Proposed Framework Based on K-Means Clustering Technique to Provide Recommendations in Designing Job Rotation

Arhens Supono*[1], Ririn Diar Astanti[1]
[1]Department of Industrial Engineering, Universitas Atma Jaya Yogyakarta, Yogyakarta, Indonesia

Email: 235612712@students.uajy.ac.id, ririn.astanti@uajy.ac.id

*Corresponding author

ABSTRACT

Designing work rotation (JR) is crucial for a company. It is necessary to design JR based on objective recommendations. With the current development of information technology, it is very possible for companies to store employee data digitally. Additionally, companies can process employee data using data mining techniques. Then the result can be used as a basis for designing JR. This research aims to provide a framework using the K-Means clustering technique to provide recommendations as a basis for designing JR. The proposed framework is implemented in a real case, specifically targeting 490 machine operators and technicians in a cigarette manufacturer in Indonesia. The clustering analysis results reveal a grouping of operators and technicians into five distinct categories. Furthermore, the characteristics of each group can be used as one criterion for providing recommendations for designing JR.

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1. INTRODUCTION

Job rotation (JR) refers to the periodic and planned movement of employees across various activities within a company (Sinha et al., 2024). Job rotation is a strategy to diversify the tasks assigned to individuals for skill development (Sebt and Ghasemi, 2021). Apart from that, JR is also defined as a learning process based on work experience carried out by employees (Burke and Moore, 2000; Bennett, 2003).

Several researchers conducted research related to the importance of JR for employees, one of which is that JR has an important role in employee career development (Kampkötter et al., 2018; Lee and Lee, 2018). JR is also a way for management in organizations to minimize boredom and fatigue when employees do their work (Szwarc et al., 2024). This is because JR can reduce physical fatigue and reduce stress due to repetitive work (Digiesi et al., 2018). Job rotation in a gradual and planned manner can contribute to the improvement of the work environment (Sebt and Ghasemi, 2021). The implementation of systematic job rotation shows an increase in productivity and job satisfaction compared to units/sections that do not implement job rotation (Jeon and Jeong, 2016). Cross-functional job rotation practices can spread knowledge within the company (Martinez-

Sanchez et al., 2020).

The work rotation program is also implemented as an effort to provide muscle rest, recover from fatigue, and maintain work capability and performance (Comper et al., 2021). In addition, JR can effectively manage workload, particularly in physical work, and minimize the risk of employee injuries (Carnahan et al., 2000). Accordingly, three objectives of work rotation were identified: (1) organizational restructuring; (2) periodic reassignment of employee job roles; and (3) enhancement of efficiency and production (Jaturanonda et al., 2006).

The JR program must be carried out well and objectively so that it can create job satisfaction and comfort for employees (Mulyadi et al., 2022; Suryaprakash and Mary, 2019). Using job rotation strategies can produce employees with a wider range of work experience, skills, and knowledge (Al-Zoubi et al., 2022). Managers and engineers implement job rotation to encourage improvement in performance and adaptability of workers (Comper et al., 2021). When carrying out or planning a rotation program, a complete understanding needs to be provided so that the negative impact of employee rotation can be minimized (Burke and Moore, 2000).

Apart from researching the importance of JR, several researchers also conducted research on the approaches used to carry out JR. The operational research approach is widely used in designing JR, such as Bhadury and Radovilsky (2007), Carnahan et al. (2000), Tharmmaphornphilas and Norman (2006), Song et al. (2016), Digiesi et al. (2018), Hanif and Hakim (2020), Szwarc et al. (2024). This approach involves various constraints, including ergonomic constraints (Assunção et al., 2022; Battini et al., 2022; Junior et al., 2023). Apart from that, several other things, such as workers' skills, are also considered (Rinaldi et al., 2022).

Currently, with the development of computer-based information technology, companies can easily store data related to human resource management, for example, recruitment data and performance appraisal data. With current data mining techniques, the stored data can be processed using data mining techniques. One of the existing data mining techniques is clustering. Clustering techniques can be used to group similar objects based on certain distinguishing variables (Ikotun et al., 2023).

From previous research, it can be seen that research discussing job rotation design based on the use of clustering techniques on data related to human resource management has not been carried out by previous researchers. There is research using cluster techniques and genetic algorithms for JR design carried out by Carnahan et al. (2000), but the variable used is task assignment hours, which is different from what is proposed in this research.

This research paper aims to address the gap in studies about JR design by using clustering methods, particularly the non-hierarchical K-Means clustering technique. It can benefit companies that do not yet have an initial design for who will be rotated to improve employee retention.

2. LITERATURE REVIEW

Several studies have been conducted regarding job rotation (JR), for example, regarding the benefits of job rotation and methods for designing job rotation. Numerous scholars have investigated the benefits of JR for employees, such as career development (Kampkötter et al., 2018; Lee and Lee, 2018). Other researchers discuss the relationship between job rotation and employee performance (Idris and Wahyudi, 2021; Helaudho et al., 2024).

Other researchers discuss the benefits of JR in avoiding working boredom (Bhadury and Radovilsky, 2007). JR can also be used to anticipate monotony and exhaustion among personnel during their tasks (Szwarc et al., 2024). Additionally, Digiesi et al. (2018) found that JR can alleviate physical fatigue and reduce stress from repetitive tasks. Job rotation must be well planned and followed by adequate training programs to minimize the negative impact on work motivation (Helaudho et al., 2024).

Carnahan et al. (2000) conducted research related to JR, where JR can reduce the likelihood of staff injuries. Jaturanonda et al. (2006) discussed the benefit of JR for productivity improvement.

Apart from discussing the benefits of JR, several previous studies have also conducted research on the JR method. Some researchers used statistical methods in designing JR., for example, structural equation modeling (Aini et al., 2020); simple percentage analysis, chi-square, and ANOVA (Suryaprakash and Mary, 2019); cross-sectional design (Alfuqaha et al., 2022); systematic and analytical observation of the real world (Messias et al., 2022); study sample and procedure (Mohan and Gomathi, 2015).

Other research with the aim of designing job rotation was also carried out using an operational research approach, such as Bhadury and Radovilsky (2007), Carnahan et al. (2010), Tharmmaphornphilas and Norman (2006), Song et al. (2016), Digiesi et al. (2018), Hanif and Hakim (2020), Szwarc et al. (2024. The robust scheduling was proposed by Szwarc et al. (2024), while Digiesi et al. (2018) designed JR using mixed integer nonlinear programming. In using the OR approach, several constraints are involved, for example, related to this approach are various constraints, including ergonomic constraints (Assunção et al., 2022; Battini et al., 2022; Junior et al., 2023) and workers' skills (Rinaldi et al., 2022). This is in line with research conducted by Jaturanonda et al. (2006), who conducted research on the criteria that influence JR, including knowledge, skills, abilities, job seniority, years of service, and age.

Previous researchers (Carnahan et al., 2000) also used clustering data mining techniques combined with a genetic algorithm. Carnahan et al. (2000) use task assignment hours as a differentiating variable. In addition, a genetic algorithm then designs JR based on the clustering results.

Based on the previous research, it can be seen that limited research has been found related to the use of data mining techniques, i.e., clustering techniques, for designing JR. Due to advanced information technology, many companies can easily store their employee data. Therefore, using the data mining technique, the data can be analyzed in order for the company to use the result as a basis for decision-making in the company, including designing JR. Therefore, this study paper intends to overcome the gap in studies about JR design by employing clustering methods, particularly the non-hierarchical K-Means clustering technique.

3. PROPOSED FRAMEWORK

This section explains the proposed framework for determining criteria for designing job rotation (JR) using the K-Means clustering technique. We hope to use the results of the proposed framework as a criterion for designing JR. We develop the criteria in the proposed framework using employee profile data. The results of this study will be useful for companies that do not yet have an initial plan for who will be rotated to increase employee retention. The proposed framework is presented in Figure 1.

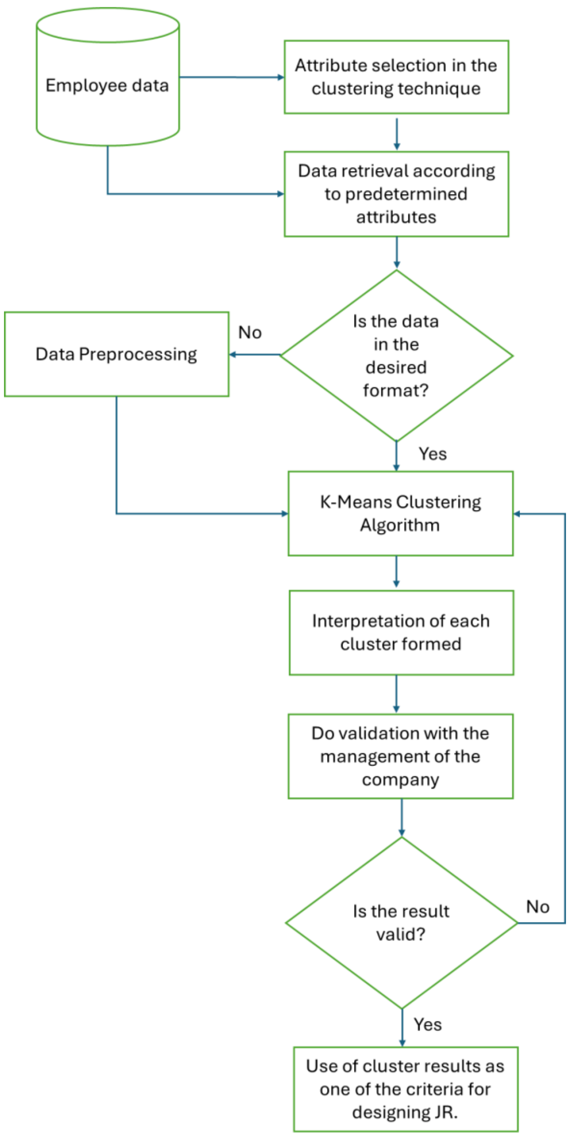

Figure 1. Proposed Framework for Determining Recommendations to Design Job Rotation using K-Means Clustering Technique

Based on Figure 1, it is seen that the stages in the proposed framework begin by selecting attributes on the company employee profile data as a differentiating variable. It includes 1) date of birth; 2) date of first employment; 3) highest education; 4) employee position. Those differentiating variables are useful for grouping employees based on similar characteristics. For example, date of birth data can be used to measure the age of workers, while the date of first employment data can be used to identify the length of service of the employee. Therefore, the differentiating variables used are: 1) age; 2) length of service; 3) highest education; 4) employee position.

Once we have determined the attribute, the next step involves retrieving the data based on the selected attribute. If the retrieved data does not meet the format requirements for the K-Means clustering technique, we perform preprocessing on it. Using K-Means clustering, the type of data required is metric data. Therefore, if the retrieved data remains in non-metric form, it must undergo conversion to metric form. For example, for the educational level, usually the type of data is non-metric (categorical), such as high school, diploma, bachelor's degree, master's degree, or doctoral degree. In the proposed framework, it is proposed that for educational level, the category is replaced with the duration of study from when a person completes basic education until completing their highest level of education, as it is stated in Table 1.

Table 1. Conversion from categorical form into metric form to represent the highest education of an employee

Highest education	Conversion in metric form (year)
High School	12
Diploma	15
Bachelor	16
Master’s degree	18

Employee roles are denoted by numerical values that signify the grade of a position; for instance, a score of 22 represents a junior operator, among others. The policies of any company can modify this value. Department classifications often consist of non-metric (categorical) data types. In the proposed structure, the department type indicates the quantity of operational manufacturing machines. The marketing department, devoid of production machinery, registers the count of machines as zero. Similarly, both the Human Resource Department and the Warehouse Department lack machines; hence, the machine count is recorded as zero. This can subsequently be utilized to distinguish between employees who directly contribute to the transformation of raw materials into finished goods in manufacturing companies (technical employees) and those who do not directly contribute to this process (non-technical employees).

After data preprocessing, the clustering phase was executed utilizing the K-Means clustering methodology. The K-Means clustering method was executed with the K-Means library available in R software. We determine the optimal number of clusters (k) utilizing the elbow method (Kodinariya and Makwana, 2013; Bholowalia and

Kumar, 2014; Umargono et al., 2020). The attributes of each established cluster are analysed after determining the ideal k value. The company may thereafter present the findings of this interpretation as a criterion for the design of JR

4. CASE STUDY

The proposed framework was implemented in a cigarette manufacturer in Indonesia, especially in the Production Engineering Department. This department is responsible for the design, installation, utility provision, and development of production machines. This department has more than 490 employees whose job is mainly as operators and technicians. As explained in Figure 1, the first step taken was to acquire employee data. The company retrieves this data from the Human Resources Database. The employee data that is taken includes the name, date of birth, date of first employment, highest education, employee position, and department. That data is then used for determining the differentiating variables which are: 1) age; 2) length of service; 3) highest education; 4) employee position. The next step is preprocessing data. Preprocessing is necessary because several differentiating variables, such as age, still have values in the format dd/mmm/yyyy. Therefore, we must preprocess the data first to ensure it is ready for processing. Microsoft Excel software performed the data preprocessing. Details of the data preprocessing carried out are as follows:

a) Change date of birth data to age in years and employee entry date to length of service in years.
b) Delete employee data from non-technical functions in the Production Engineering Department (Procurement, Development & Data Services, Planner, Admin).
c) Changing non-matrix data into matrix data for the latest education data. Conversion is based on years of education, as provided in Table 1.
d) Normalize data for age, length of service, and highest education.
e) Changing non-matrix data into matrix data for the latest education data. The conversion process is based on the number of years of education.
f) Changing non-matrix data into matrix data for the employee role using the level of expertise determined by the company. The values range from 6 to 22.

After the preprocessing step, the number of data rows is still the same as the initial data, which is 494 rows and 4 columns. The data is ready to be further analyzed using the K-Means clustering technique. Table 2 presents an example of preprocessed data.

The ready data undergoes a clustering process using R software and the library. Determining the optimal k value is carried out using the elbow method, as shown in Figure 2.

Based on Figure 2, it is known that the optimal value of k, where there is no increase in the WSS value (within the sum square), is at k=5. Clustering results can be seen in Figure 3.

Next, we interpret the characteristics of each formed cluster. The characteristics of each cluster formed can be seen in Table 3.

Based on the results of the profiling, the process of making rotation recommendations continues, which can be used by management as a basis for considering employee rotation in its department.

The results of the clustering carried out gave rise to 4 categories out of 5 clusters, which can be used as a recommendation when designing JR. Table 4 displays the four resulting categories.

The results of the clustering technique were then validated. Validation was performed by management. Their familiarity with team members' day-to-day performance enabled informed verification of cluster assignments. If management deems the number of clusters formed and the characteristics of each cluster appropriate, the clustering results can then be used as a reference by management as a basis for job rotation (JR).

Table 2. Preprocessed Data

Employee Position	Age	Length of Service	Highest Education
22	51	32	12
15	53	26	12
15	44	25	12
15	45	26	12
15	46	25	12
22	51	32	12
22	42	20	15
15	44	25	12
9	30	8	15
22	41	19	15

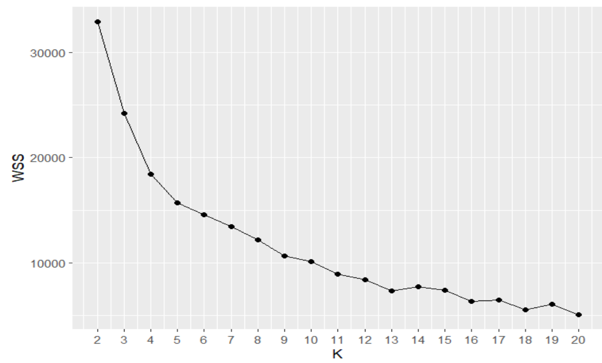

Figure 2. Optimum value of k

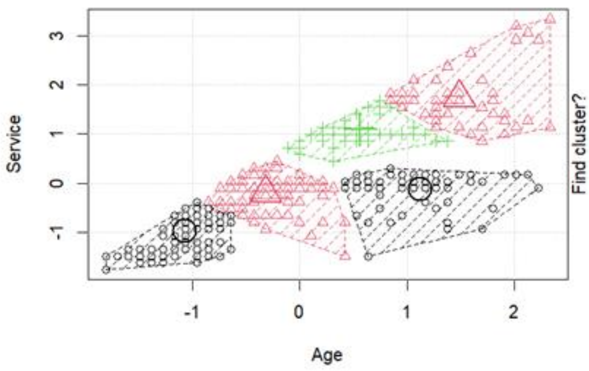

Figure 3. Clustering result

Table 3. Characteristics of each cluster formed

Cluster	Age	Length of services (years)	Employee Position	Highest Education
1	33-49	>11	All technician	The majority minimum bachelor's degree.
2	38-58	>19	Majority technician	All high school graduates
3	32-57	6-15	Majority technician	All high school graduates
4	19-42	1-15	Majority operator	All high school graduates
5	23-38	1-14	Majority technician	Majority diploma graduated

Table 4. Four resulting categories for JR Recommendation

Cluster	Four resulting categories for JR Recommendation
1	a) This cluster comprises employees who have a long service life, extensive experience in technical areas, and a bachelor's degree educational background. b) Rotation across technical departments to expand competencies and gain new experience to avoid boredom, considering the work period has been quite long (enrichment). c) Employees who perform well in this cluster enter the talent pool role of Senior Supervisor or Senior Engineer and can be rotated to engineer functions to develop employee potential (enlargement).
2&3	a) This cluster comprises employees who have a long service life, extensive experience in technical areas, and a bachelor's degree educational background. b) Rotation across technical departments to expand competencies and gain new experience to avoid boredom, considering the work period has been quite long (Enrichment). c) Employees who perform well in this cluster enter the talent pool role of Senior Supervisor or Senior Engineer and can be rotated to the engineer function to carry out their duties. d) Rotation across technical departments to expand competencies and gain new experience to avoid boredom, considering the work period has been quite long (enrichment).Employees who perform well in this cluster enter the talent pool role of Supervisor or Engineer and can be rotated to engineer or operations functions to develop employee potential (enlargement). Increase employee potential (enlargement).
4	a) This cluster employee is still a new category, so there is no need for rotation in the near future, and they have a high school education background. b) Employees with good performance are rotated to maintenance functions to complete competencies (enrichment).
5	a) This cluster comprises employees with new terms of service, meaning they will not require a rotation soon, and they possess a diploma-level educational background. b) Employees who perform well in this cluster enter the talent pool as supervisors or engineers and can be rotated to engineer or operations functions to develop employee potential (enlargement).

5. CONCLUSIONS

The case study demonstrated that the suggested framework could evaluate employee data utilizing four essential attributes: 1) age; 2) length of service; 3) highest education; 4) employee position. This analysis uses the K-Means clustering approach. Jaturanonda et al. (2006) advocated the utilization of this property. Carnahan et al. (2000) employ a clustering technique that considers solely one attribute: task assignment hour. The clustering results were utilized to develop JR using a genetic method.

In this study, the proposed framework enables the categorization of employees based on four qualities. Formed clusters can signify specific features of employees. The K-Means clustering approach can categorize employees into five distinct categories. These five clusters yield four sorts of personnel. The design of JR can thereafter incorporate these cluster properties.

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