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Potentials of Activity Based Costing (ABC) Modeling in Developing Expert System for Cost Estimation in Job Shops

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Abstract

Maintaining profitability and operational efficiency in competitive manufacturing environment entails accurate cost estimation. The need for expert system development for accurate cost estimation in job shops, where custom, low-volume products manufacturing becomes crucial. This study leverages the Activity-Based Costing (ABC) model, a method known for its precision in assigning costs to products based on the activities required for their production. The expert system is design to assist small and medium-sized enterprises (SMEs) in making informed pricing decisions by providing reliable cost estimates. Developed using JavaScript, Tailwind CSS, and Zustand for state management, the system offers an intuitive user interface and real-time feedback. Developing an expert system for cost estimation in a job shop using the Activity-Based Costing (ABC) model fills the gap in traditional methods and other less accurate costing methods by providing a more accurate and detailed approach to cost estimation. The expert system was tested using eleven jobs executed by a job shop, the cost variance analysis uncovered a substantial 20.73% decrease in total income, totaling N63,320, highlighting the company's oversight in accounting for critical cost factors. The ABC model, as demonstrated in the study, offers a more precise way to calculate overhead costs and determine the total cost of a product. By integrating expert knowledge and utilizing a dynamic programming approach, the proposed model enhances the accuracy and efficiency of cost estimation under uncertainty, outperforming existing models and providing a user-friendly mechanism for job shop managers.

Keywords: *Expert system, cost estimation, activity-based costing (ABC) model, job shop, small and medium-sized enterprises (SMEs).*

1. Introduction

In a dynamic modern manufacturing system, the ability to accurately estimate costs in a job shop environment is paramount. Product manufacturing expenses play a critical role in strategic planning and decision-making. Research and development departments of manufacturing setups were primarily concerned with cost estimation (Prior *et al.*, 2024). Job shop manufacturing system is characterized by dynamic production environment and multifaceted operational demands, necessitates meticulous attention to job costing due to its inherent complexity and variability. In this context, the development of an expert system tailored for cost estimation represents a significant leap forward in the pursuit of efficiency and precision in manufacturing operations (Bodendorf & Franke, 2024). The concept of an expert system which, simulates the decision-making ability of a human expert, has been a subject of interest for decades. These systems are design to solve complex problems by reasoning through bodies of knowledge, represented mainly as if-then rules rather than through conventional procedural code (Paraschos *et al.*, 2024). The job shop manufacturing system, characterized by its flexibility to handle a variety of work pieces and operations, presents unique challenges for cost estimation due to its inherent complexity and variability. Traditional cost estimation methods often fall short in such settings, leading to inaccuracies that can ripple through the entire production process, affecting scheduling, resource allocation, and ultimately, profitability (Kenny *et al.*, 2024; Rashid & Kausik, 2024).

Recent advancements in artificial intelligence have paved the way for expert systems into the realm of cost estimation. This integration has shown promising results in enhancing the accuracy and reliability of cost estimations, thereby supporting strategic decision-making and competitive bidding processes. By harnessing the power of expert system, the system is expected to offer a more detailed understanding of cost drivers and facilitate the optimization of manufacturing processes (Duran *et al.*, 2024). The significance of this research lies not only in its potential to revolutionize cost estimation practices but also in its contribution to the broader field of intelligent manufacturing systems. By harnessing the potential of advanced technologies, organizations can transcend the limitations of traditional costing methodologies and embark on a transformative journey towards using expert system (Dao & Nguyen, 2024).

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1.1 Concept of Cost Estimation in Job shop

Cost estimation in job shop environments is a challenging and dynamic field that integrates insights from operations management, industrial engineering, and financial analysis (Jorgensen & Shepperd, 2007). Job shops, with their high variety and low volume production, present unique difficulties in cost estimation due to the variability and complexity of their operations (Kumar & Saha, 2025). Unlike standardized production lines, job shops handle a wide range of orders with specific requirements, necessitating flexible and accurate cost estimation approaches. Frequent changeovers, diverse process routing, and fluctuating demand patterns in job shops make traditional cost estimation methods less effective. The unpredictable nature of job shop production requires precise and adaptable strategies to ensure competitive pricing and profitability (Amiri *et al.*, 2024; Mukilan *et al.*, 2024).

To effectively estimate costs in job shops, one must understand the involutions of production processes, material and labor costs, and overhead allocation. This involves integrating detailed cost data with advanced analytical tools to predict expenses accurately and manage financial resources efficiently (Mockevičienė & Vedlūga, 2024). Utilizing technologies such as artificial intelligence and data analytics can significantly enhance the accuracy of cost estimation, enabling better financial planning and resource allocation (Ahmed *et al.*, 2024).

1.2 Traditional Approaches to Cost Estimation

In project-based environments, traditional cost estimation methods have typically involved manual processes and heuristic decision-making. Estimators, relying on their expertise and past experience, have historically forecasted costs by leveraging intuition and historical data (Akram *et al.*, 2024). Common practices include using past project costs, expert opinions, and comparisons with similar projects to estimate expenses. Tools such as spreadsheets or basic financial models are often employed to manually calculate costs and create budget forecasts, considering the project's perceived requirements and resource limitations (Bhattacharya *et al.*, 2024). However, these traditional cost estimation approaches come with notable drawbacks. They tend to struggle with adapting to changes in project conditions and evolving scopes. Often, they do not adequately account for the complex relationships between various cost factors, leading to inaccurate estimates and potential cost overruns. Additionally, traditional methods typically lack real-time data and advanced analytic, making it challenging estimators to anticipate financial risks or optimize budgeting decisions. As a result, estimations are frequently based on historical trends and anecdotal evidence rather than comprehensive, data-driven analysis whereas, good data and information are necessary for effective cost estimate (Amiri *et al.*, 2024). Human estimators in traditional cost estimation may be subject to biases or personal preferences, affecting the accuracy of their forecasts (Dao & Nguyen, 2024). Without robust decision support systems, there is a heightened risk of inconsistency and variability, which can lead to budget inaccuracies and inefficiencies. Additionally, these traditional methods often face challenges in communication and coordination among different project teams or departments. The reliance on manual processes and decentralized decision-making can impede collaboration and information sharing, thereby reducing the overall effectiveness of cost management. As a result, while traditional cost estimation has been widespread in manufacturing environments, its limitations are becoming more apparent in handling the complexities and uncertainties that exist in job shops. Advanced technologies, such as expert systems and predictive analytic, present promising opportunities to address these issues and improve cost estimation practices in dynamic project settings (Mukilan *et al.*, 2024).

1.3 *Challenges in Cost Estimation*

Cost estimation in project-based environments presents numerous challenges that can impede financial planning and project performance. These challenges stem from the inherent complexity and uncertainty associated with diverse project requirements, fluctuating resource costs, and scope changes. One significant challenge is the unpredictability of project scope, which complicates accurate cost forecasting and budget allocation. Projects often undergo scope changes or expansions, necessitating rapid adjustments to cost estimates to align with new objectives while controlling expenses (Akram *et al.*, 2024). Additionally, the variability in resource costs further complicates cost estimation efforts. Prices for materials, labor, and equipment can fluctuate due to market conditions, supply chain disruptions, or economic factors, introducing uncertainty into the budgeting process. This variability makes it difficult to maintain accurate and reliable cost projections over the project life cycle (Kenny *et al.*, 2024).

Labor constraints and skill shortages also present significant challenges in cost estimation. The need for specialized skills and expertise can vary widely across different projects, requiring precise forecasting of labor costs and availability. Shortages of skilled workers or mismatches between project demands and available talent can lead to increased labor costs, project delays, and budget overruns (Iliemena & Amedu, 2019). Furthermore, the complexity of modern projects often involves multiple stakeholders and interdisciplinary teams, which can complicate communication and coordination. Inefficiencies in information sharing and decision-making processes can hinder the accuracy of cost estimates, as different departments may have varying priorities and perspectives on budgetary requirements.

Moreover, traditional cost estimation methods have been widely used; their limitations are increasingly evident in the face of modern project complexities. Advanced tools and techniques, such as predictive analytic and integrated project management software, offer-promising solutions to enhance the accuracy and reliability of cost estimation practices in dynamic project environments. Previous cost estimation methods such as human-based judgment, analogical cost estimation, and parametric cost estimation each have specific gaps that can hinder accuracy and efficiency (Anireddy, 2024). Cost estimation methods are diverse and widely utilized across various industries. When choosing an appropriate method for cost estimation, key factors include the precision of available data and the timeline constraints. Cost estimation techniques can generally be divided into two categories: qualitative and quantitative methods (Paraschos *et al.*, 2024). Human judgment relies on the expertise and intuition of individuals, often used in the absence of detailed data, and can be quick and flexible. However, it is subject to bias and inconsistencies, highly variable based on individual experience, and difficult to reproduce and justify. Activity-Based Costing (ABC) assigns costs based on activities and their resource consumption, providing a detailed and accurate allocation of costs, and is useful for understanding overhead and indirect costs. Nonetheless, ABC is time-consuming and complex to implement, requires detailed data on activities and resource usage, and can be costly to maintain and update manually (Pashkevich *et al.*, 2023). Analogous cost estimation uses historical data from similar projects to estimate costs, making it quick and easy to apply, and is useful in early project phases with limited data. Its limitations include being less accurate due to differences between projects, heavily relying on the availability of comparable historical data, and potentially overlooking unique project aspects (Duran *et al.*, 2024). Parametric cost estimation uses statistical models and historical data to predict costs based on project parameters, providing a systematic and quantitative approach, and can handle complex relationships between cost drivers. However, it requires reliable and relevant historical data, and the accuracy of the model depends on the quality and relevance of the data, which may be less intuitive and harder to explain without technical backgrounds (Bhattacharya *et al.*, 2024).

Cost estimation in job shop environments involves addressing the complexities of dynamic production while ensuring precise financial forecasting. By leveraging advanced technologies, organizations can unlock new leading edge of streamlined cost estimation process, improved operation efficiency and enhance competitiveness in manufacturing industry. This study has leveraged on the advanced technologies by developing an expert system to give a precise cost estimate of activities in job shops using Activity-Based Costing model.

2.0 Material and Method

2.1. Concept of model development

In developing an expert system, acquisition of knowledge require for the development is very crucial. Among the required knowledge for the development of this expert system is to state the mathematical model to estimate the costs based on specific project cost drivers. Stating mathematical model for cost estimator involves expressing the relationship between input parameters and the estimated cost using mathematical equations. A commonly used mathematical model for cost estimation in job shops is the Activity-Based Costing (ABC) model. ABC allocates costs to each activity based on their consumption of resources, providing a more accurate estimation of costs compared to traditional methods. Experts in cost estimation in job shops often rely on ABC model due to its effectiveness in allocating costs to individual activities based on resource consumption. It provides a more accurate estimation of costs compared to other models (Effiong & Akpan, 2019).

2.2. *Cost Model*

The mathematical model allows for a detailed analysis of resource utilization and cost drivers within job shop environments, enabling informed decision-making in resource allocation and budgeting processes.

$$\text{Material cost denoted by } (MC) = \sum_{i=1}^{n} (Q_i \times C_i) \tag{1}$$

Where, n = Number of different materials
Q_i= Quantity of material i
C_i= Cost per unit of material i

$$\text{Labor cost denoted by } (LC) = \sum_{j=1}^{m} (H_j \times R_j) \tag{2}$$

Where, m = Number of different labor activities
H_j = Hourly wage rate for labor involved in activity j
R_j = Labour time spent on activity j

Machine cost denoted by $MHC = \sum_{k=1}^{p}(H_k \times R_k)$ 3

Where, p = Number of different machine activities

H_k = Machine hours for activity k

R_k = Hourly machine rate for activities k

Overhead cost denoted by $(OC) = \frac{Total\ Overhead\ Costs}{Total\ Labour\ Hours}$ × Labor hours for the Job 4

Total equipment cost $TEC = \frac{Total\ Tooling\ Cost}{Number\ of\ jobs}$ 5

Inspection and Quality Cost denoted by $IQC = \sum_{l=1}^{q}(H_l \times R_l)$ 6

where q = Number of different inspection activities

H_l = Hours for inspection activity l

R_l = Hourly rate for quality control labor involved in activity l

Outsourcing cost denoted by $OSC = \sum_{m=1}^{r}(C_m + S_m)$ 7

where r = Number of outsourced component/processes

C_m = Cost of outsourced component/process m

S_m= Cost per unit of material Shipping and handling fees for outsourced component/process m

Lead time cost denoted by LTC = Rush Order Fee

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Total cost denoted by $TC = MC + LC + MHC + OC + TEC + IQC + OSC + LTC$ 9

Where,

MC = Material Cost

LC = Labour Cost

MHC= Machine Cost

OC= Overhead Cost

TEC= Total Equipment Costs

IQC= Inspection and Quality Costs

OSC= Outsourcing Costs

LTC= Lead Time Costs

2.3. Choice of Programming Language

Selecting the best applicable technology is important in expert system development after stating the mathematical model for estimating the cost. In this case, JavaScript programming language was chosen as the primary technology, while Visual Studio code (Vscode) as the code editor. JavaScript selected is for optimal resource utilization and enables the development of complex algorithms required for accurate cost estimation. JavaScript for web-based interfaces, Tailwind-CSS is utilized for styling the user interface, ensuring a professional and intuitive user experience. JavaScript frameworks such as react.js and remix were considered for rapid prototyping and responsive design, enabling the system to adapt seamlessly to different devices and screen sizes. Zustand for state management ensuring that updates to the state were propagated.

Algorithm is a system procedure that takes some input and produces a corresponding output. It is a set of instructions that is used to solve a specific problem or perform a particular task (Dao & Nguyen, 2024). The procedure (algorithm) used for the development of this expert system is shown in Figure 1.

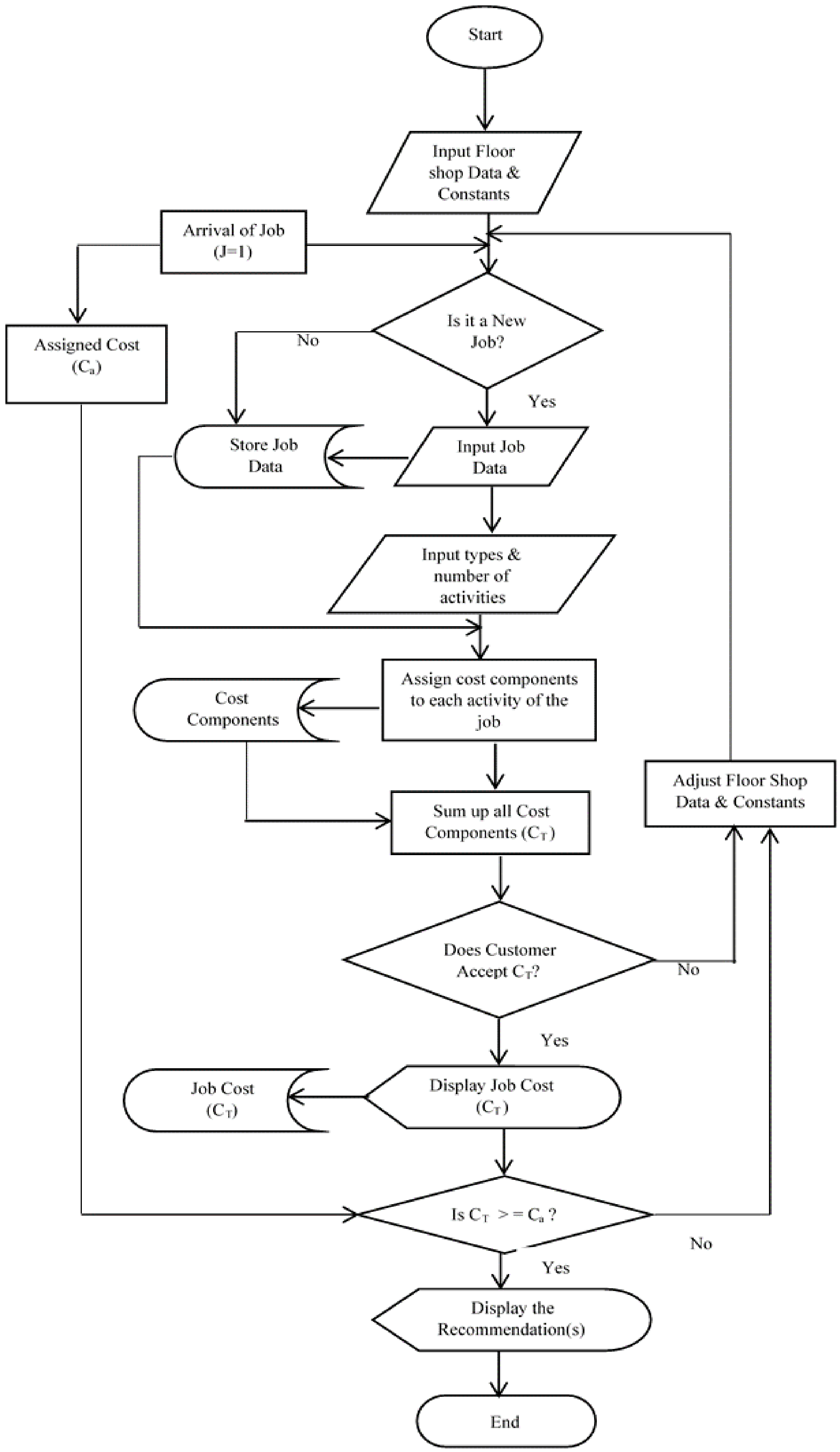

Figure 1: *The Expert system algorithm*

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The following are the major stepwise procedures of the Expert System Algorithm:
1. Start: The process begins when a user initiates a cost estimation request for a new project in the job shop environment.
2. Identify Job shop Activities: List all the activities involved in the job shop.
3. Identify Cost Drivers: Determine the cost drivers for each activity.
4. Calculate Cost per Activity: Sum up all the cost driver rates to calculate the cost per activity.
5. Develop Cost Estimation Rules: Create rules or guidelines based on the data for estimating the cost of new jobs.
6. Test the System: Run test cases to validate the accuracy of the cost estimate.
7. Deploy System: Deploy the expert system for use in the job shop.
8. End: The process concludes once the total estimated cost is available to the user, and the user can proceed with decision-making or further planning based on the cost estimation results.

2.4 Iterative Development Process

This expert system was developed through an iterative process, which allowed for continuous feedback and improvements at every stage. User input and suggestions were carefully considered to upgrade the system's functionality, improve user interface for proper functioning. By using this iterative method, the final expert system was able to produce accurate cost predictions.

2.5 User Interface Design

The designed user interface (UI) will guide the user through the input process and display the results in a clear and understandable manner. The designed UI contains Figma and tailwindcss, incorporating elements such as input fields buttons, tables, and result displays. It ensures a seamless and responsive user experience across different devices and screen sizes. The expert system's interface is simple to use and well organized. Users could enter job specifications, including material requirements, labor hours, and machine usage, through a simple data entry process. The system provided clear guidance at each step, with real-time feedback and error checking to ensure a seamless and accurate input process. Fig 2 shows the user interface of the Expert System and Fig. 3 shows the data input window.

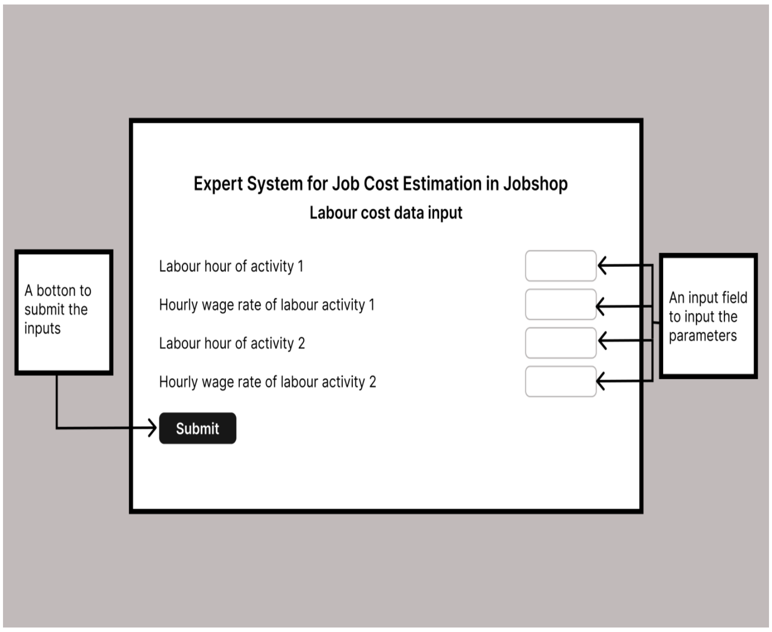

Figure 2: *The user interface*

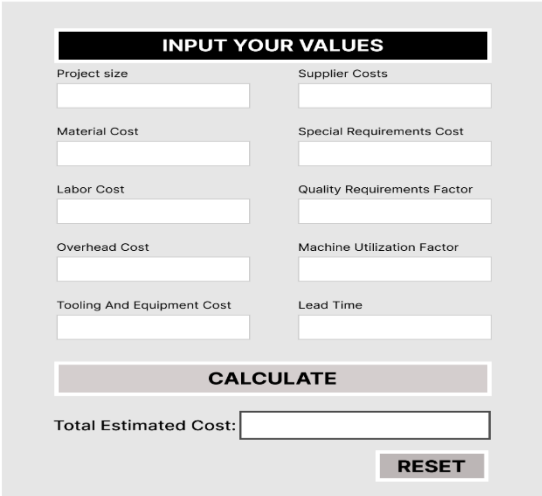

Figure 3: *Data input window*

2.6 Testing and Validation:

The accuracy and reliability of the expert system were tested and validated to ensure its correctness. Known solutions were used to evaluate the system, and it was verified for efficiency and accuracy. Bugs and errors were addressed and the system was iteratively improved until consistent and accurate results were produced.

3.0 Result and Discussion

The expert system was designed with the primary goal of delivering precise cost estimations for job shop. It was deployed to an existing job shop where the costing of jobs is predominantly done base on the intuitive of the foreman. This method has led to unnecessary bargaining and underpricing which eventually affects the profitability and sustainability of the job shop.

From the existing records in the company, eleven (11) jobs that were performed in a particular month were used to test the effectiveness of the expert system. The previous costs at which the jobs were produced for the customers are referred to as assigned costs (C_a) while the costs from the expert system are referred to as total cost (C_T). These costs and the difference between C_a and C_T are shown in Table 1.

Table 1: Cost variance analysis: assigned costs (C_a) vs. expert system costs (C_T)

Job	1	2	3	4	5	6	7	8	9	10	11	Total
Assigned Cost (C_a)	25,000	17,500	32,000	18,000	14,000	29,000	45,000	20,500	44,000	28,500	32,000	305,500
Total Cost (C_T)	36,850	22,350	30,120	24,750	17,850	33,450	53,250	25,750	51,250	31,750	41,450	368,820
Difference	11,850	4,850	-1,880	6,750	3,850	4,450	8,250	5,250	7,250	3,250	9,450	63,320

Table 1 reveals that, with the exception of Job 3, the company's assigned job costs are consistently lower than those generated by the Expert system. Consequently, this has resulted in a significant reduction of N63,320 (20.73%) in the company's total income for the month. This discrepancy can be attributed to the company's failure to comprehensively consider essential cost components, such as manpower, equipment, and indirect costs, as well as its neglect of accounting for each activity involved in job production when determining assigned costs.

This finding supports the assertion made by Effiong and Akpan (2019) that traditional costing systems often yield unreliable and inaccurate cost information, whereas Activity-Based Costing (ABC) systems can facilitate competitive advantages and enhance productivity performance. Additionally, Popesko (2009) notes that traditional or intuitive methods are unable to manage a company's overheads effectively and that Activity-Based Costing (ABC) is the only method that reduces inaccurate overhead cost allocation.

Figure 4 illustrates the internal inconsistencies among the eleven (11) company-assigned job costs. This irregularity stems from human bias and imperfection in making consistent decisions. In contrast, Expert systems are known to enhance accuracy and consistency in decision-making, facilitate faster problem-solving, and provide cost-effectiveness by reducing reliance on human experts (Saibene *et al.*, 2021).

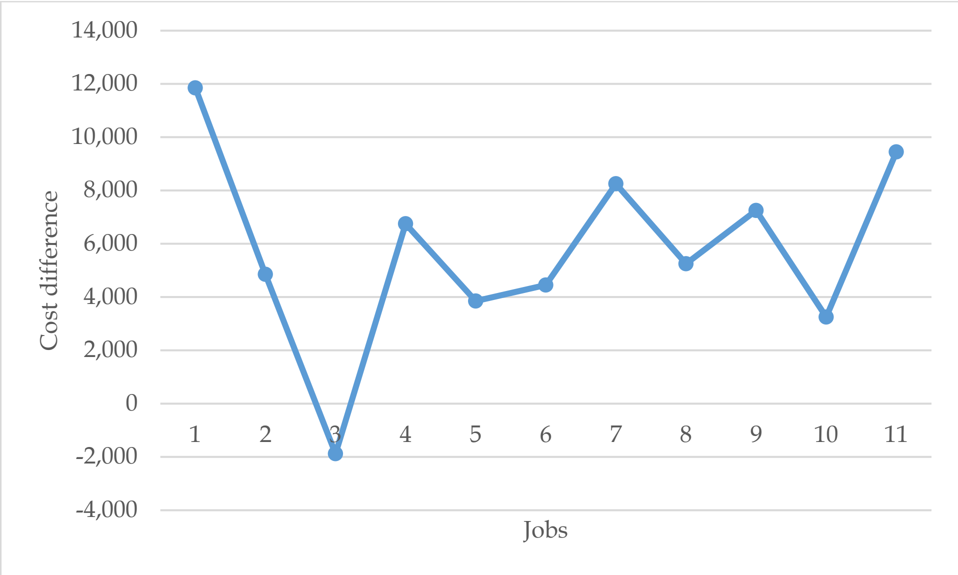

Figure 4: Internal inconsistencies in company-assigned job costs

4.0 Conclusion

This study has developed an expert system for cost estimation in job shop environments, leveraging the Activity-Based Costing (ABC) model and JavaScript programming language. The expert system provides a precise and reliable cost estimation tool, addressing the limitations of traditional cost estimation methods.

The results of the study demonstrate the effectiveness of the expert system in reducing cost estimation errors and enhancing profitability. The cost variance analysis revealed a significant reduction of N63,320 (20.73%) in the company's total income for the month, attributed to the company's failure to comprehensively consider essential cost components.

The findings of this study support the assertion that Activity-Based Costing (ABC) systems can facilitate competitive advantages and enhance productivity performance. The expert system developed in this research enhances accuracy and consistency in decision-making, facilitates faster problem-solving, and provides cost-effectiveness by reducing reliance on human experts.

The implications of this study are significant, as it provides a novel solution for cost estimation in job shop environments most especially in the developing nations. The expert system can be applied in various manufacturing settings, enabling organizations to optimize their cost estimation processes, improve profitability, and enhance competitiveness.

Future research directions include exploring the application of machine learning algorithms to improve the accuracy of cost estimation, integrating the expert system with other manufacturing systems, and investigating the impact of the expert system on supply chain management.

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