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Improving Engineers' Utilization and Performance in Electricity Company

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Abstract— *The objective of the current study is to enhance the practice and productivity of Engineers at the Saudi Electricity Company (SEC) in a project-based setting. The research explores the ineffectiveness of employees' allocation which makes it common for engineers to be sometimes disregarded resulting in wastage of human resources. The specific goals were to study the distribution of tasks, determine the most demanding categories in terms of time spent, and use simulation and machine learning to suggest specific strategies for optimization Key findings revealed that computer-based tasks accounted for a significant portion of engineers' daily work. SIMIO experiments have shown that engineers could handle more than one project at any time as long as the conditions were designed to be favorable.*

Keywords— *Workflow Minning, SIMIO Simulation, Workforce Optimization, Manpower Allocation, Task Categorization, Performance Prediction, Machine learning.*

I. Introduction

The Saudi Electricity Company (SEC) is considered among the major power generation and distribution companies in Saudi Arabia. It engages in three core activities of electricity generation, electricity transmission, and electricity distribution. Even though SEC is a power generation company, it still employs Engineering Consultants for different phases of its projects, especially technical, supervision, and commissioning functions. One of the major problems is the idle time that engineers experience due to project delays or other interruptions in a time frame.

The purpose of this study is to investigate these issues and provide solutions that will help in the employment of manpower, reducing idle time and enhancing the effectiveness with which
tasks are allocated to different participants in SEC's projects. The research employs task categorization, workflow mining, and SIMIO simulation techniques to model and examine the manpower allocation processes.

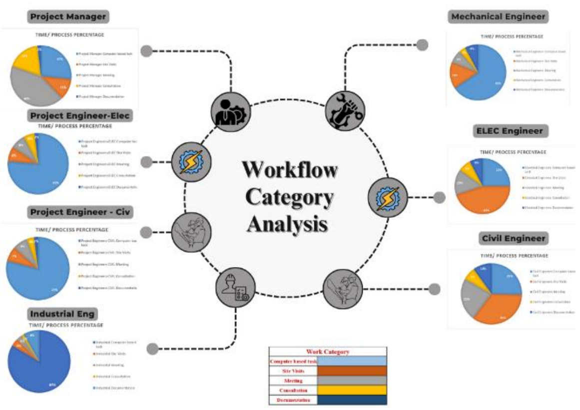

Figure 1. Workflow Analysis

Research Objectives

The objectives of this research are as follows:

1. To identify which work categories (e.g., computer-based tasks, site visits, meetings) consume the most time among engineers.
2. To define an approach that measures utilization and daily job achievement using process mining.
3. To analyze the acquired data and determine which work categories have higher utilization rates.
4. To enhance optimization of resource allocation to align with the company's vision of better manpower utilization.
5. To develop and implement models that predict engineer performance based on specific criteria, enhancing the recruitment process.

II. Methodology

This research devises a combination of simulations and machine learning to assess manpower utilization and task allocation efficiency at SEC. The workflow mining included the categorization of the computer work tasks, site tasks, meetings with other stakeholders, consultation, and documentation which were some of the tasks performed daily by the engineers. Utilizing interaction with expert engineers and monitoring working modes, data was gathered to determine the time investment in the respective task views. For instance, the time estimates for the different tasks implied 15 minutes for issuing a letter, twenty minutes for requesting a shutdown from SAP, and one hundred and twenty minutes for issuing a change order.

The collected data was then related to SIMIO simulation models to measure process flows, analyze possible areas of decreasing waiting time, and plan the resource distribution and usage in more effective ways. Finally, Machine learning was employed to ensure higher efficient engineers by using Data gathered Annually of Engineers' performance.

III. Data Preparation and Cleaning

Before analyzing engineer workflows, the dataset underwent thorough preparation and cleaning to ensure accuracy. Data was sourced from task logs, yearly evaluations, and direct observations, but inconsistencies and anomalies were present.

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Data Cleaning Techniques

Several key steps were taken to clean the data:

1. *Inconsistent Formats:*

Inconsistent entries were repaired with acceptable procedures. This may have included data validation by human observation of original documents or repeated observations.

2. *Handling Missing Data:*

Missing values, particularly in the start and end times, were addressed through interpolation and consultation with expert engineers to maintain data integrity.

3. *Normalization:*

Z-scores were used to normalize task durations, ensuring values across categories were comparable and eliminating bias caused by different time ranges.

TABLE 1. Z-Score Values of Mechanical Engineer Outliers

Observation	Value	Z-score
Obs78	184.000	4.234
Obs301	153.000	3.343
Obs33	153.000	3.343
Obs16	152.000	3.314
Obs59	149.000	3.227
Obs22	148.000	3.199
Obs9	148.000	3.199
Obs2	144.000	3.084
Obs126	136.000	2.854
Obs40	133.000	2.767
Obs69	118.000	2.336
Obs74	117.000	2.307
Obs39	110.000	2.106
Obs82	109.000	2.077

4. *Outlier Detection:*

Boxplots and statistical methods like Grubbs' test were applied to detect outliers in task durations. Extreme values were either removed or flagged for review.

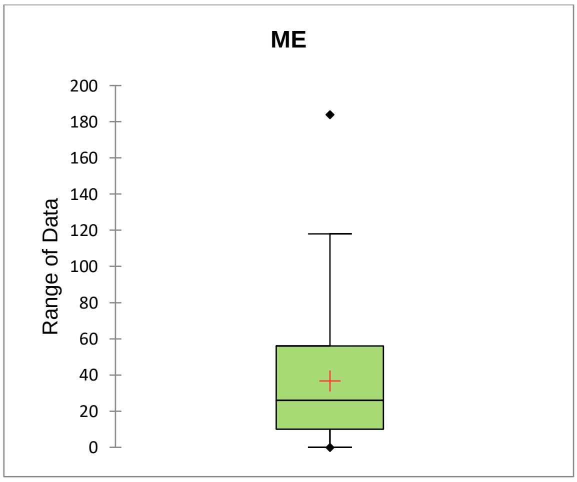

Figure 2. Mechanical Engineer Service Time Boxplot

5. *Validating Data Distributions:*

After cleaning, data was checked against expected probability distributions for inter-arrival and service times using tests like the Kolmogorov-Smirnov and Chi-square tests.

Data Validation

The cleaned dataset was validated to ensure its accuracy and representativeness. Statistical tests confirmed the data was suitable for use in SIMIO simulations and machine learning models, providing a reliable foundation for further analysis.

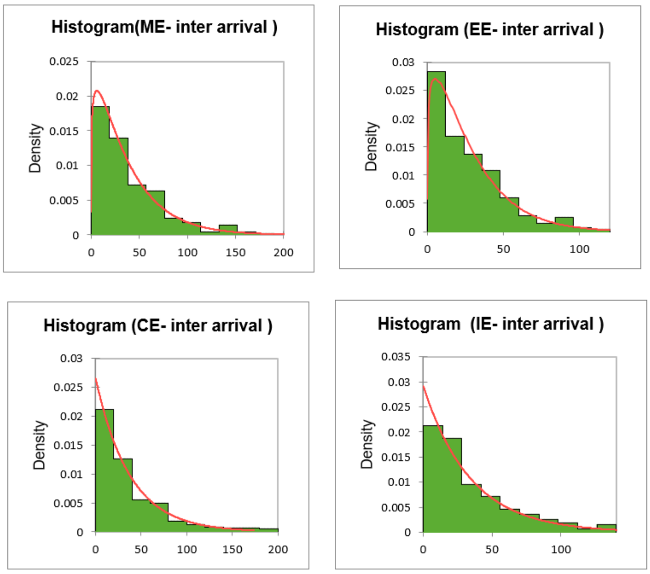

Figure 3- Inter-arrival of Different Types of Email

Within the workflow mining activities, computer-based tasks, such as email correspondence and document review were performed most often on a day-to-day by the engineers. On the other hand, site works, meetings and consultations were important but much less frequently done than computer-based work. Such a finding made the research to focus its optimization on the improvement of efficiency of computer-based

6. *Workflow Mining and Task Segregation*

Workflow mining was conducted to identify which types of tasks consumed the most time for engineers. The analysis revealed that computer-based tasks accounted for the majority of their daily activities. Based on these findings, data related to computer-based tasks was gathered and categorized in the task segregation table.

The Task Segregation & Duration table presents this data, detailing the various computer-based tasks and their average durations. These task segregation data were established as a standard, simplifying the process of data collection for similar tasks in the future. This standardization ensures consistency and reliability in future simulations, as the same categorization can be applied to other tasks within the same category.

TABLE 2: Sample of task Segregation & duration

#	Tasks	Time Estimation (Min.)
1	Request for Issuing Letter	15
2	Request for Corresponding letter	10
3	Shutdown Information	5
4	Apply for Shutdown Request at SAP	20
5	Apply the Safety Documents for Shutdown Request	15
6	Corresponding of Information about contractors	7
7	Corresponding of Progress Report	30
8	Update the project progress status at SAP	8
9	Interview Evaluation	6
10	Issuing Change Order	120

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7. SIMIO Simulation

The engineer engagement processes such as the time taken to complete a task, time between arrivals and the time required for a task to go through the approval process were critical parameters and were the foci of the SIMIO modeling. For the model, various task allocation strategies were tried and it emerged that under optimized conditions, engineers could work on several projects at the same time.

Examining numerous task reallocation scenarios, such as changing the ways in which tasks are shared among engineers, the models illustrate that multi-project workflows may effectively reduce a multi-task engineer's idle time and not stress their capacity. This articulates the case for having multi-project assignments as a means to improve engineering manpower utilization.

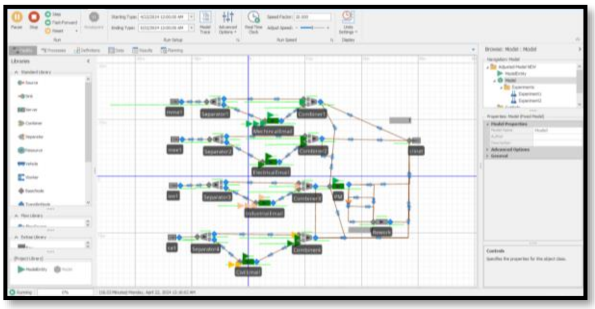

Figure 4. Model within Simio.

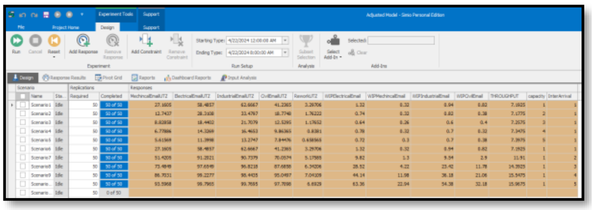

Figure 5. Experimental Environmental

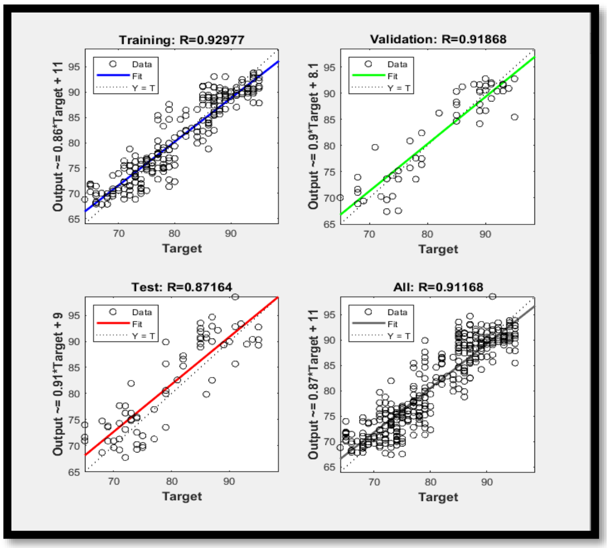

Figure 6. Regression Line Between Different Input

8. Machine Learning for Performance Prediction

Machine learning models were applied to predict the future performance of engineers based on factors such as years of experience, certifications, and previous job roles. Neural networks were used for clustering and fitting the data, with an accuracy rate of 84.5%. The machine learning approach allows SEC to make data-driven decisions in recruitment and workforce management by identifying engineers who are likely to perform well in future assignments. This prediction model improves the recruitment process by ensuring that engineers with high predicted performance are placed in roles that maximize their contributions to project outcomes.

IV. Results and Discussion

The workflow mining and SIMIO simulations indicated that activities of engineering work mostly include computer-based activities as shown in table (3) in appendix. The research proved that in the ideal case, engineers are able to handle multiple projects at the same time which in turn reduces the downtime. Furthermore, communication paths may also be shortened and the rework frequency reduced to enhance the efficiency of engineers.

There is potential for machine learning models to enhance the value of management practices by accurately predicting future engineer outputs, which is significant for recruitment process enhancement. The SEC now has the ability to apply direct engineers to specific projects based on their skills and capabilities resulting in more efficient use of resources and project improvement.

V. Conclusion

This research highlights the importance of optimizing engineer utilization through task categorization, workflow mining, and machine learning. With the help of SIMIO simulations, the research established that engineers can work on several projects at the same time, therefore avoiding unnecessary downtimes. Pre-employment assessments using machine learning techniques were also essential in forecasting the prospective performance and project-related recruitments.

outcomes of this research can be used in various fields that operate on a very similar project-based model. Real-time integration of workflow metrics for future studies would be an interesting avenue for further achieving optimization.

VI. Recommendations

The study offers several recommendations for improving manpower utilization:

- Implement multi-project workflows to reduce idle time.
- Streamline communication paths to decrease rework rates.
- Utilize machine learning models to predict engineer performance and improve recruitment processes.

These strategies will help SEC optimize its engineering manpower and improve project efficiency.

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APPENDIX

TABLE 3: Time Consumption of Engineer Daily Shift

Work Category	Engineers under the study- higher time utilization rate on computer-based task							
	Project Engineer ELEC		Project Engineer - Civil		Mechanical/HSE Engineer		Industrial Engineer	
	time in Min	time Consumed of shift	time in Min	time Consumed of shift	time in Min	time Consumed of shift	time in Min	time Consumed of shift
Computer-based task	193.19	40%	206.55	43%	171.36	36%	304.1	63%
Site Visits	20	4%	20	4%	40	8%	15	3%
Meeting	20	4%	20	4%	20	4%	10	2%
Consultation	15	3%	10	2%	10	2%	5	1%
Documentation	5	1%	5	1%	20	4%	30	6%