)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F11	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,1)	(0.173,0.2,0.245)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F12	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0.5,0.5,0.5)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F14	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,1)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)
F15	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,1)	(0,0,0)	(0,0,0)	(0,0,0)
F16	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,1)	(0,0,0)	(0,0,0)
F18	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0.173,0.2,0.245)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,1)	(0,0,0)
F20	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0.245,0.3,0.346)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,1)

Table 6. The final sorted weights of the CSFs.

No.	Symbol	Final Fuzzy Weight	The Final Weight of Items
1	F4	(0.068,0.112,0.163)	0.113
2	F5	(0.062,0.1,0.147)	0.101
3	F20	(0.06,0.089,0.136)	0.092
4	F6	(0.053,0.076,0.113)	0.078
5	F11	(0.046,0.069,0.102)	0.07
6	F3	(0.039,0.067,0.1)	0.068
7	F15	(0.046,0.067,0.098)	0.068
8	F8	(0.042,0.064,0.101)	0.066
9	F10	(0.042,0.063,0.094)	0.065
10	F18	(0.044,0.062,0.093)	0.064
11	F1	(0.035,0.058,0.087)	0.059
12	F16	(0.041,0.056,0.09)	0.059
13	F14	(0.035,0.049,0.073)	0.051
14	F7	(0.027,0.039,0.054)	0.04
15	F12	(0.022,0.031,0.043)	0.032

According to Table 6, it can be concluded that the most important factors are formulated in Figure 4. Most of these items are discussed in other improvement projects, such as the variation of CSFs with different degrees of importance. The key to building a successful RCM project starts with a pre-implementation phase. In this phase, some questions that need to be answered are: How much it costs? Do we have the necessary resources? Who will be responsible for leading the effort? Do the manager and staff have sufficient knowledge about RCM? How do you manage the implementation of RCM tasks? Who will be involved? The spirit of employees' cooperation before the implementation of RCM also needs to be increased to support the success of RCM pre-implementation.

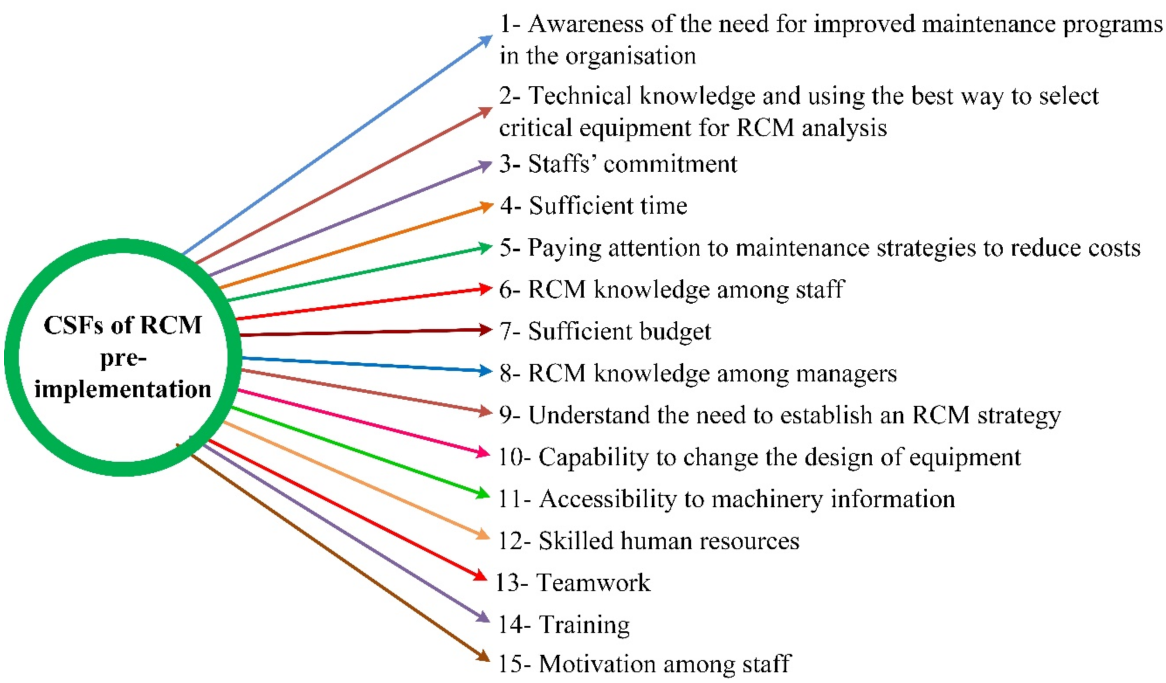

Figure 4. The prioritised CSFs of RCM in the pre-implementation phase.

5. Conclusions

A nominal group technique has been applied as a general methodology in this study. This method involves two main processes: (i) Determination of the CSFs using expert's group discussion, and (ii)

Prioritising the determining factors using Fuzzy ANP. As a result, fifteen success factors are important to be considered by organisations before they implement the RCM. Awareness of the need for improved maintenance programs in the organisation was classed as the highest priority, with a final weight of 0.113, followed by technical knowledge and using the best way to select critical equipment for RCM analysis, with a final weight of 0.101. The third priority is staffs' commitment with a final weight of 0.092. The fourth priority is sufficient time, with a final weight of 0.078. The fifth priority is paying attention to maintenance strategies to reduce costs, with a final weight of 0.07. The sixth and seventh priorities are sequentially placed by RCM knowledge among staff and a sufficient budget, which received a similar final weight of 0.068. The eighth priority is RCM knowledge among managers, with a final weight of 0.066. The ninth priority is understanding the need to establish an RCM strategy, with a final weight of 0.065. The tenth priority is the capability to change the design of equipment, with a final weight of 0.064. The eleventh and twelfth priorities are consecutively represented by accessibility to machinery information and skilled human resources, with similar final weights of 0.059. The thirteenth priority is teamwork, with a final weight of 0.051. The fifteenth priority is training, with a final weight of 0.04. The lowest priority is the motivation among staff, with a final weight of 0.032.

This study contributes to both theoretical development and practice. From an academic point of view, this study would advance the growth of RCM research by filling the knowledge gap in the related topic. The method used in this study, namely the nominal group approach, is still rarely applied for determining the CSFs. From a practical perspective, the identification of CSFs is useful for maintaining strategic planning efforts. They are important for organisations to avoid and mitigate unpredictable problems that emerge during RCM implementation. These CSFs would improve the strategic analysis and thinking required to implement RCM effectively. The framework proposed here can be applied as a decision support system for senior managers and practitioners involved in maintenance strategies. This paper contributes to existing knowledge as it provides an objective approach for practitioners to focus on the most critical factors and improve overall performance by progressively considering the identified CSFs.

This study was carried out by considering the characteristics of oil and gas organisations, which emphasises on improving the reliability of refineries. Petrochemical industries are classified as high-risk companies with a dire need for cost management, where prices are very flexible and vulnerable to changes in supply and demand. Their components are toxic, explosive, and flammable, so it is necessary to have a systematic maintenance program to ensure safety and consistency cost-effectiveness. This program can be further extended to other industries, such as manufacturing, through the application of additional criteria. Customising, according to the circumstances of the situations, the identified CSFs and the proposed framework, can be applied in other industries, particularly in developing countries. The CSFs ranking is distinctive for each country and, therefore, the outcomes of the present study cannot be directly applied to other countries. The CSF ranking also varies from one country to another, even the priority o each CSF may change over time.

Further studies need to be done to advance the results of this study. A study proposing a strategic planning process with the identified CSFs that culminate the development of an integrated strategic planning framework for the implementation of RCM would be valuable for the manufacturing organisations. It would provide some holistic strategic plans that describe the current status of organisations, targets, goals for the future, and approaches for going forward.

Author Contributions: M.Z.: Developing the methodology, investigation, writing the manuscript. A.G.C.: Developing the first draft, developing the methodology, manuscript checking and editing. F.A.G.: Extending the methodology, writing the manuscript. J.J.K.: Project supervision and coordination, funding acquisition, adjusting the methodology, manuscript checking and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research has been supported by the EU project "Sustainable Process Integration Laboratory—SPIL", project No. CZ.02.1.01/0.0/0.0/15_003/0000456 funded by EU "CZ Operational Programme Research, Development and Education", Priority 1: Strengthening capacity for quality research.

Conflicts of Interest: The authors declare no conflict of interest.

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