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Application of an Expert System for Critical Equipment Identification in Production Plant

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ABSTRACT
This paper presents the development of an expert system for identifying the critical equipment in a production plant on which Condition Based Maintenance (CBM) is required for early detection of faults. The system adopts analytical knowledge obtained from mathematical model and utilizes a forward and backward chaining inference scheme. The system was developed using Visual Basic 6.0 (Enterprise Edition) and Microsoft Access Application as front and back end engines respectively while Structured Query Language (SQL) is used for querying and modifying data and managing databases. The verification and validation of the Expert System was carried out using data collected from a Refinery and Petrochemical Company, in Ekpan-Warri, Nigeria which include; equipment types, labor rates, equipment rates, number of failures, average time taken to restore the failed equipment, hourly maintenance cost, purchase cost and the expected life span of the rotating equipment. The performance evaluation results showed that the system capable of identifying the most critical equipment in the plant and that plant availability is increased by scheduling maintenance activities on the identified critical equipment.

Keywords: Expert system, critical equipment, production plant, visual basic, Microsoft access

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I. INTRODUCTION

In recent years, expert systems have received greater attention from organizations because of their ability to enhance productivity and to aid the decision making process, especially when human experts are difficult to find and retain [1]. Expert system technology has captured the interest of professionals in a number of fields. Several notable expert systems have been developed in such diverse areas as engineering, science, business and medicine. In these areas, expert systems have been widely used to perform a variety of functions, including interpreting and identifying, planning and scheduling, process monitoring and control, diagnosis and troubleshooting, designing and manufacturing, among others. The deployment of expert systems in these areas has increased the quality, efficiency and competitive leverage of the operations of organization implementing the technology. Various definitions of expert system have been suggested through the years by different authors [2-5]. The common point being that they are all a branch of Artificial Intelligence (AI) that imitates the reasoning process and decision making skills of human experts when solving specific problem in a narrow domain. Expert system is usually a small component of a larger computer application, and is integrated with conventional programs so that it can use existing applications and data. The use of expert system arises out of the need to compensate for the limitations of human expertise: such as physical and mental limitations, inconsistency and bias. The various categories of expert systems include Rule-Based Systems, Fuzzy Logic Expert System, Knowledge-Based Systems, Neural Networks, among others [6, 7]. However, the spectrum of application of expert systems technology to industrial problems has been clustered around: process monitoring and control, fault detection, diagnosis and prognosis, as well as maintenance planning and scheduling [6]. Research works on expert systems application in equipment identification and maintenance strategy selection are quite scanty in the area of mechanical systems.

However, some notable works have been published in this field of study. Some have developed an expert fault diagnostic system for the repair and maintenance of bulldozer work equipment faults [8]. The expert system developed is capable of troubleshooting the causes of failure of the bulldozer work equipment. The detected faults; be it low or high hydraulic valve pressure, abnormal noise in the control valve are documented accordingly and these information are used to proffer solutions to effect repair and maintenance of equipment for optimum performance.

In another study, a method for identifying critical equipment of power plant based on criticality analysis using selected multiple criteria. The criticality analysis was used to rank the risk associated with each failure mode identified during the Failure Mode Effect Criticality Analysis (FMECA) [9]. The most critical equipment was then categorized to the least one using the score of the criticality index. In the same vein, Poesch et al. [10] presented a concept of probabilistic expert system using Bayesian network in order to effectively support human decision making and to accelerate problem solving processes. The application of Bayesian network for the knowledge base ensures that reasoning under uncertainty is possible and effective. A Bayesian network forms the basis of the system as it has the ability to describe complex dependencies and as well allows efficient inference algorithm and reasoning under uncertainty. The expert system was validated at a high power industrial laser manufacturer and shows very promising first results. However, a long term validation would be required to verify the effectiveness of the expert system.

In a recent study, a two-step decision making approach was applied for identifying critical equipment in an electrode graphite manufacturing plant. Validation was done using an innovative methodology of normalization for Analytical Hierarchy Process (AHP) and Preference Ranking Evaluation Method for Enrichment Evaluations (PROMETHEE) method. This approach identified the utility and screw compressor as the critical section and critical equipment respectively [11]. This study presents an expert system that makes use of dynamic criteria and allows for system update was developed for identifying critical equipment in a production plant. Maintenance cost is one of the main expenditure items in production companies that implement automated production systems, and this cost can represent as much as 15% to 70% of the total production cost [12–14]. In order to maintain competitiveness in the global market, higher productivity with minimum production cost becomes the main target [15]. Maintenance requirement in production plant is critical as unplanned breakdowns would adversely affect the entire production system. Considering either productivity or production costs; none can be separated from maintenance issues. Presently, the traditional breakdown and schedule maintenance approach is being replaced by the concept of Condition Based Maintenance (CBM). In addition to signal processing and subsequent diagnostic analysis, condition-based maintenance technology requires storage of large volumes of both quantitative and qualitative information which should be organized and accessed in a timely and efficient manner.

Critical equipment is one whose failure can affect plant's continued production and safety as well as personnel safety. Its role is very essential in production plants because its failure usually results in major economic setback of the process, with consequent gross marginal production loss for the company [16]. There are numerous methods currently available to assist in targeting assets that are most critical to the plant, such as Cost Based Criticality (CBC) assessment method and Cost Benefit Analysis (CBA) method [11, 17-19]. However, many of these approaches are static and do not allow system update as operating conditions change.

This study adopts a strategic model that is based on exponentially distributed failure probability concept as the knowledge source to develop an intelligent tool (expert system) for identifying critical equipment in a production plant. This is to ensure effective condition based maintenance planning on the critical equipment with consequent reduction in downtime and production losses.

II. EXPERT SYSTEM STRUCTURE

In order to retrieve facts and apply heuristics efficiently, the knowledge within the expert system must be organized in an easily accessible format. Figure 1 shows the structure of the expert system for identifying critical equipment.

2.1 Expert System Structure

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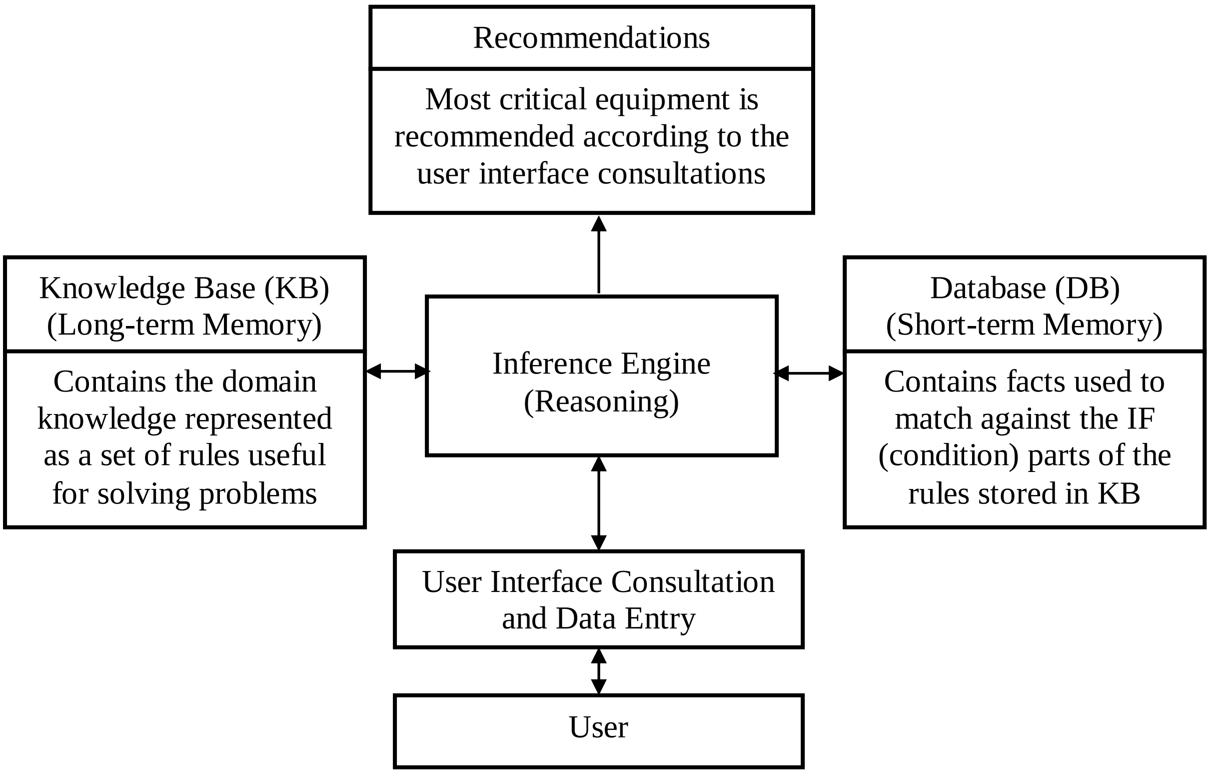


Figure 1: Structure of the Expert System

Figure 1 shows the structure of the expert system. The knowledge base (long-term memory) forms the heart of the expert system and contains declarative descriptions of expert information, problem solving rules, procedures or intrinsic data necessary for problem solving in a particular domain. In engineering concepts, semantic nets, frames and (if-then) rules are the most common strategies for representing knowledge. However, rules are the most popular type of knowledge representation technique because they provide formal way of representing recommendations, directives and strategies.

The database contains set of facts used to match against the IF (condition) parts of the rules stored in the knowledge base, while the inference engine carries out the reasoning whereby the expert system reaches a solution. It links the rules given in the knowledge base with the facts provided in the database to reach the required conclusion. Finally, the inference engine gives the recommended critical equipment. The communication between a user seeking a solution to a problem and an expert system is achieved via the user interface.

III. DESIGN AND DEVELOPMENT OF EXPERT SYSTEM

This work adopts the following approaches in developing the expert system:

- Knowledge acquisition
- Knowledge representation
- System development
- System validation

3.1 Knowledge Acquisition

Knowledge acquisition refers to the process of obtaining the required domain knowledge by the Expert System. The knowledge may be analytical knowledge obtained from mathematical model or heuristic knowledge obtain from domain human expert or a combination of both knowledge sources derived from experts and/or documented in journals, texts among others.

3.1.1 Expert System Knowledge Source

In this study, analytical knowledge was elicited from mathematical model in a research paper for identifying critical equipment in a production plant (petrochemical carbon black plant)

3.1.2 Data Collection

The data used in this study was collected from Warri Refinery and Petrochemical Company Carbon Black

Plant. This plant is one of the most modern plants in the world and uses the furnace process. It comprises of rotating equipment such as compressor and pumps, as well as static equipment which include pulverizer, pelletizer, dryer, bucket elevator, and reactors.

Data on labour rates, equipment rates, annual number of failures, average time taken to restore the failed equipment, and hourly maintenance cost (in Naira) were collected for the whole plant, Table 1-3. Also, the purchase cost and expected life span of the compressor and pumps were collected, Table 4.

Table 1: Daily Labor Rates (10 Hours/Day) Inclusive of Profit/Overhead, VAT/Tax, Safety Wears and Insurance at Work

S/N	Manpower Category	Rate (Naira/Day)
1	Special skill (Expatriate)	84,600
2	Engineer	29,500
3	Technician	14,700
4	Helper	6,000

Table 2: Manpower required for Maintenance of Rotating Equipment in the Carbon Black Plant

Equipment Type	Special Skill	Mechanical Engineer	Electrical Engineer	Instrument Engineer	Technician	Helper
Compressor	1	1	1	1	3	3
Pump 1	-	-	-	-	3	2
Pump 2	-	-	-	-	3	2
Pulverizer	-	1	-	-	6	3
Palletizer	-	1	-	-	6	3
Dryer	-	1	-	-	6	3
Bucket Elevator	-	1	-	-	6	3
Magnetic Separator	-	1	-	-	6	3
Screener	-	1	-	-	6	3

Table 3: Maintenance Data for Carbon Black Oil Furnace Process Plant

Equipment		Annual Failure	Hours of Maintenance	Failure Rate	Cost (₦) of running a standby
1	Compressor (Air)	1	10	1	2500000
2	Pump (1)-Oil	1	10	1	900000
3	Pump (2)-Fuel/Gas	1	10	1	900000
4	Pulverizer	1	10	1	-
5	Pelletizer	1	10	1	-
6	Dryer	2	10	0.5	-
7	Bucket Elevator	1	10	1	-
8	Magnetic Separator	1	10	1	-
9	Screener	1	10	1	-
10	Reactor	Turn Around Maintenance			
11	Air Pre-heater	Turn Around Maintenance			
12	Oil Pre-heater	Turn Around Maintenance			
13	Agglomerator	Turn Around Maintenance			
14	Bag Filter	Turn Around Maintenance			
15	Air Lock	Turn Around Maintenance			
16	Collection Cyclone	Turn Around Maintenance			
17	Pulverizing Cyclone	Turn Around Maintenance			
18	Surge Tank	Turn Around Maintenance			
19	Carbon Black Storage	Turn Around Maintenance			

Table 4: Equipment Cost and Expected Life Span

S/N	Equipment type	Purchase cost ((₦)	Expected life span of equipment (years)
1	Compressor	75,000,000	30
2	Pump 1	27,000,000	30
3	Pump 2	27,000,000	30

3.2 Knowledge Representation
The knowledge base contains the domain knowledge useful for solving problems. The knowledge is represented as a set of rule, and each rule specifies a relation, recommendation, directive, strategy or heuristic and has the IF (condition) THEN (action) structure. When the condition part of a rule is satisfied, the rule is said to fire and the action part is executed.

3.3 Expert System Development
In developing the expert system, flowchart and algorithm were first developed to illustrate the sequence of operations to be performed. Coding was done using Visual Basic programming language which serves as front end engine while the database was designed using Microsoft Access 2003 and this serves as back end engine. Structured Query Language (SQL) was used for querying, modifying data and managing databases.

Visual basic was used to ensure that the system supports efficient inferencing and good interface facilities with external programs and systems, allows for the representation of knowledge using IF-THEN-ELSE production rules. It also provides user-friendly interface consisting menu bars and buttons to help user during data input to the system and facilities to explicitly display results. A modular approach was adopted in the design of the expert system to ensure great flexibility in updating or adding modules in the future. The expert system module for identifying critical equipment is shown in Figure 4. While Figures 5-8 present screenshots of various interfaces such as equipment setting, manpower setting, manpower cost and maintenance data update.

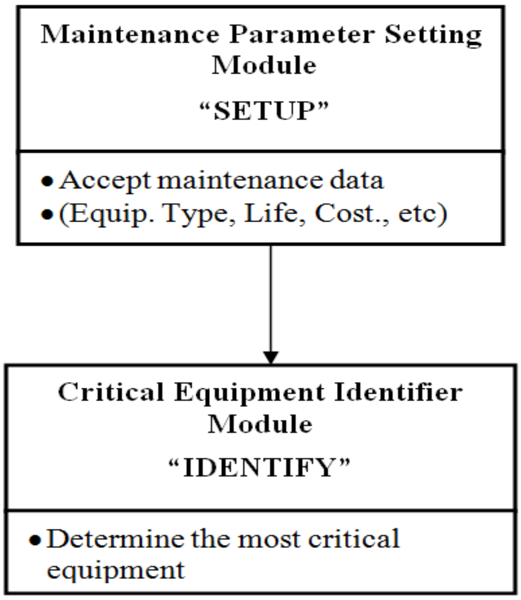


Figure 4: Expert System Modules

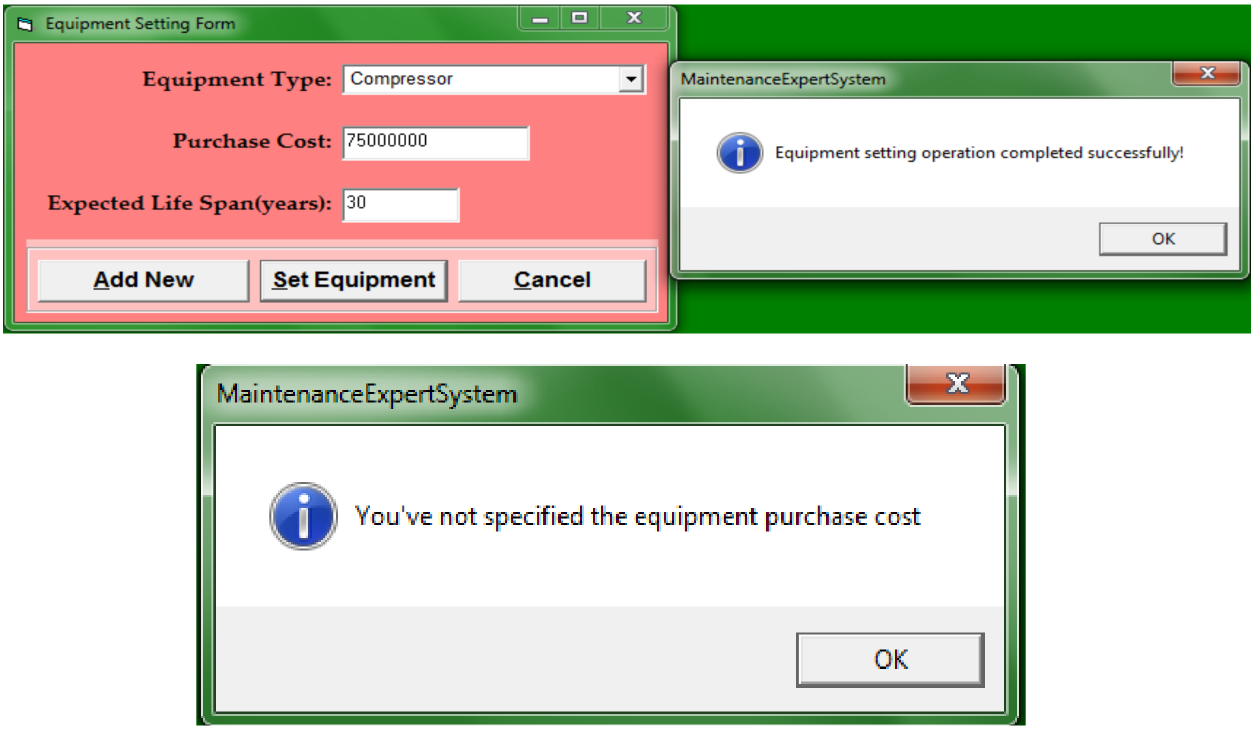


Figure 5 Equipment Setting Interface and Error Alert on Equipment Setting

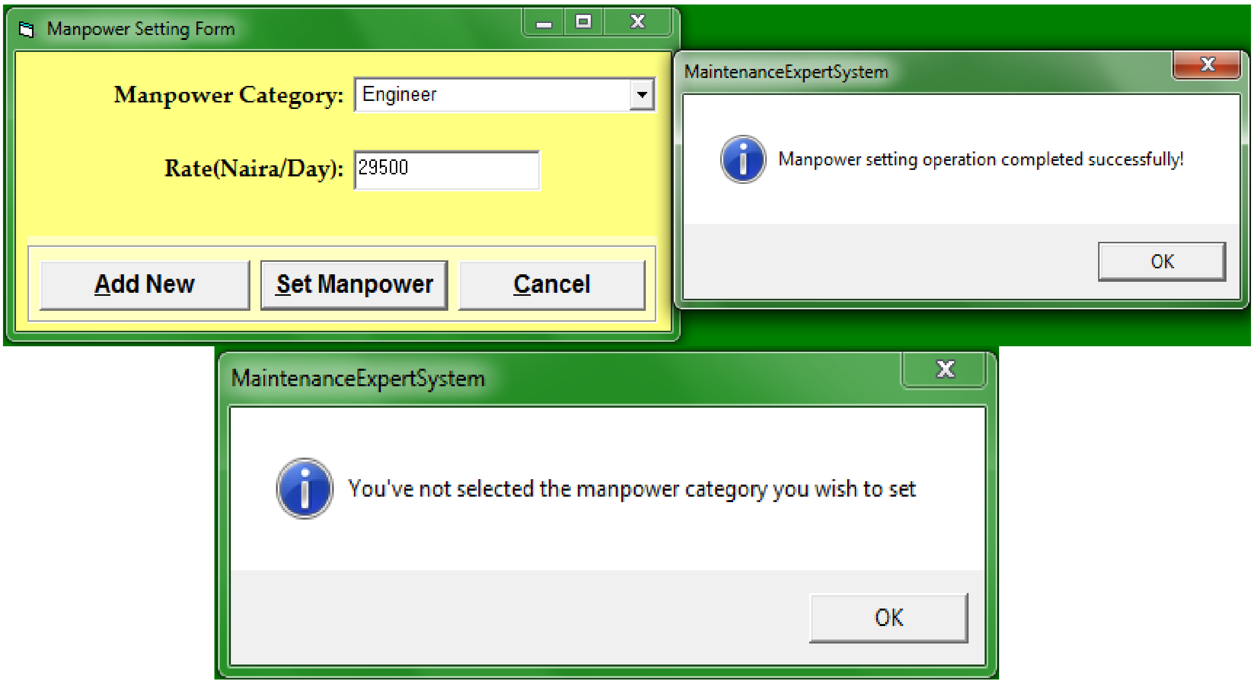


Figure 6 Manpower Setting Interface and Error Alert on Manpower Setting

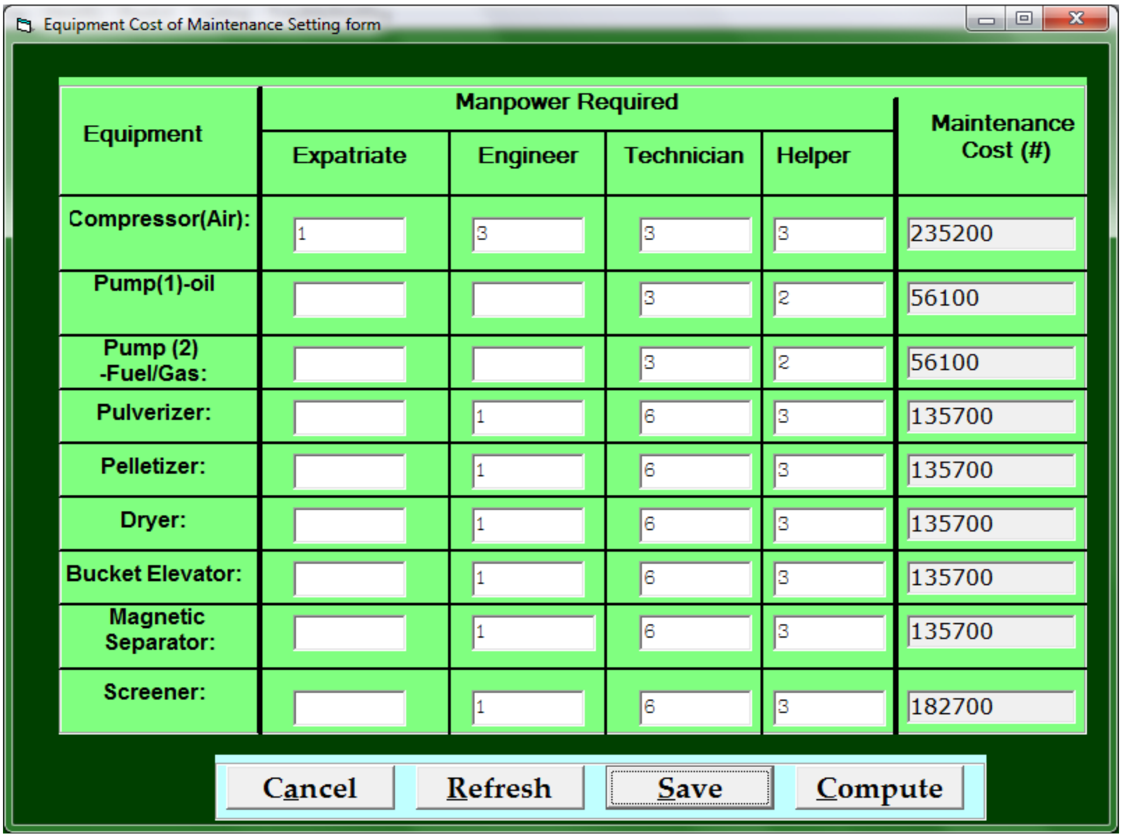


Figure 7 Interface for Computing Manpower Cost

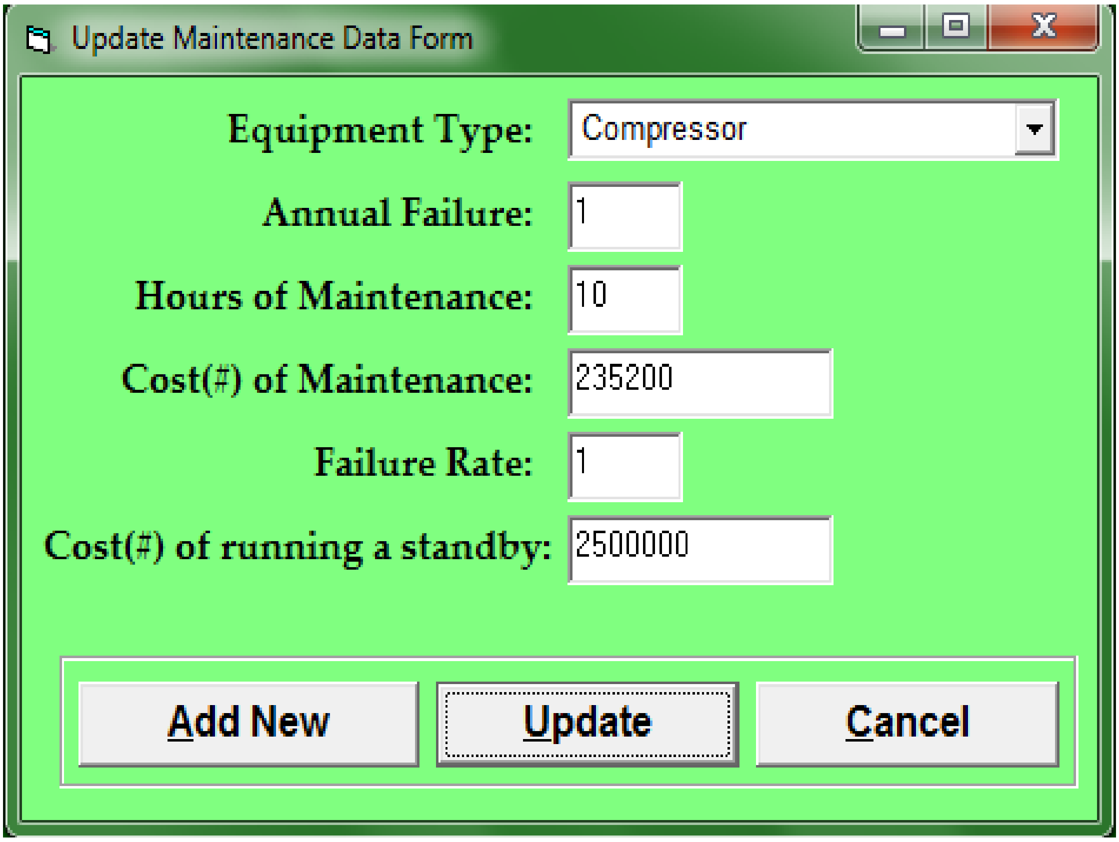


Figure 8 Interface for Maintenance Data Update

IV. RESULT AND DISCUSSION

The expert system is designed in such a way that the user interacts with the system through a series of input and dialogue forms. The forms allow the user to either select required parameters from predefined lists, or to enter them manually. The most critical equipment in the plant is identified by supplying appropriate data in the equipment setting and manpower setting forms and then updating maintenance data such as equipment type, annual failure and hours of maintenance, manpower required, failure rate and cost of running standby equipment. Based on the information supplied, the expert system generates output report which indicates the most critical equipment from the list of equipment in the plant. For example, to identify the most critical equipment in the carbon black plant in which nine equipment may experience failure at any quarter of the year, Table 3, the inference block diagram illustrating the process for one of the equipment (compressor) is shown in Figure 9. While the expert system output results are shown in Figures 10 to 13. Similar inference control mechanism applies for other eight equipment and the output results are presented along with that of the compressor for all four quarters of the year.

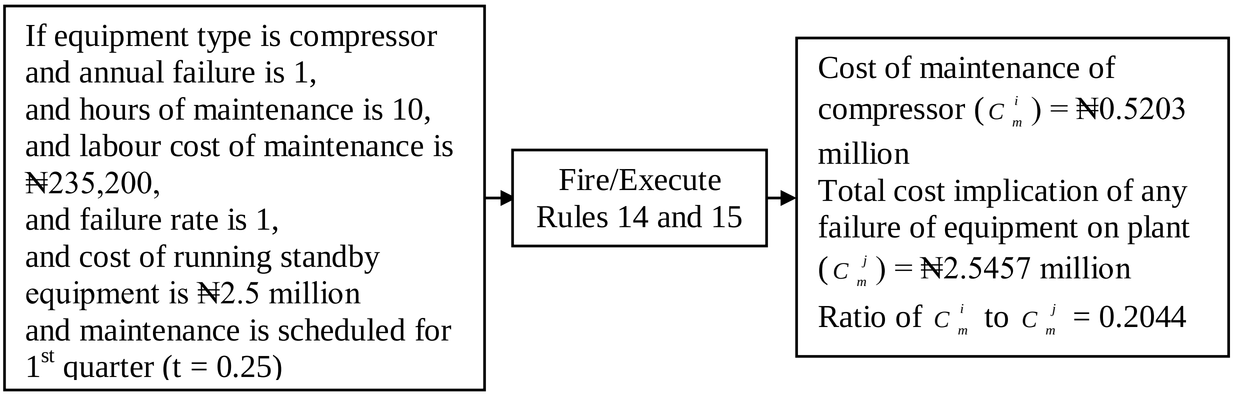
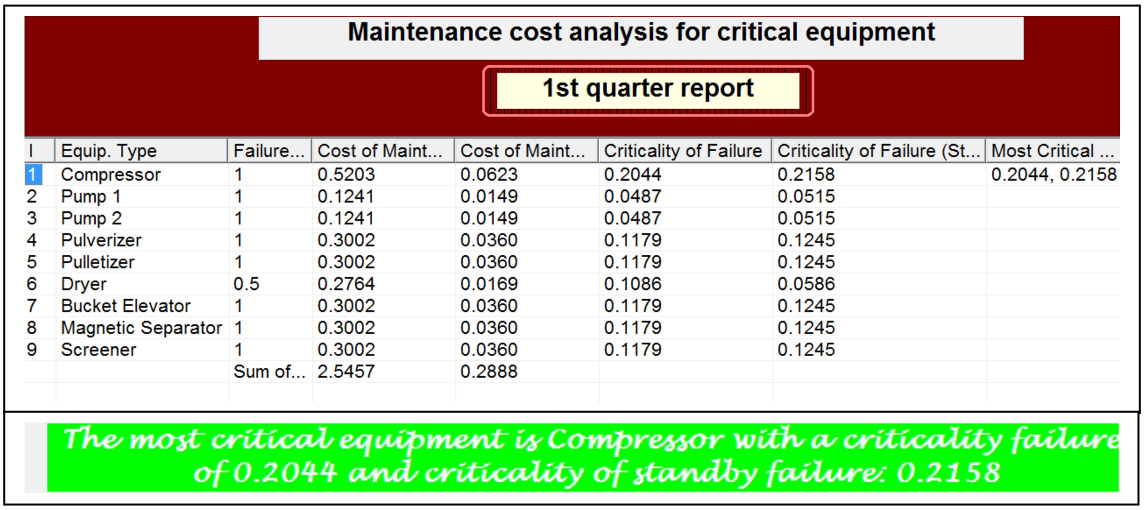


Figure 9 Inference Engine Block Diagram on Identification of Critical Equipment



I	Equip. Type	Failure...	Cost of Maint...	Cost of Maint...	Criticality of Failure	Criticality of Failure (St...	Most Critical ...
1	Compressor	1	0.5203	0.0623	0.2044	0.2158	0.2044, 0.2158
2	Pump 1	1	0.1241	0.0149	0.0487	0.0515	
3	Pump 2	1	0.1241	0.0149	0.0487	0.0515	
4	Pulverizer	1	0.3002	0.0360	0.1179	0.1245	
5	Pulletizer	1	0.3002	0.0360	0.1179	0.1245	
6	Dryer	0.5	0.2764	0.0169	0.1086	0.0586	
7	Bucket Elevator	1	0.3002	0.0360	0.1179	0.1245	
8	Magnetic Separator	1	0.3002	0.0360	0.1179	0.1245	
9	Screener	1	0.3002	0.0360	0.1179	0.1245	
		Sum of...	2.5457	0.2888			

The most critical equipment is Compressor with a criticality failure of 0.2044 and criticality of standby failure: 0.2158

Figure 10 Expert System Report on Critical Equipment Identification (1st Quarter)

Maintenance cost analysis for critical equipment

2nd quarter report

I	Equip. Type	Failure...	Cost of Maint...	Cost of Maint...	Criticality of Failure	Criticality of Failure (St...	Most Critical ...
1	Compressor	1	0.9254	0.2122	0.2031	0.2148	0.2031, 0.2148
2	Pump 1	1	0.2207	0.0506	0.0484	0.0512	
3	Pump 2	1	0.2207	0.0506	0.0484	0.0512	
4	Pulverizer	1	0.5339	0.1224	0.1172	0.1239	
5	Pulletizer	1	0.5339	0.1224	0.1172	0.1239	
6	Dryer	0.5	0.5203	0.0623	0.1142	0.0631	
7	Bucket Elevator	1	0.5339	0.1224	0.1172	0.1239	
8	Magnetic Separator	1	0.5339	0.1224	0.1172	0.1239	
9	Screener	1	0.5339	0.1224	0.1172	0.1239	
		Sum of...	4.5569	0.9877			

The most critical equipment is Compressor with a criticality failure of 0.2031 and criticality of standby failure: 0.2148

Figure 11 Expert System Report on Critical Equipment Identification (2nd Quarter)

Maintenance cost analysis for critical equipment

3rd quarter report

I	Equip. Type	Failure...	Cost of Maint...	Cost of Maint...	Criticality of Failure	Criticality of Failure (St...	Most Critica
1	Compressor	1	1.2410	0.4077	0.2018	0.2137	0.2018, 0.2
2	Pump 1	1	0.2960	0.0973	0.0481	0.0510	
3	Pump 2	1	0.2960	0.0973	0.0481	0.0510	
4	Pulverizer	1	0.7160	0.2352	0.1165	0.1233	
5	Pulletizer	1	0.7160	0.2352	0.1165	0.1233	
6	Dryer	0.5	0.7355	0.1293	0.1196	0.0678	
7	Bucket Elevator	1	0.7160	0.2352	0.1165	0.1233	
8	Magnetic Separator	1	0.7160	0.2352	0.1165	0.1233	
9	Screener	1	0.7160	0.2352	0.1165	0.1233	
		Sum of...	6.1485	1.9078			

The most critical equipment is Compressor with a criticality failure of 0.2018 and criticality of standby failure: 0.2137

Figure 12 Expert System Report on Critical Equipment Identification (3rd Quarter)

Maintenance cost analysis for critical equipment

4th quarter report

I	Equip. Type	Failure...	Cost of Maint...	Cost of Maint...	Criticality of Failure	Criticality of Failure (St...	Most Critical
1	Compressor	1	1.4867	0.6215	0.2006	0.2126	0.2006, 0.21
2	Pump 1	1	0.3546	0.1482	0.0479	0.0507	
3	Pump 2	1	0.3546	0.1482	0.0479	0.0507	
4	Pulverizer	1	0.8578	0.3586	0.1158	0.1227	
5	Pulletizer	1	0.8578	0.3586	0.1158	0.1227	
6	Dryer	0.5	0.9254	0.2122	0.1249	0.0726	
7	Bucket Elevator	1	0.8578	0.3586	0.1158	0.1227	
8	Magnetic Separator	1	0.8578	0.3586	0.1158	0.1227	
9	Screener	1	0.8578	0.3586	0.1158	0.1227	
		Sum of...	7.4104	2.9230			

The most critical equipment is Compressor with a criticality failure of 0.2006 and criticality of standby failure: 0.2126

Figure 13 Expert System Report on Critical Equipment Identification (4th Quarter)

The expert system results in Figures 9-12 show that of all the nine equipment analyzed, the cost implication of any failure of these equipment in terms of production loss and maintenance indicates that failure cost implication was highest for compressor under non-standby and standby equipment installation scenarios. The failure cost increased with increased maintenance scheduling period and reached the highest at the last (fourth) quarter. For instance, in the first quarter the cost incurred due to equipment failure was about 0.52 million naira when there is no standby equipment; but with the installation of standby equipment, this cost was reduced to 0.0623 million naira.

4.1 Verification and Validation of Expert System

Verification tests were performed on the expert system module after the system had been completed. The system was extensively validated by domain human expert (chief engineer) who is responsible for the maintenance planning and execution of the carbon black plant of Warri Refinery and Petrochemical Company. This was performed to ensure that the system provide the correct results and meets the user's requirement.

Test Case: Identification of Most Critical Equipment
Significant Input:
Equipment type = compressor
Annual failure = 1
Hours of maintenance = 10
Cost of maintenance = N235,200
Failure rate = 1
Cost of running standby = N2,500,000
Maintenance schedule period = 0.25 (1^{st} quarter)
Output by "IDENTIFY" module.
Cost of maintenance of compressor = N0.5203 Million
Cost of maintenance of standby = N0.0623 Million
Criticality of failure of compressor = 0.2044 (the compressor is the most critical equipment because it has the highest ratio of Costs of maintenance of equipment i (C_m^i) to Cost implication of any failure of equipment i on the plant (C_m^j) for all the nine equipment considered.
Criticality of failure of standby equipment = 0.2158
Output correct? Yes.

A total of 40 tests cases were examined during the system's validation as shown in Table 5

Table 5: Validation of Expert System

Expert System Modules Test Cases:	Cases Tested	Cases Successful	Cases Partially Successful	Cases Unsuccessful	Approximate Percentage of Success
IDENTIFY Logics	40	40	0	0	100

The expert system test results showed that the system is consistently close to 100% accuracy and capable of identifying the most critical equipment in the petrochemical carbon black plant.

V. CONCLUSION

An expert system has been developed for identifying critical equipment in a production plant. The expert system makes use of analytical knowledge obtained from a mathematical model and data was collected from the carbon black production plant in Warri Refinery and Petrochemical Company. The expert system utilizes a forward and backward chaining inference schemes in which the user has to supply data and/or relevant information to the system to generate knowledgeable recommendation that aids the identification of critical equipment in the plant.

The system was developed using Visual Basic 6.0 (Enterprise Edition) and Microsoft Access Application as front and back end engines respectively, while Structured Query Language (SQL) was used for querying, modifying data and managing databases. The developed expert system provides consistent answers for repetitive decisions, processes and tasks. It can hold significant levels of information and reduce dependence upon one expert as it can be used by many users more frequently.

This study has provided a decision tool for economic maintenance scheduling by identifying the critical equipment in a production plant on which maintenance activities could be effectively planned to reduce downtime and production losses. The expert system could serve as a better alternative tool for reducing maintenance time with consequent reduction in maintenance cost, distribution of expertise, and documenting knowledge for emerging engineers.

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