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Managing finished goods inventory-maintenance engineering interaction subject to technical manufacturing information complexity employing an associated fuzzy-system dynamics approach

Desmond Eseoghene Ighravwe[1)] and Sunday Ayoola Oke*[2)]

[1)]Department of Mechanical Engineering, The Bells University of Technology, Ota, Nigeria
[2)]Department of Mechanical Engineering, Faculty of Engineering, University of Lagos, Akoka-Yaba, Lagos, Nigeria

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Abstract

Despite experiencing industrialisation, Nigerian business organisations are largely in turbulent environments and have a significant need to manage their inventories effectively in collaboration with their production and maintenance departments. Research on this issue is still incomplete. The objective of this communication is to demonstrate the use of a system dynamics (SD) method in the enhancement of inventory practices in relation to maintenance engineering in a factory. As a method, SD showcases an enhanced insight into the complexity of dynamics associated with inventory cum maintenance practices. The SD technique was successfully employed to model and analyse variables to gain insight and pin-point the principal compelling factors in inventory management system of manufacturing organisations. A fuzzy-SD model was used to evaluate the stock levels of finished goods, the number of experienced technicians and in the number of unavailable machines in manufacturing systems. The proposed model is a combination of a fuzzy inference system, SD, TOPSIS, the WASPAS method and aggregated rank sum. Enhancement of inventory performance is displayed as a workable model that can be implemented to handle complicated inventories in factories to achieve improved performance in manufacturing.

Keywords: Performance enhancements, Inventory, System dynamics, Maintenance, Fuzzy inference system, Multi-criteria tools, Aggregated rank sum

1. Introduction

There is ever-growing pressure for cost reduction and quicker decision making in manufacturing systems. This has driven inventory systems to heavily depend on information technology with the unprecedented and expanding of manufacturing clouds as well as manufacturing data digitisation [1]. An inventory system is a complex interaction of several distinct parts which are ultimately connected. In manufacturing, an inventory system is heavily reliant on maintenance, which is itself dependent on the number and effectiveness of maintenance technicians and machine availability. An inventory system depends on a number of variables other than maintenance, such as the availability of funding, storage space, and logistics variables, among others. In the current work, these variables are considered passive. Development of a system dynamics (SD) model is based on maintenance alone. Thus, a maintenance system is considered a principal influence on inventory stocks in manufacturing. Consequently, more advanced modelling in the future could downplay maintenance and make other variables more important.

In view of the above arguments, the principal aim of this study was to design an associated fuzzy-SD model for dealing with the problem of stock levels of finished goods in a manufacturing operation. The fuzzy-SD model attempts to address the following research questions. First, we ask what is an acceptable number of experienced maintenance technicians required for a manufacturing system? We further probed to determine the acceptable number of unavailable machines for production activities. Furthermore, what would be the acceptable stock level of finished goods in inventory based on the answers to the first two questions? In the current communication, our perception is somewhat different from other researchers about the acceptable stock levels of finished goods in inventory. Most established theories on inventory are associated with policy formulation with an assumption that the environment is unimportant. However, this is not true. Several factors and functions influence inventory, including maintenance. Thus, we argue that the assumptions of most previous models on inventory are at least in part flawed, particularly with respect to the impact of these external factors upon inventory are strongly acknowledged in performance. Earlier theories are used today and no better alternatives exist.

The current study explains how to address a finished goods inventory problem in a manner that is more practical. Furthermore, the advantage of using this approach is that industries will be able to formulate and solve such problems. This communication provides a benchmark for engineering

*Corresponding author.
Email address: sa_oke@yahoo.com
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educators in the establishment of other important approaches [2]. It does not consider the significant influence of accounting and management actions on inventory to restrict the scope of the work. The study is comprehensive in its analysis in dealing with the interaction of maintenance with inventory. Previous work has largely dwelt upon interactions involving machine breakdowns, machine usage and stock levels. That machine breakdown largely influences the production of finished goods is broadly accepted and this becomes the starting point of this communication's modelling. The maintenance technician is at the centre of the action. Thus, the attributes of the technician with respect to machine repair rates are analysed. A relationship is then established between the first and second sub-systems to model the interaction between machine availability and the rate of machine usage. Finally, consideration is given to the stock level.

The method of SD yields an improved insight into the dynamics of complex inventory systems [3-4]. The approach of SD has tremendous utility when employed for system representation and as an instrument for analysis. It gives insights into information-oriented and data-driven inventory management systems. The prime motivation of the current communication is to establish away in which planning and controlling the complexity involved in inventory dynamics through the use of SD can be enhanced. Real-time and undisturbed information flow from machine downtime and machine availability variables and consequentially enhanced system outputs are expected from the proper implementation of SD in the current investigation. In the current communication, SD is a necessary and essential instrument for progress in inventory systems as well as for the radical transformation of information flow in a maintenance system.

Nowadays, Nigeria, like several other nations is saddled with diverse challenges that affect businesses – financial challenges, problems due to weather, political instability, social problems and a host of others. These challenges are often characterised by complicated interacting variables. They may be effectively resolved by employing system dynamics. Nevertheless, in certain circumstances, the causal loops, which are the foundations for system dynamics, may not be fully explained since there is vagueness and imprecision in the considerations. A literature approach is to employ other models together with system dynamics. Fuzzy logic has been found to be a good fit in this situation. Hence, integration of fuzzy logic and system dynamics to yield fuzzy system dynamics was done in the present work.

The aim of this study is to design a fuzzy-SD model for dealing with the problem of controlling stock levels of finished goods in a manufacturing system. The fuzzy-SD model attempts to address the following research questions:
i. What is the acceptable stock level of a finished goods inventory?
ii. What is the number of experienced technicians required for maintenance activities?
iii. What is the acceptable number of unavailable machines?

These questions are addressed in the current study using TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) methodology. The proposed model is a simulation developed using a fuzzy inference system, SD, TOPSIS, WASPAS (weighted aggregate sum product assessment) methods and an aggregated rank sum.

2. Literature review

Several attempts have been made to model manufacturing operations using SD methods. These models often consider exogenous and endogenous parameters that affect manufacturing operations. The SD literature has witnessed the integration of other scientific tools into the SD framework (e.g., balance scorecard, fuzzy logic, analytical network processes, TOPSIS and neural networks). Furthermore, SD models have been used with issues of manufacturing system sustainability. This has helped to increase the applicability of SD models in manufacturing systems analysis.

Orji and Wei [5] addressed the problem of supplier selection with respect to sustainability factors using fuzzy TOPSIS and SD methods. The SD method results showed that supplier performance was influenced by sustainability factors in an exponential manner. Disney et al. [3] studied the issue of supply chain management in manufacturing industries using an SD approach. Their study revealed that under a vendor-managed inventory system, transportation cost savings can be achieved in short and long term scenarios. Tesfamariam and Lindberg [6] presented a combined SD and analytical network process (ANP) approach for manufacturing system configuration analysis. Three manufacturing system configurations (job shop, cellular shop and dedicated lines) were considered in the study. Based on an illustrative example, the SD model was able to identify the best configuration was a job shop. Georgiadis and Michaloudis [7] presented an SD model that focused on job shop performance improvement. Their SD model generated optimal values for work in process inventories, tardy jobs and average backlogged orders as a means of improving job shop performance.

Dejonckheere et al. [8] used an SD model to analyse replenishment policy for order-up-to condition. Their model addressed the problem of smooth ordering characteristics of a system under a forecasted demand situation. Georgiadis and Besiou [9] solved the problem of electrical and electronic equipment sustainability using an SD method. They presented a case study of a single product from a single producer in Greece. Their results showed that regulatory issues concerning long-term environmental matters can be handled using an SD model. Seidel et al. [10] developed an SD model for business process sustainability for small and medium scale enterprises (SMEs). Their study revealed that financial and managerial factors affect the implementation of SME sustainability models.

Vlachos et al. [11] demonstrated the use of an SD model as a tool for managing a manufacturing system with reverse supply chain features. Their SD model considered the issue of environmentally friendly manufacturing operations. Wang et al. [12] applied an SD model to address the problem of subsidised recycling and remanufacturing. The SD model performance was studied under various types of subsidy scenarios. The conclusions of their study showed that the suitability of a subsidy depends on the stage of the remanufacturing industry. Shahanaghi and Yazdian [13] used an SD model to analysed total productive maintenance (TPM) implementation in a manufacturing system. They concluded that a TPM approach has the potential to address the issues of process quality and machine reliability.

Akkermans and van Oorschot [14] incorporated an SD model into a balanced scorecard framework. The SD model was able to establish the interrelationships among key variables that can be used for balanced scorecard implementation. Sharma et al. [15] investigated the applicability of an SD model as a tool for evaluating the performance index of a distributor. The SD model was based on the interactions among "results" and "enablers" variables of a distributor. Goh et al. [16] modelled the factors that affect occupational health and safety programme performance at mining sites using an integrated SD model. Their findings revealed that accidents that are systematic in nature can be prevented using an SD model. Venkateswaran and Son [4] presented combined z-transformation techniques and SD model for production-inventory stability problem. Information variation was used to test the stability of the SD model. They were able to show that frequency information updates are required to successfully manage a system with high inventory and work-in-process values.

Akkermans and van Helden [17] analysed the interrelationships among factors that are critical to enterprise resource planning (ERP) implementation using an SD model. Their findings showed that the success or failure of an ERP system is dependent on external (software vendor) and internal (project team) factors. Rabelo et al. [18] applied a combined an artificial neural network (ANN) and SD model to study the impacts of external and internal variables on the supply chain of a manufacturing system. An ANN model was employed to analyse supply chain behaviour using the output variables of an SD model as its input variables. Their findings attribute fluctuations in supply chain behaviour to internal factors of a manufacturing system. Jambekar [19] presented an SD model for manufacturing process improvement. The SD model was used to establish the interrelationships among maintenance, production and quality variables in a manufacturing system. They observed that their SD model has the potential of identifying and rectifying quality issues that are caused by equipment related problems.

From the above literature, it is clear that SD models have been successfully developed to enhance company sustainability. However, there is sparse information on simultaneous analysis of stock levels of finished goods, the number of experienced technicians' required for maintenance activities and the number of unavailable machines. The interconnection with maintenance is also lacking in existing structures. This literature gap is addressed in the current research. The current study presents a methodology for solving this problem in the next section.

3. Methodology

The proposed fuzzy-SD model was designed by first presenting the SD aspects of the model. The fuzzy inference aspects of the model were then considered (Figure 1). The proposed model is made up of three sub-systems. The first sub-system deals with the determination of rates of machine breakdown, while the second sub-system evaluates the rate of machine usage. The value of stock level is evaluated using a third sub-system.

3.1 System dynamics

System dynamics describes an innovative and effective computer-assisted method for manufacturing or business design and analysis in which the dynamic manner in which problems arise in such systems are modelled to account for as many quantifiable variables as possible. The salient elements of a system dynamics method are the causal loops, interactions and feedback.

The design of the proposed model starts by considering the variables that affect the rates of machine breakdown. This study considers maintenance technician attributes with respect to machinery repair rates. The causal loop diagram for the first sub-system is presented as Figure 2. This causal loop is a goal seeking loop. Its purpose is to study the effects

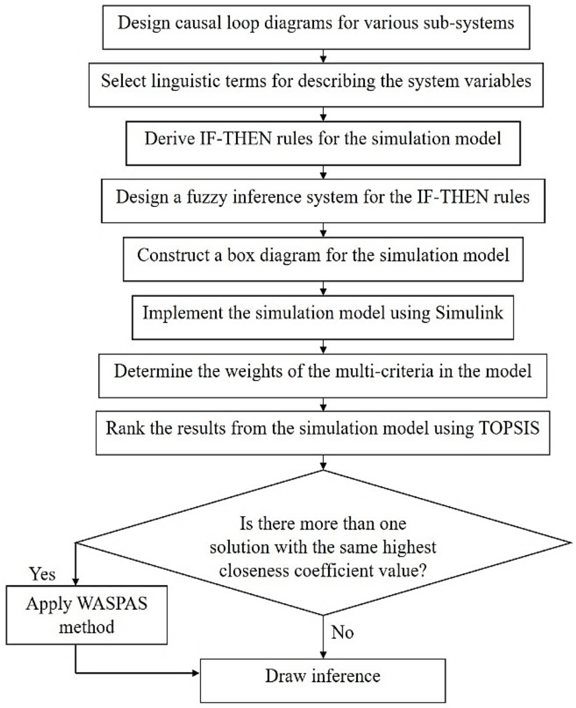

Figure 1 A fuzzy-SD model for stock level monitoring in manufacturing systems

of the number of unavailable machines on finished goods inventory and requirements for technicians. When the number of inoperative machines is low, there will be an increase in the number of machines that will be used for production activities. This will increase the amount of finished goods and the number of technicians that are required for machine maintenance. The requirements for technicians are based on the frequency of machine breakdown and the service rate of the technicians. There is a need for continuous evaluation of the technicians' experience by maintenance managers to ensure a minimal level of machine availability. Whenever there is shortage of experienced technicians, new technicians are hired. The new technicians are expected to increase the population pool of experienced technicians after minor training programs. Additionally, the rate of at which machines leave a maintenance pool will increase. This will have a direct effect on the number of available machines.

The main concern of most production managers is to ensure that a constant level of machine availability is maintained. This is necessary to support the expected machine usage. Given that the production rate of a production line is constant, the expected production volume from a system can be determined. The need to know the expected production volume from a system is to appropriately manage the demand for a product. A causal loop diagram that connects the number of unavailable machine and production volume to address the problem of production volume is shown (Figure 3). This diagram depicts a growth-generating loop. Consideration is given to the issue of minor stoppages that may result from machine breakdowns. This is necessary to properly manage the available production time. Machine breakdowns affect the quality of products from a system and therefore reduce the level of stock.

Some manufacturing systems use the concept of outsourced production activities to minimise the problem of

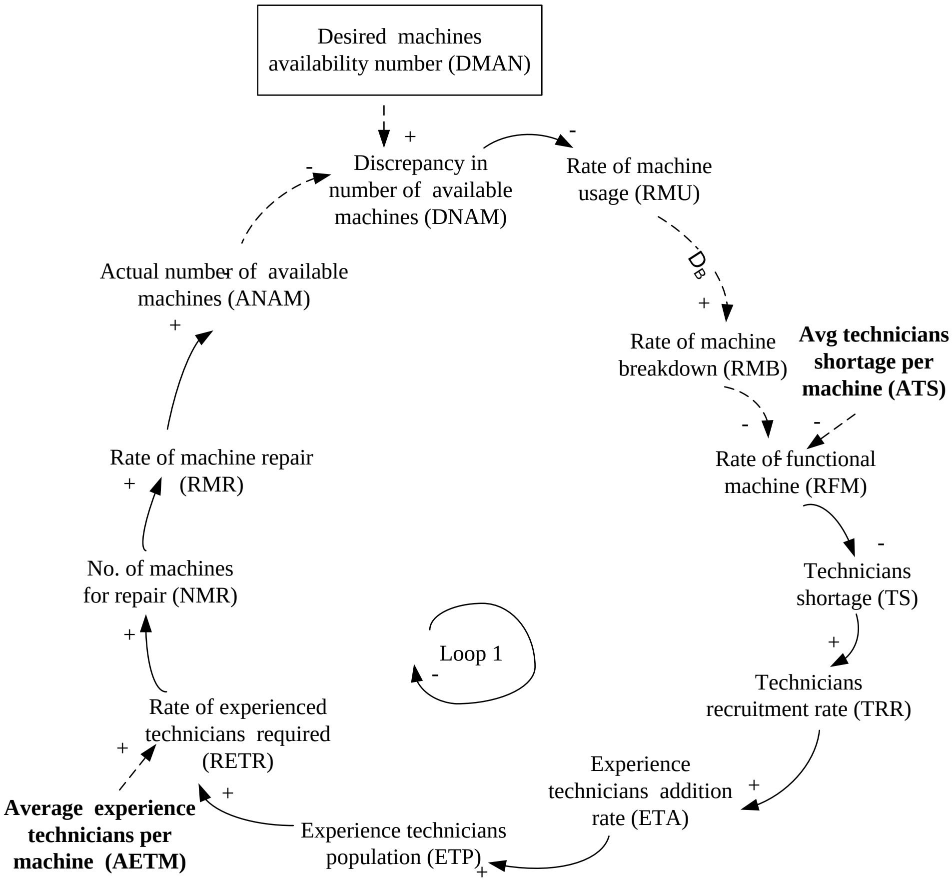

Figure 2 Causal loop for machine breakdown

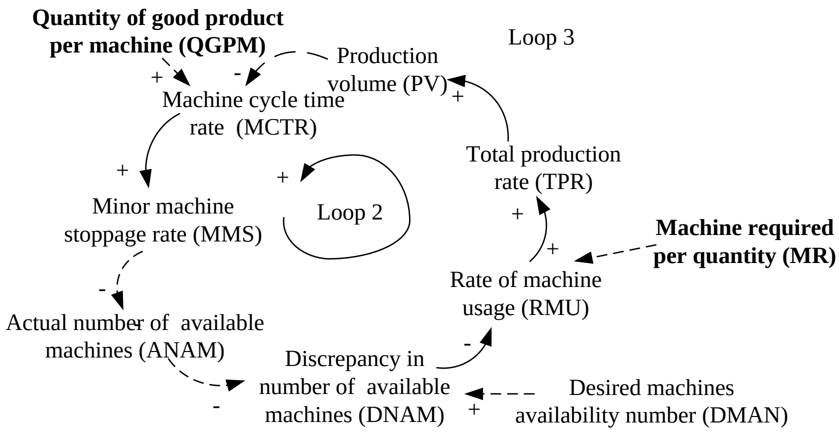

Figure 3 Causal loop for rate of machine usage

stock shortage. Also, the concept of vendor efficiency for raw materials has been adopted to reduce the occurrence of stock shortages. A goal seeking causal loop that relates stock levels and production volume is considered in this study (Figure 4). This loop shows that the amount of stock in the system during a period is affected by the actual volume of good products produced by the system and outsourced production activities. It also considers product demand and damage that can occur during storage of products as factors that reduce stock levels. Damage may occur as a result of handling problems or product shelf life expiry.

The interrelationship between maintenance activities and stock levels is established using the number of available machines and machine usage (Figure 5). The integrated causal loop diagram provides a means of simulating stock levels under a multi-factor scenario. During machine usage, the issue of delay caused by breakdown (D_B) is considered.

3.2 Simulation model

Based on Figure 5, a box diagram for the simulation model was designed (Figure 6). This model was based on the concept of a fuzzy inference system. It helps in the design of IF-THEN rules for the various relationships in Figure 5 [20]. To design an IF-THEN rule, linguistic terms are used to describe the relationships. Each of the variables in Figure 6

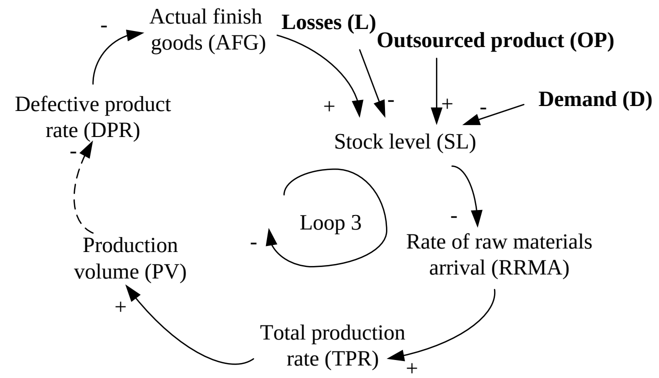

Figure 4 Causal loop for stock levels

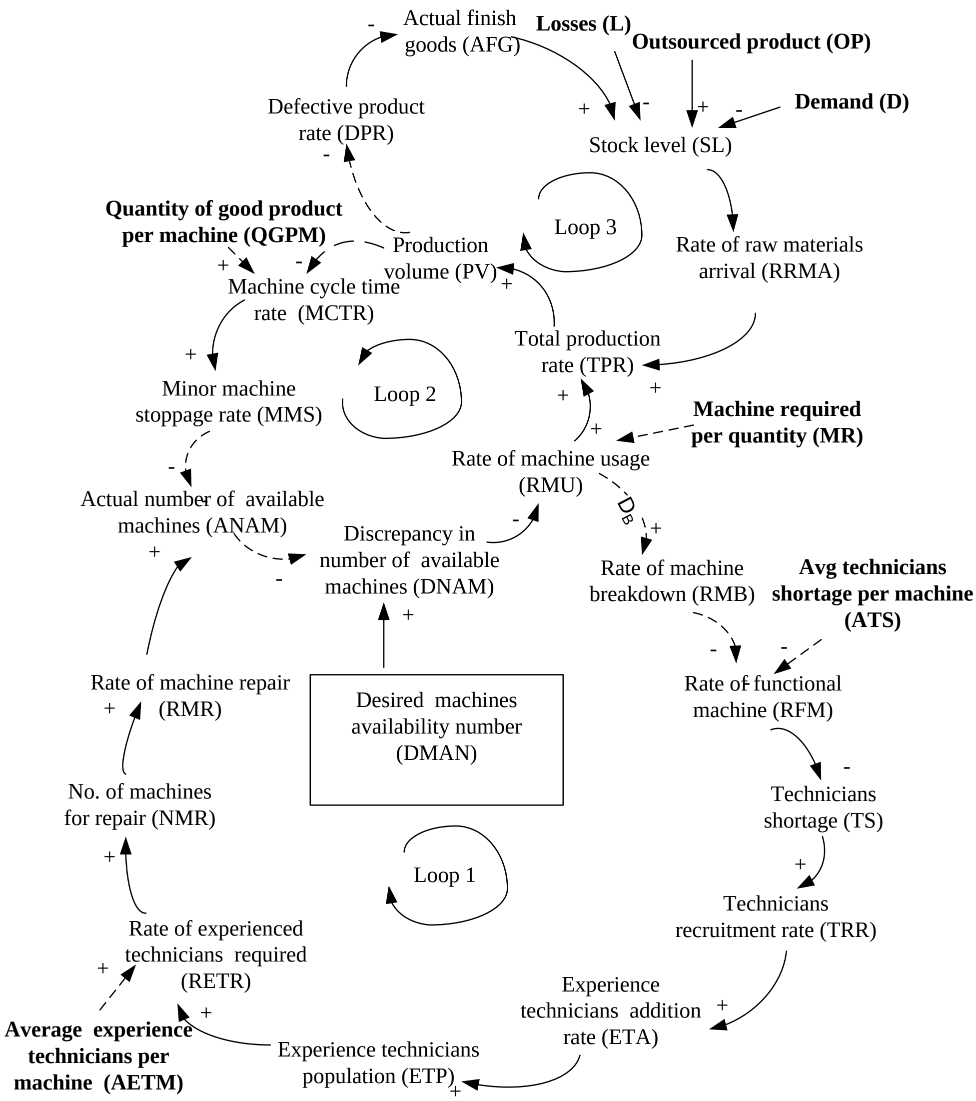

Figure 5 Integrated causal loop diagram

is represented by sets of IF-THEN rules. This study considers a three-scale partitioning system to describe the stock level (Table 1). Model performance is affected by the external variables that influence stock level. These variables are AETM, ATS, DMAN, MR, QGPM, D, OP and L while the full meanings of these variables are shown in Figure 5.

For a relationship in which an increase in the value of a variable results in a corresponding decrease in another variable, Figure 7 is used in generating an IF-THEN statement. The concept of one-to mapping is used in presenting the knowledge based system in the proposed model. The membership functions that are used to describe the relationships between inputs and outputs in goal-seeking

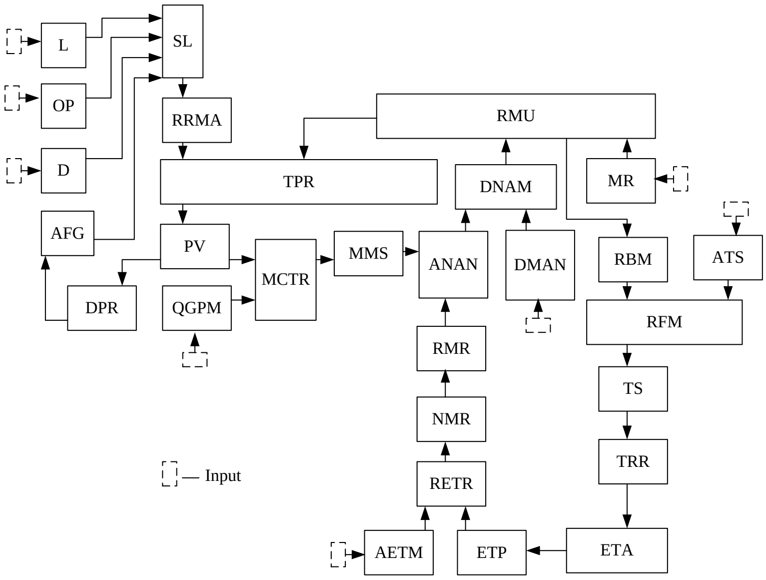

Figure 6 Box diagram for stock level simulation

Table 1 Linguistic terms for describing stock quantity

Linguistic term	Low	Moderate	High
Symbol	L	M	H

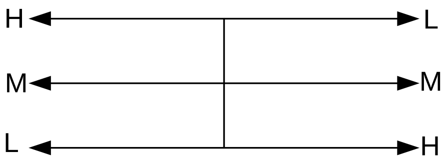

Figure 7 Linguistic terms scale

and growth-generating loops are triangular membership functions.

3.2.1 Fuzzy knowledge-based for causal loop 1

The If-Then rules for the first loop are presented as follows:

Rule 1A If DNAM is high then RMU is low, Else If DNAM is moderate then RMU is moderate, Else If DNAM is low then RMU is high.

Rule 2A If RMB is high then RFM is low, Else If RMB is moderate then RFM is moderate, Else If RMB is low then RFM is high.

Rule 3A If ATS is high then RFM is low, Else If ATS is moderate then RFM is moderate, Else If ATS is low then RFM is high.

Rule 4A If RFM is high then TS is low, Else If RFM is moderate then TS is moderate, Else If RFM is low then TS is high.

Rule 5A If TS is high then TRR is high, Else If TS is moderate then TRR is moderate, Else If TS is low then TRR is low.

Rule 6A If TRR is high then ETA is high, Else If TRR is moderate then ETA is moderate, Else If TRR is low then ETA is low.

Rule 7A If ETA is high then ETP is high, Else If ETA is moderate then ETP is moderate, Else If ETA is low then ETP is low.

Rule 8A If ETP is high then RETR is high, Else If ETP is moderate then RETR is moderate, Else If ETP is low then RETR is low.

Rule 9A If AETM is high then RETR is high, Else If AETM is moderate then RETR is moderate, Else If AETM is low then RETR is low.

Rule 10A If RETR is high then NMR is high, Else If RETR is moderate then NMR is moderate, Else If RETR is low then NMR is low.

Rule 11A If NMR is high then RMR is high, Else If NMR is moderate then RMR is moderate, Else If NMR is low then RMR is low.

Rule 12A If RMR is high then ANAM is high, Else If RMR is moderate then ANAM is moderate, Else If RMR is low then ANAM is low.

Rule 13A If MMS is high then ANAM is low, Else If MMS is moderate then ANAM is moderate, Else If MMS is low then ANAM is high.

Rule 14A If ANAM is high then DNAM is low, Else If ANAM is moderate then DNAM is moderate, Else If ANAM is low then DNAM is high.

Rule 15A If DMAN is high then DNAM is high, Else If DMAN is moderate then DNAM is moderate, Else If DMAN is low then DNAM is low.

3.2.2 Fuzzy knowledge-based for causal loop 2

The If-Then rules for the second loop are presented as follows:

Rule1B If DNAM is high then RMU is low, Else If DNAM is moderate then RMU is very moderate, Else If DNAM is low then RMU is high.

Rule 2B If MR is high then RMU is high, Else If MR is moderate then RMU is moderate, Else If MR is low then RMU is low.

Rule 3B If RMU is high then TPR is high, RMU is moderate then TPR is moderate, Else If RMU is low then TPR is low.

Rule 4B If TPR is very high then PV is very high, Else If TPR is high then PV is high, Else If

TPR is moderate then PV is moderate, Else If TPR is low then PV is low.

Rule 5B If PV is high then RMU is low, Else If PV is moderate then MCTR is very moderate, Else If PV is low then MCTR is high.

Rule 6B If QGRM is high then MCTR is high, Else If QGRM is moderate then MCTR is moderate, Else If QGRM is low then MCTR is low.

Rule 7B If MCTR is high then MMS is high, Else If MCTR is moderate then MMS is moderate, Else If MCTR is low then MMS is low.

Rule 8B If MMS is high then ANAM is low, Else If MMS is moderate then ANAM is very moderate, Else If MMS is low then ANAM is high.

Rule 9B If ANAM is high then DNAM is low, Else If ANAM is moderate then DNAM is moderate, Else If ANAM is low then DNAM is high.

Rule 10B If DMAN is high then DNAM is high, Else If DMAN is moderate then DNAM is moderate, Else If DMAN is low then DNAM is low.

3.2.3 Fuzzy knowledge-based for causal loop 3

The If-Then rules for the third loop are presented as follows:

Rule 1C If L is high then SL is high, Else If L is moderate then SL is moderate, Else If L is low then SL is low.

Rule 2C If OP is high then SL is low, Else If OP is moderate then SL is moderate, Else If OP is low then SL is high.

Rule 3C If D is high then SL is high, Else If D is moderate then SL is moderate, Else If D is low then SL is low.

Rule 4C If AFG is high then SL is low, Else If AFG is moderate then SL is moderate, Else If AFG is low then SL is high.

Rule 5C If SL is high then RRMA is high, Else If SL is moderate then RRMA is moderate, Else If SL is low then RRMA is low.

Rule 6C If RRMA is high then TPR is high, Else If RRMA is moderate then TPR is moderate, Else If RRMA is low then TPR is low.

Rule 7C If TPR is high then PV is high, Else If TPR is moderate then PV is moderate, Else If TPR is low then PV is low.

Rule 8C If PV is high then DPR is low, Else If PV is moderate then DPR is moderate, Else If PV is low then DPR is high.

Rule 9C If DPR is high then AFG is low, Else If DPR is moderate then AFG is moderate, Else If DPR is low then AFG is high.

3.3 TOPSIS

Application of simulation models gives decision-makers the opportunity to study the effects of various combinations of operational variables. However, there is still a need to know the best combination of the operational variables that gives the best results when considering multiple criteria. The current study applied TOPSIS to determine the best combination of operational variables. It considered three criteria. The criteria were obtained from the research questions of this study as the stock level of finished goods (x_1), the number of experienced technicians required for maintenance activities (x_2) and the number of unavailable machines (x_3).

The application of TOPSIS method involves five steps. The outline of these steps is presented as follows [21-25]:

Step 1: Formulation of a normalised decision matrix

This step formats the data sets so that data values all fit into a range that is within 0 and 1 (Equation 1):

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}} \qquad (1)$$

where x_{ij} represents parameter i for simulation run j, and r_{ij} is the normalised value of parameter i for simulation run j.

Step 2: Formulation of a weighted normalised decision matrix

Consideration of the weights of each variable is used in generating a weighted normalised decision matrix (Equation 2). The weights for the variables are determined using an aggregated rank-sum approach [26-27]. This approach requires responses from various decision-makers (Equation 3):

$$v_{ij} = w_i r_{ij} \qquad (2)$$

$$\bar{w}_i = \frac{1}{P}\sum_{p=1}^{P} \frac{2\left(m+1-r_{ip}\right)}{m\left(m+1\right)} \qquad (3)$$

$$w_i = \frac{\bar{w}_i}{\sum_{i=1}^{n} \bar{w}_i} \qquad (4)$$

where, v_{ij} represents the weighted normalised values of parameter i with respect to simulation run j, w_i is the weight of parameter i (Equation 4), m represents total number of parameters and P is the number of decision-makers.

Step 3: Evaluation of the ideal and non-ideal solutions

The value of the ideal solution depends on whether the desired variable value under considered is a benefit or cost-based variable. For benefit-based variables, the maximum value is taken as the ideal solution, while for cost-based variables, the minimum value is considered optimal. This analogy is also applicable to non-ideal solutions (Equations 5 to 8):

$$A^1 = \left(v_1^1, \ldots, v_m^1\right) \qquad (5)$$

$$v_i^1 = \begin{cases} \max(v_{ij}) & if \;\; benefit-based \\ \min(v_{ij}) & if \;\; \cos t-based \end{cases} \qquad (6)$$

$$A^2 = \left(v_1^2, \ldots, v_m^2\right) \qquad (7)$$

$$v_i^2 = \begin{cases} \min(v_{ij}) & if \ \ benefit-based \\ \\ \max(v_{ij}) & if \ \ \cos t-based \end{cases} \tag{8}$$

where, v_i^1 represents the ideal solution for parameter i, and v_i^2 is the non-ideal solution for parameter *i*.

Step 4: Estimation of the alternative distances from the ideal and non-ideal solutions

The distance of an alternative solution from the ideal solution is expressed as Equation (9), while Equation (10) represents the distance between alternative and non-ideal solutions.

$$D_j^+ = \sqrt{\sum_{i=1}^{m}\left(v_i^+ - v_{ij}\right)} \tag{9}$$

$$D_j^- = \sqrt{\sum_{i=1}^{m}\left(v_i^- - v_{ij}\right)} \tag{10}$$

where, D_j^+ represents the distance of simulation run *j* solutions from the ideal solution, and D_j^- is the distance of simulation run *j* solutions from the "non-ideal" solutions.

Step 5: Determination of the closeness coefficient of the alternatives

The values of the alternative closeness are determined to rank the alternatives as in Equation (11). The highest ranked alternative is the alternative with a relative closeness value approaching 1, while the lowest ranked alternative is the least relative closeness value and it approaches a value of 0.

$$C_j = \frac{D_j^-}{D_j^+ + D_j^-} \tag{11}$$

where, C_j represents the closeness coefficient of simulation run *j*.

3.4 WASPAS method

Due to the ease of the WASPAS method implementation, it has enjoyed wide acceptance as a multi-criteria tool for decision-making processes among researchers and industrial practitioners [28]. There are three implementation steps for WASPAS. They are normalisation, computation of WASPAS values and a selection process. Unlike the TOPSIS method, which does not place emphasis on whether a variable is beneficial or cost-oriented during normalisation of data sets, the WASPAS method considers the orientation of a variable. The normalisation of benefit-oriented variables is expressed as Equation (12), while Equation (13) is considered as a normalisation expression cost-oriented variable [28].

$$r_{ij} = x_{ij} / \max_i x_{ij} \tag{12}$$

$$r_{ij} = \min_i x_{ij} / x_{ij} \tag{13}$$

where, $\max_i x_{ij}$ represents the maximum value among different x_{ij} values, and $\min_i x_{ij}$ is the minimum value among various x_{ij} values.

Determination of the WASPAS values of the various solutions to a problem is done by first computing the weighted sum (Equation 14) and weighted product (Equation 15) values of each solution. Based on a constant parameter (λ) whose value lies between 0 and 1, the weighted sum and weighted product values for the solutions are linearly combined (Equation 16). The selection of the best solution for a problem is taken as the solution that has the highest WASPAS values.

$$Q_j^{(1)} = \sum_{i=1}^{m} \bar{x}_{ij} w_i \tag{14}$$

$$Q_j^{(2)} = \prod_{i=1}^{m} \bar{x}_{ij}^{w_i} \tag{15}$$

$$Q_j = \lambda Q_i^1 + \left(1-\lambda\right) Q_j^2 \tag{16}$$

where, $Q_j^{(1)}$ represents the weighted sum assessment of simulation run j, $Q_j^{(2)}$ is the weighted product assessment of simulation run j, Q_j represents the weighted aggregated sum product assessment of simulation run j, and λ is a constant parameter.

The summarized procedure for the fuzzy-SD model is given as follows:

1. Develop causal loop diagrams for machine breakdown, rates of machine usage and stock levels.
2. Combine these causal loop diagrams into an integrated causal loop diagram.
3. Create a box diagram for the integrated causal loop diagrams.
4. Select linguistic terms for the variables in the integrated causal loop diagrams.
5. Select membership functions for the linguistic terms in step 4.
6. Create IF-Then rules for the three causal loops that constitute the integrated causal loop diagrams.
7. Determine the maximum and minimum values of the variables in the values of using experts' judgements.
8. Determine to number of simulation runs for the integrated causal loop diagrams evaluation.
9. Run the integrated causal loop diagrams using Simulink.
10. Determine the importance (weights) of stock levels of finished goods, the number of experienced technicians' required for maintenance activities and the number of unavailable machines using an aggregate rank-sum approach.
11. Determine the number of combinations that have the same highest closeness coefficients using the TOPSIS method.
12. Select the best combination among the highest closeness coefficient values using the WASPAS method.

4. Case study

The proposed framework was tested in a manufacturing company that specialises in the production of alcoholic drinks. During the framework testing, three decision-makers were consulted (D_1, D_2 and D_3). Due to the confidentiality of information, the management of the company stated that the required information can only be provided in terms of percentages. Thus, a questionnaire was designed to collect the required information. To obtain good performance from an SD model, the expected minimum number of iterations that is required should be at least 30 [29]. In the current study, 230 iterations were considered in investigating the performance of the proposed fuzzy-SD model. The information that was used to run the proposed model is presented in Table 2.

Figure 8 shows that stock levels did not have a regular pattern. This could be attributed to the demand for the company's products. In real-life, product demand does not follow a regular pattern. This causes variation in stock levels. Another factor which could be responsible for the irregular stock levels pattern is the volume of finished goods. Change in machine availability influences the production volume. The results presented in Figure 8 showed that the discrepancies in the number of available machines had an irregular pattern. Thus, the issue of an irregular pattern in stock levels could be traced to the irregular pattern in Figure 9. To have a clear picture of the impact of machines' availability on stock level from the proposed model perspective, there is a need to consider the number of experienced technicians required for maintenance activities.

There seem to be close relationships between the number of unavailable machines and the number of experienced technicians required. This relationship could be considered as a direct one. This is because an increase (decrease) in machine availability is associated with a corresponding increase in the rate of experienced technicians required. This could be interpreted as the fewer the number of unavailable machines, the less the number of experienced technicians required. Also, with lower stock levels will require a higher amount of production and maintenance activities. With an increase in maintenance activities, it is expected that a corresponding increase in the rate of experienced technicians required will occur. Thus, the relationship between stock level and rate of experienced technicians required is indirect.

To gain a quick understanding of the values in Figures 8 to 10, statistical measures of these results were computed and are presented in Table 3. The information in this table will help in monitoring these parametric values to enhance the performance of the company. The information in Table 3 presents a general answer to the questions that were raised in Section 1. A more specific answer to these questions was generated using the TOPSIS methodology in Section 3. First, parametric settings that occurred more than once were reduced to only one instance in the implementation of the TOPSIS methodology. This led to the reduction of the data points from 230 to 103 (Table 4).

Table 2 Limits of the model parameters

Variable	D_1		D_2		D_3		Average	
	Min	Max	Min	Max	Min	Max	Min	Max
Actual finish goods (%)	40	70	30	60	30	70	33.33	66.67
Losses (%)	25	40	20	40	20	100	21.67	60.00
Outsourced products (%)	15	75	10	70	40	60	21.67	68.33
Demand (%)	30	85	40	80	40	60	36.67	75.00
Stock level (%)	15	80	20	90	30	70	21.67	80.00
Rate of raw material arrival (%)	20	80	10	60	30	70	20.00	70.00
Total production rate (%)	35	60	45	85	10	90	30.00	78.33
Production volume (%)	45	60	27	100	10	90	27.33	83.33
Defective product rate (%)	10	30	10	30	40	60	20.00	40.00
Machine cycle time rate (%)	20	40	15	65	30	70	21.67	58.33
Quality of good product per machine (%)	20	50	5	95	40	60	21.67	68.33
Minor machine stoppage (%)	10	30	10	50	30	50	16.67	43.33
Machine required per quantity (%)	24	62	24	70	22	75	23.33	69.00
Actual number of available machines (%)	30	70	40	60	5	49	25.00	59.67
Discrepancy in number of available machines (%)	20	60	20	70	30	76	23.33	68.67
Desired machine availability number (%)	30	70	40	60	30	70	33.33	66.67
Rate of machine usage (%)	7	90	50	80	40	60	32.33	76.67
Rate of machine breakdown (%)	15	40	10	80	10	100	11.67	73.33
Average technicians shortage per machine (%)	20	60	24	70	30	100	24.67	76.67
Rate of functional machine (%)	20	90	20	80	30	100	23.33	90.00
Technicians shortage (%)	25	65	23	70	30	100	26.00	78.33
Technicians' recruitment rate (%)	22	90	24	90	0	100	15.33	93.33
Experience technicians' addition rate (%)	25	50	30	70	0	100	18.33	73.33
Experience technicians population (%)	40	60	35	50	2	40	25.67	50.00
Average experience technicians per machine (%)	35	45	20	70	10	50	21.67	55.00
Rate of experience technicians required (%)	35	50	10	80	10	40	18.33	56.67
Number of machine for repair (%)	30	62	32	60	6	100	22.67	74.00
Rate of machine repair (%)	20	68	20	70	0	100	13.33	79.33

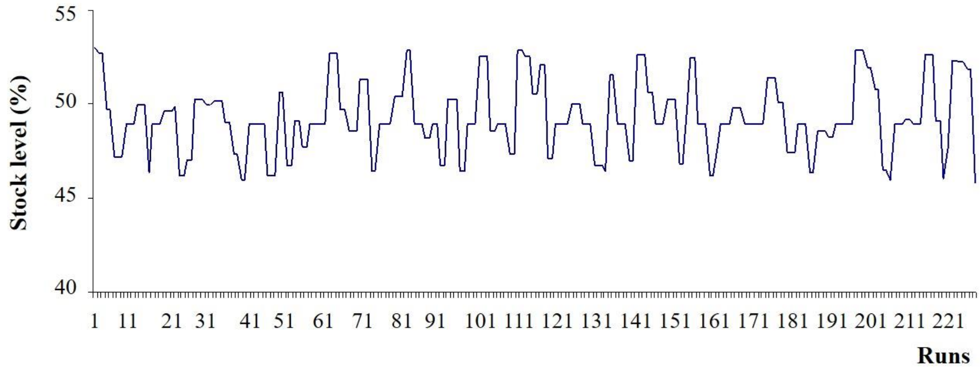

Figure 8 Simulated values of stock levels for various periods

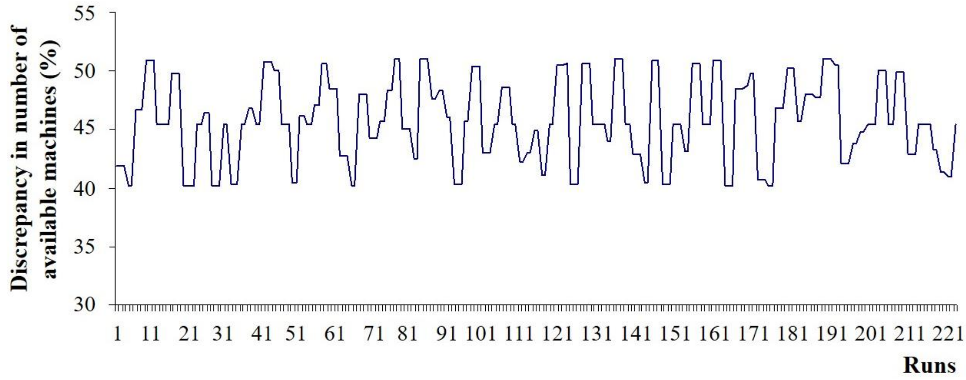

Figure 9 Simulated values for the number of unavailable machines

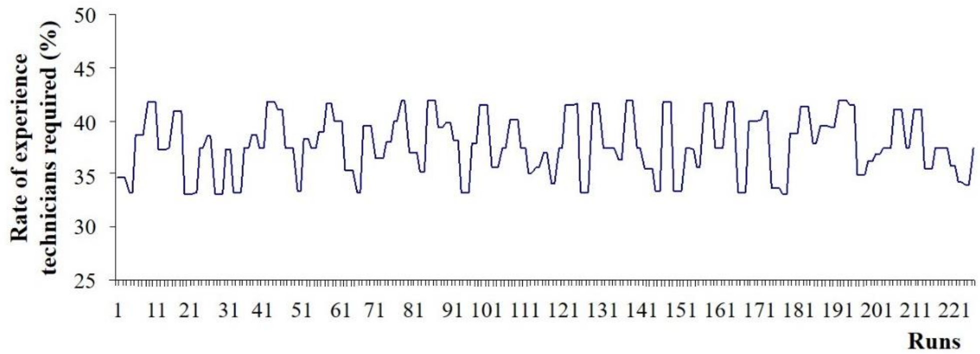

Figure 10 Simulated values for the number of experience technicians required

Table 3 Statistics measures of the model results

Measure	x_1	x_2	x_3
Min	45.814	33.114	40.206
Max	53.006	41.891	51.087
Average	49.312	37.749	45.780
S.D	1.887	2.868	3.583

The construction of the weighted decision matrix is based on the aggregated rank-sum method that was discussed in Section 3. Based on the responses from the decision-makers, the most important variable is discrepancy in the numbers of available machines (Table 6). Stock level is considered as the least important variable by the decision-makers (Table 6). The combination of the information in Tables 5 and 6 was used to generate the information in the weighted decision matrix (Table 7).

The information in Table 7 was used to determine the ideal and non-ideal solutions for the various variables in Table 7. The results obtained were then used to evaluate the distances of each solution from the ideal and non-ideal solutions (Table 8). Evaluation of the most suitable solution from the information in Table 4 was done by computing the proportional distance of each solution (Table 8).

Table 4 Decision matrix

Sol. No.	x_1	x_2	x_3	Sol. No.	x_1	x_2	x_3	Sol. No.	x_1	x_2	x_3
1	53.006	34.707	41.919	35	48.921	39.914	48.395	69	49.945	37.305	45.371
2	52.688	34.707	41.919	36	48.921	41.885	51.080	70	52.491	35.651	43.093
3	52.697	34.707	41.919	37	50.427	37.053	45.045	71	48.921	41.619	50.723
4	49.746	33.199	40.228	38	52.848	35.143	42.443	72	46.161	37.500	45.439
5	47.203	38.618	46.652	39	48.921	41.874	51.065	73	47.721	37.500	45.431
6	47.212	38.624	46.661	40	48.211	39.345	47.626	74	48.921	41.756	50.906
7	48.921	41.728	50.869	41	48.921	39.864	48.326	75	49.806	33.209	40.236
8	49.961	37.297	45.370	42	46.707	38.192	46.088	76	48.921	39.997	48.509
9	46.373	37.500	45.440	43	50.267	33.308	40.320	77	48.921	40.133	48.697
10	48.921	40.926	49.785	44	46.411	37.905	45.719	78	48.921	40.891	49.738
11	49.656	33.162	40.206	45	48.921	41.423	50.460	79	51.382	33.657	40.687
12	49.874	33.223	40.246	46	52.552	35.577	42.993	80	50.090	33.124	40.212
13	46.162	37.500	45.439	47	48.535	37.500	45.417	81	47.405	38.773	46.860
14	47.051	38.494	46.488	48	48.921	40.075	48.619	82	48.921	41.290	50.279
15	50.290	33.114	40.227	49	47.353	37.500	45.435	83	46.382	37.876	45.684
16	49.963	37.296	45.370	50	52.885	34.992	42.261	84	48.537	39.575	47.935
17	50.146	33.280	40.293	51	52.522	35.614	43.043	85	48.277	39.391	47.689
18	49.061	37.500	45.404	52	50.581	36.967	44.920	86	48.921	41.891	51.087
19	47.368	38.746	46.823	53	52.067	34.047	41.136	87	48.921	41.452	50.498
20	45.942	37.500	45.419	54	47.125	37.500	45.437	88	52.840	34.920	42.174
21	48.921	41.708	50.842	55	48.921	41.517	50.585	89	51.903	36.141	43.760
22	48.921	41.084	50.002	56	48.921	41.592	50.686	90	50.789	36.846	44.746
23	46.216	37.500	45.439	57	50.018	33.251	40.269	91	46.515	37.500	45.440
24	50.672	33.416	40.427	58	48.921	41.563	50.648	92	45.961	37.500	45.418
25	46.746	38.228	46.136	59	46.709	37.500	45.439	93	48.921	41.083	49.999
26	49.101	37.500	45.403	60	46.443	37.500	45.440	94	49.208	37.500	45.399
27	47.696	38.983	47.141	61	51.587	36.349	44.046	95	48.921	41.037	49.937
28	48.921	41.599	50.695	62	48.921	41.880	51.073	96	52.599	35.520	42.917
29	48.921	40.008	48.524	63	46.942	37.500	45.438	97	49.118	37.500	45.402
30	52.684	35.403	42.765	64	52.639	35.466	42.846	98	46.027	37.500	45.438
31	49.754	33.201	40.229	65	50.646	33.408	40.419	99	47.622	37.500	45.432
32	48.534	39.572	47.932	66	48.921	41.782	50.942	100	52.328	35.822	43.324
33	51.358	36.496	44.251	67	50.289	33.313	40.325	101	52.225	34.179	41.291
34	46.425	37.919	45.737	68	46.791	37.500	45.439	102	51.882	33.915	40.981
								103	45.814	37.500	45.428

Table 5 Normalised decision matrix

Sol. No.	x_1	x_2	x_3	Sol. No.	x_1	x_2	x_3	Sol. No.	x_1	x_2	x_3
1	0.106	0.091	0.090	35	0.098	0.104	0.104	69	0.100	0.097	0.098
2	0.105	0.091	0.090	36	0.098	0.109	0.110	70	0.105	0.093	0.093
3	0.105	0.091	0.090	37	0.101	0.097	0.097	71	0.098	0.109	0.109
4	0.100	0.087	0.087	38	0.106	0.092	0.091	72	0.092	0.098	0.098
5	0.094	0.101	0.101	39	0.098	0.109	0.110	73	0.095	0.098	0.098
6	0.094	0.101	0.101	40	0.096	0.103	0.103	74	0.098	0.109	0.110
7	0.098	0.109	0.110	41	0.098	0.104	0.104	75	0.100	0.087	0.087
8	0.100	0.097	0.098	42	0.093	0.100	0.099	76	0.098	0.104	0.105
9	0.093	0.098	0.098	43	0.101	0.087	0.087	77	0.098	0.105	0.105
10	0.098	0.107	0.107	44	0.093	0.099	0.098	78	0.098	0.107	0.107
11	0.099	0.087	0.087	45	0.098	0.108	0.109	79	0.103	0.088	0.088
12	0.100	0.087	0.087	46	0.105	0.093	0.093	80	0.100	0.087	0.087
13	0.092	0.098	0.098	47	0.097	0.098	0.098	81	0.095	0.101	0.101
14	0.094	0.101	0.100	48	0.098	0.105	0.105	82	0.098	0.108	0.108
15	0.101	0.087	0.087	49	0.095	0.098	0.098	83	0.093	0.099	0.098
16	0.100	0.097	0.098	50	0.106	0.091	0.091	84	0.097	0.103	0.103
17	0.100	0.087	0.087	51	0.105	0.093	0.093	85	0.097	0.103	0.103
18	0.098	0.098	0.098	52	0.101	0.097	0.097	86	0.098	0.109	0.110
19	0.095	0.101	0.101	53	0.104	0.089	0.089	87	0.098	0.108	0.109
20	0.092	0.098	0.098	54	0.094	0.098	0.098	88	0.106	0.091	0.091
21	0.098	0.109	0.110	55	0.098	0.108	0.109	89	0.104	0.094	0.094
22	0.098	0.107	0.108	56	0.098	0.109	0.109	90	0.102	0.096	0.096
23	0.092	0.098	0.098	57	0.100	0.087	0.087	91	0.093	0.098	0.098
24	0.101	0.087	0.087	58	0.098	0.109	0.109	92	0.092	0.098	0.098
25	0.094	0.100	0.099	59	0.093	0.098	0.098	93	0.098	0.107	0.108
26	0.098	0.098	0.098	60	0.093	0.098	0.098	94	0.098	0.098	0.098
27	0.095	0.102	0.102	61	0.103	0.095	0.095	95	0.098	0.107	0.108
28	0.098	0.109	0.109	62	0.098	0.109	0.110	96	0.105	0.093	0.092
29	0.098	0.105	0.105	63	0.094	0.098	0.098	97	0.098	0.098	0.098
30	0.105	0.092	0.092	64	0.105	0.093	0.092	98	0.092	0.098	0.098
31	0.100	0.087	0.087	65	0.101	0.087	0.087	99	0.095	0.098	0.098
32	0.097	0.103	0.103	66	0.098	0.109	0.110	100	0.105	0.094	0.093
33	0.103	0.095	0.095	67	0.101	0.087	0.087	101	0.104	0.089	0.089
34	0.093	0.099	0.099	68	0.094	0.098	0.098	102	0.104	0.089	0.088
								103	0.092	0.098	0.098

Table 6 Weights for the selected parameters

Variable	D_1	D_2	D_3	$\overline{w}_i$	w_i
x_1	1	1	3	0.39	0.29
x_2	1	1	2	0.44	0.33
x_3	1	1	1	0.50	0.38

Table 7 Weighted normalised decision matrix

Sol. No.	x_1	x_2	x_3	Sol. No.	x_1	x_2	x_3	Sol. No.	x_1	x_2	x_3
1	0.031	0.030	0.034	35	0.028	0.034	0.040	69	0.029	0.032	0.037
2	0.031	0.030	0.034	36	0.028	0.036	0.042	70	0.030	0.031	0.035
3	0.031	0.030	0.034	37	0.029	0.032	0.037	71	0.028	0.036	0.042
4	0.029	0.029	0.033	38	0.031	0.030	0.035	72	0.027	0.032	0.037
5	0.027	0.033	0.038	39	0.028	0.036	0.042	73	0.028	0.032	0.037
6	0.027	0.033	0.038	40	0.028	0.034	0.039	74	0.028	0.036	0.042
7	0.028	0.036	0.042	41	0.028	0.034	0.040	75	0.029	0.029	0.033
8	0.029	0.032	0.037	42	0.027	0.033	0.038	76	0.028	0.034	0.040
9	0.027	0.032	0.037	43	0.029	0.029	0.033	77	0.028	0.035	0.040
10	0.028	0.035	0.041	44	0.027	0.033	0.037	78	0.028	0.035	0.041
11	0.029	0.029	0.033	45	0.028	0.036	0.041	79	0.030	0.029	0.033
12	0.029	0.029	0.033	46	0.030	0.031	0.035	80	0.029	0.029	0.033
13	0.027	0.032	0.037	47	0.028	0.032	0.037	81	0.028	0.033	0.038
14	0.027	0.033	0.038	48	0.028	0.035	0.040	82	0.028	0.036	0.041
15	0.029	0.029	0.033	49	0.027	0.032	0.037	83	0.027	0.033	0.037
16	0.029	0.032	0.037	50	0.031	0.030	0.035	84	0.028	0.034	0.039
17	0.029	0.029	0.033	51	0.030	0.031	0.035	85	0.028	0.034	0.039
18	0.028	0.032	0.037	52	0.029	0.032	0.037	86	0.028	0.036	0.042
19	0.027	0.033	0.038	53	0.030	0.029	0.034	87	0.028	0.036	0.041
20	0.027	0.032	0.037	54	0.027	0.032	0.037	88	0.031	0.030	0.035
21	0.028	0.036	0.042	55	0.028	0.036	0.041	89	0.030	0.031	0.036
22	0.028	0.035	0.041	56	0.028	0.036	0.041	90	0.029	0.032	0.037
23	0.027	0.032	0.037	57	0.029	0.029	0.033	91	0.027	0.032	0.037
24	0.029	0.029	0.033	58	0.028	0.036	0.041	92	0.027	0.032	0.037
25	0.027	0.033	0.038	59	0.027	0.032	0.037	93	0.028	0.035	0.041
26	0.028	0.032	0.037	60	0.027	0.032	0.037	94	0.029	0.032	0.037
27	0.028	0.034	0.039	61	0.030	0.031	0.036	95	0.028	0.035	0.041
28	0.028	0.036	0.042	62	0.028	0.036	0.042	96	0.031	0.031	0.035
29	0.028	0.034	0.040	63	0.027	0.032	0.037	97	0.029	0.032	0.037
30	0.031	0.031	0.035	64	0.031	0.031	0.035	98	0.027	0.032	0.037
31	0.029	0.029	0.033	65	0.029	0.029	0.033	99	0.028	0.032	0.037
32	0.028	0.034	0.039	66	0.028	0.036	0.042	100	0.030	0.031	0.035
33	0.030	0.031	0.036	67	0.029	0.029	0.033	101	0.030	0.029	0.034
34	0.027	0.033	0.037	68	0.027	0.032	0.037	102	0.030	0.029	0.034
								103	0.027	0.032	0.037

The results in Table 8 show that more than one solution had the same maximal value in terms of proportional distance (Table 9). Another multi-criteria tool (WASPAS) was considered to select the best combination.

The information in Table 10 was normalised by considering stock levels and the number of experienced technicians required as benefit-oriented variables. The discrepancy in the number of available machines was considered a cost-oriented variable (Table 10).

The weights in Table 6 were considered to compute the weighted sum and weighted product values of each solution. The current study combined the values of the weighted sum and weighted product values of each solution with $\lambda = 0.5$ [28]. Based on the results, the best value for the stock level was 53.006%. The associated number of experienced technicians required for maintenance activities was 34.707%, while the expected number of unavailable machines was 41.919%. It should be noted that a similar approach (i.e., WASPAS method) could be used to determine the worst solution (Table 11).

5. Industrial implications

This communication presents a number of attractive implications for the management of manufacturing systems based on the SD application scheme:

1) For general managers, controlling both the inventory system, particularly the stock out inventory with respect to maintenance activities, is a challenging endeavour. Ineffective analysis of maintenance problems would obviously lead to not meeting order quantities from the finished stock inventory. This has a huge economic loss dimension as well as loss of goodwill to the plant. This communication therefore aids general managers in selecting proper choices and practices, oriented to controlling machine breakdown, machine availability and stock level inventory factors. Additionally, a general manager is motivated to expose the advantages of SD to colleagues that would assist in one way or the other to achieve the system's goals. It will also trigger

Table 8 Distances from ideal and non-ideal solution as well as proportional distance

Sol. No.	D_j^+	D_j^-	C_j	Sol. No.	D_j^+	D_j^-	C_j	Sol. No.	D_j^+	D_j^-	C_j
1	0.009	0.006	0.578*	35	0.007	0.007	0.471	69	0.006	0.006	0.513
2	0.009	0.006	0.575	36	0.008	0.009	0.458**	70	0.008	0.006	0.574
3	0.009	0.006	0.576	37	0.007	0.006	0.525	71	0.008	0.009	0.458**
4	0.009	0.008	0.543	38	0.008	0.006	0.578*	72	0.006	0.007	0.462
5	0.006	0.007	0.468	39	0.008	0.009	0.458**	73	0.006	0.007	0.484
6	0.006	0.007	0.468	40	0.006	0.007	0.470	74	0.008	0.009	0.458**
7	0.008	0.009	0.458**	41	0.007	0.007	0.472	75	0.009	0.008	0.544
8	0.006	0.006	0.513	42	0.006	0.007	0.468	76	0.007	0.007	0.470
9	0.006	0.007	0.465	43	0.009	0.008	0.548	77	0.007	0.008	0.469
10	0.007	0.008	0.461	44	0.006	0.007	0.469	78	0.007	0.008	0.462
11	0.009	0.008	0.542	45	0.007	0.009	0.459	79	0.009	0.007	0.560
12	0.009	0.008	0.544	46	0.008	0.006	0.575	80	0.009	0.008	0.544
13	0.006	0.007	0.462	47	0.006	0.006	0.497	81	0.006	0.007	0.468
14	0.006	0.007	0.468	48	0.007	0.007	0.469	82	0.007	0.009	0.459
15	0.009	0.008	0.545	49	0.006	0.007	0.478	83	0.006	0.007	0.469
16	0.006	0.006	0.513	50	0.009	0.006	0.578*	84	0.006	0.007	0.471
17	0.009	0.008	0.547	51	0.008	0.006	0.574	85	0.006	0.007	0.470
18	0.006	0.006	0.506	52	0.007	0.006	0.530	86	0.008	0.009	0.458**
19	0.006	0.007	0.468	53	0.009	0.007	0.567	87	0.007	0.009	0.459
20	0.006	0.007	0.460	54	0.006	0.007	0.475	88	0.009	0.006	0.577
21	0.008	0.009	0.458**	55	0.008	0.009	0.459	89	0.007	0.006	0.563
22	0.007	0.008	0.460	56	0.008	0.009	0.458**	90	0.007	0.006	0.535
23	0.006	0.007	0.463	57	0.009	0.008	0.546	91	0.006	0.007	0.467
24	0.009	0.007	0.552	58	0.008	0.009	0.458**	92	0.006	0.007	0.460
25	0.006	0.007	0.468	59	0.006	0.007	0.469	93	0.007	0.008	0.460
26	0.006	0.006	0.507	60	0.006	0.007	0.466	94	0.006	0.006	0.508
27	0.006	0.007	0.468	61	0.007	0.006	0.556	95	0.007	0.008	0.461
28	0.008	0.009	0.458**	62	0.008	0.009	0.458**	96	0.008	0.006	0.575
29	0.007	0.007	0.470	63	0.006	0.007	0.472	97	0.006	0.006	0.507
30	0.008	0.006	0.577	64	0.008	0.006	0.576	98	0.006	0.007	0.460
31	0.009	0.008	0.543	65	0.009	0.007	0.552	99	0.006	0.007	0.482
32	0.006	0.007	0.471	66	0.008	0.009	0.458**	100	0.008	0.006	0.571
33	0.007	0.006	0.550	67	0.009	0.008	0.549	101	0.009	0.007	0.569
34	0.006	0.007	0.469	68	0.006	0.007	0.470	102	0.009	0.007	0.565
								103	0.006	0.007	0.458**

* Most suitable combinations ** Least suitable combinations

Table 9 Most suitable combinations

Sol. No.	x_1	x_2	x_3	Proportional distance
1	52.889	34.992	42.261	0.578
38	52.848	35.143	42.443	0.578
50	53.006	34.707	41.919	0.578

the interest of the general managers in broadcasting the benefits of the SD applications to factory workers as well as to management.

2) The analysis revealed that general managers have an opportunity to identify the aspects of maintenance practices, in terms of equipment breakdown and machine availability as well as on which inventory issues they should focus their attention. This would aid in enhancing the efficiency of the SD application. Furthermore, significant influence on customer perceptions of the organisation, the reputation of the organisation in the market place, satisfaction of customers (internal and external to the organisation) will be created.

3) This communication created a unique connection between the community of SD researchers with industry that was modelled and applications of SD in manufacturing. It offers an outstanding connection between the community of workers in SD and industrial practitioners.

4) This communication was able to establish the dynamic characteristics of an inventory maintenance system. Hence, it triggers the formulation of the inventory policies on maintenance issues that could aid in the elimination of adverse conditions concerning the inventory and maintenance. It could also aid in estimating the implications arising from variations in system structures.

Table 10 Normalised decision matrix for the WASPAS method

Sol. No.	x_1	x_2	x_3
1	0.998	0.996	0.992
38	0.997	1.000	0.988
50	1.000	0.988	1.000

Table 11 WASPAS results

Sol. No.	Q_s^1	Q_s^2	Q_s
1	0.995	0.995	0.995
38	0.994	0.994	0.994
50*	0.996	0.996	0.996

5) Practically, SD has gained respect and is being used as an instrument for instruction. In the particular instance considered in this communication, SD is noted as a useful instrument for studying the phenomenon of the effect of information know-how on future maintenance and inventory systems. These types of predictions are difficult to make without the use of SD.
6) This current communication also highlights some advantages of SD, specifically in its advancement. However, the investigation may not show advantages in some cultural contexts. Nevertheless, the current research is the first to consider SD in modelling the inventory system-maintenance scenario in manufacturing.
7) This investigation showcases the level of inventory and maintenance variables from the perspective of Nigerian manufacturing. It shows the significance of SD under a situation of changing finished stock inventory and varying maintenance variables. A most interesting outcome is that, as a scholarly document, this paper sheds light on SD practices from the perspective of a growing national economy.
8) The investigation showcases the significant effect of prominent factors to assist a general manager to identify specific problems in this enhanced implementation of SD. In a nutshell, the current investigation shows significant advantages of studying the practical issues of SD.
9) From the perceptive of technology, the approach showcases the current communication aids by using a multidisciplinary approach in meeting the industrial challenges faced by the general managers of manufacturing industries.

6. Conclusions

In this study, a fuzzy-SD model for finished goods stock level control was introduced. The model also has the capacity to control the number of experienced technicians required for maintenance activities as well as the numbers of unavailable machines. This model combines an SD model, fuzzy inference system, a TOPSIS method and a WASPAS method. An illustration of the fuzzy-SD model was presented using information that was obtained from an alcohol production company. The results showed that the model was effective in aiding decision makings in solving management problems.

A contribution of this study is the application of an SD model in simulating the relationships among stock levels, the number of maintenance technicians and machine availability. Another contribution of this study is the use of a fuzzy inference system in converting the SD model into a simulation model. Additionally, the incorporation of aggregated rank-sum, TOPSIS and WASPAS methods into an SD model was a contribution of this study.

Nevertheless, this study did not consider the issue of skill transfer from one technician to another in a maintenance system. This problem can be modelled using SD approach as a further study. Another application of an SD approach in a maintenance system is evaluation of the effect of combining various maintenance practices on overall equipment effectiveness. A model that combines an SD model and meta-heuristics (evolutionary and swarm algorithms) in determining the optimal parametric settings of various variables in a maintenance SD model is required. Univariate (e.g., moving average) or multi-variate (e.g., regression and artificial neural network) models can be used to design predictive models [8, 18]. This will reduce the need for frequent running of the proposed model under new sets of data.

7. References

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