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A weighted goal programming model for maintenance workforce optimisation in a process industry

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Abstract

The recent upsurge in the economic distress being experienced by organisations, particularly in terms of the sustainability challenges they face, raises new concerns that strongly motivate maintenance workforce structural re-modelling. Maintenance workforce planning is an interdisciplinary area, spanning maintenance, industrial engineering, and human-resource planning. There are accounts in the available literature of different analytical models being developed, re-modelled, and implemented for maintenance workforce planning, but new insights into research focusing on budgeted funds, worker distribution, and performance metrics (availability and quality of work done), as well as hiring and firing costs are badly needed. In order to respond to this call, we adopted a case-study approach to the optimisation of maintenance workforce variables based on weighted goal programming, a genetic algorithm (GA), and Euclidean distance with these parameters being treated in a unique manner. A selected optimisation model from the available literature was used to a formulate model for a brewery plant maintenance system. The formulated model was solved using a genetic algorithm (GA), particle swarm optimisation and differential evolution algorithm. The results obtained were compared and it was observed that a GA was the most suitable solution method for the formulated model. The GA results showed that the maximum number of full-time workers hired or fired for the different worker categories were the same (one worker). The values of worker's efficiency and availability were above 80%, while the quality of work done by the workers was above 70%. The results showed that the solution from the weighted goal programming, GA, and Euclidean distance were satisfactory.

Keywords: Meta-heuristics; Euclidean distance; Maintenance workforce planning; Weighted goal programming.

1. Introduction

Over the years, maintenance workforce information has been used as a means for improving maintenance management practices and decisions [1 - 3]. This information has helped in identifying, troubleshooting, and solving maintenance workforce problems in manufacturing systems [4 - 7]. Maintenance workforce planning is a business process that enables organisations to identify and analyse what kind of maintenance workforce structure (future size, type, and quality) will be necessary for it to accomplish its objectives [8]. The motivations for generating maintenance workforce information in manufacturing systems are not limited to increasing machine efficiency or availability. They also include improving workers' morale and system safety, among other goals. Improved machine efficiency and availability are achieved through the reduction of machine breakdowns, acceptable workforce levels, and reductions in the cost of materials [5, 9 & 10]. Effective workforce allocation and utilisation that takes different variables and parameters (management policies, workloads, multi-skilling, hiring and firing costs and quality of work done) into account is a result-driven workforce management option [6 & 11]. Developing countries face serious challenges in in maintaining their manufacturing industries. These challenges result from a wide array of workforce-associated problems (such as shortages of workers, poor workforce remuneration, and insufficient performance evaluation). These problems threaten manufacturing sustainability and the health of manufacturing systems in developing countries.

Nomenclature

x_{ijt}	number of workers in maintenance section *i* belonging to worker category *j* that is required for maintenance activity at period *t*
c_{ijt}	unit cost of a worker in maintenance section *i* belonging to worker category *j* that is required for maintenance activity at period *t*
PD_{ijt}	unit expected productivity level of workers in maintenance section *i* belonging to worker category *j* that is required for maintenance activity at period *t*
r_{ijt}	unit productivity of a worker in maintenance section *i* belonging to worker category *j* that is required for maintenance activity at period *t*
x_{i1t}	number of workers in maintenance section *i* belonging to full-time worker category required for maintenance activity at period *t*
x_{i2t}	number of workers in maintenance section *i* belonging to casual worker category required for maintenance activity at period *t*
E	expected value of maintenance workers
h_{ijt}	number of hired workers in maintenance section *i* belonging to worker category *j* that is required for maintenance activity at period *t*
f_{ijt}	number of fired workers in maintenance section *i* belonging to worker category *j* that is required for maintenance activity at period *t*
hc_{ijt}	unit cost of hiring a worker in maintenance section *i* belonging to worker category *j* that is required for maintenance activity at period *t*
fc_{ijt}	unit cost of firing a worker in maintenance section *i* belonging to worker category *j* that is required for maintenance activity at period *t*
w_t	total workload for workers in maintenance section *i*
R_i	ratio of workload to be carried out to number of full-time maintenance workers in maintenance section *i*
w_{i1t}	workload for workers in maintenance section *i* belonging to full-time worker category that is required for maintenance activity at period *t*
w_{i2t}	workload for workers in maintenance section *i* belonging to casual worker category that is required for maintenance activity at period *t*
w_{ijt}	amount of workload for workers in maintenance section *i* belonging to worker category *j* required for maintenance activity at period *t*
W_t	total maintenance workload at period *t*
$\hat{\alpha}_t$	prescribed probability level for stochastic values of WC_t at period *t*
$\vec{a}_t$	minimum value of WC_t at period *t*
$\vec{b}_t$	maximum value of WC_t at period *t*
f_t	priority factor at period *t*
u_{ijt}	amount of use factor of a worker in maintenance section *i* belonging to worker category *j* required for maintenance activity at period *t*
$\bar{w}_{ijt}$	total amount of time allocated to a worker in maintenance section *i* belonging to worker category *j* required for maintenance activity at period *t*
X_t	total workforce size at period *t*
WOE_t	overall workforce effectiveness at period *t*
a_{ijt}	actual days a worker in maintenance section *i* belonging to worker category *j* is required for maintenance activity at period *t*
$\hat{a}_{ijt}$	expected days a worker in maintenance section *i* belonging to worker category *j* is required for maintenance activity at period *t*
p_{ijt}	actual performance of a worker in maintenance section *i* belonging to worker category *j* required for maintenance activity at period *t*
$\hat{p}_{ijt}$	expected performance of a worker in maintenance section *i* belonging to worker category *j* required for maintenance activity at period *t*
q_{ijt}	actual quality of workdone of a worker in maintenance section *i* belonging to worker category *j* required for activity at period *t*
$\hat{q}_{ijt}$	expected quality of workdone of a worker in maintenance section *i* belonging to worker category *j* required for maintenance activity at period *t*
$x_{\max,i}$	maximum number of workers in maintenance section *i*

$x_{ij,\min}$	minimum number of workers in maintenance section *i* belonging to worker category *j* required for maintenance activity
TR_{ijt}	turnover rate of a workers in maintenance section *i* belonging to worker category *j* that is required for maintenance activity at period *t*
SR_{ijt}	proportion of time a worker in maintenance section *i* belonging to worker category *j* required for maintenance activity at period *t* is absent from work
SR_t	expected maintenance workforce unavailability

Recently, arguments have begun to emerge that emphasise the need to reduce workforce costs in order to improve manufacturing system profits. This has led to business owners using mathematical models in analysing the performance of maintenance systems [2, 4 & 12].

The increasing world population, proliferation of automated industrial plants, and changing preferences of consumers have all contributed to the high demand for a skilled workforce to carry out various manufacturing functions. Consequently, industrial managers and labour unions are increasingly responding to the need for effective workforce management [13 & 14]. Maintenance is one function in organisations that is affected by pressure to improve workforce analysis in order to more effectively manage workers' remuneration.

The effective management of the maintenance systems is challenging and complex [15]. It requires a deep understanding of the variables and parameters that influence the workforce such as environmental factors (workplace temperature, workplace layout, fatigue, stress, and motivation), cost factors (salaries, training, hiring and firing costs, and bonuses) and maintenance practices [4 & 16].

Maintenance workforce models have helped foster understanding with regard to variables and parameters that enhance maintenance system performance. They have also helped businesses develop strategies to reduce and cope with workforce maintenance problems using scientific tools. Evolutionary algorithms, Euclidean distance, goal programming、 and swarm algorithms are among the scientific tools that are frequently used to determine the optimal values of maintenance variables [4, 15, 17 & 18]. Most of the available literature on maintenance and workload analysis is primarily focused on applying weighted goal programming and Euclidean distance to multi-objective analysis in non-manufacturing systems. However, there is also a compelling need for a study that considers the application of weighted goal programming and Euclidean distance in manufacturing systems. The aim of this study was, thus, to apply weighted goal programming, Euclidean distance, and a GA to solve a multi-objective maintenance workforce model. We created a model that deals with maintenance workforce, expenses and workforce performance in order to achieve this goal [15].

The remaining sections of this study are organised as follows: Section 2 presents the research methodology, while section 3 contains the description of the case study. Results and discussions are contained in section 4. The conclusions of this study are presented in section 5.

2. Research Methodology

This study used an evolutionary algorithm, particle swarm optimisation (PSO) algorithm, as well as weighted goal programming and Euclidean distance as solution methods for an existing nonlinear maintenance workforce optimisation model (Figure 1). The research consisted of two phases: The first phase was the creation of the nonlinear optimisation model. The second phase involved the application of meta-heuristics as a solution for the formulated model.

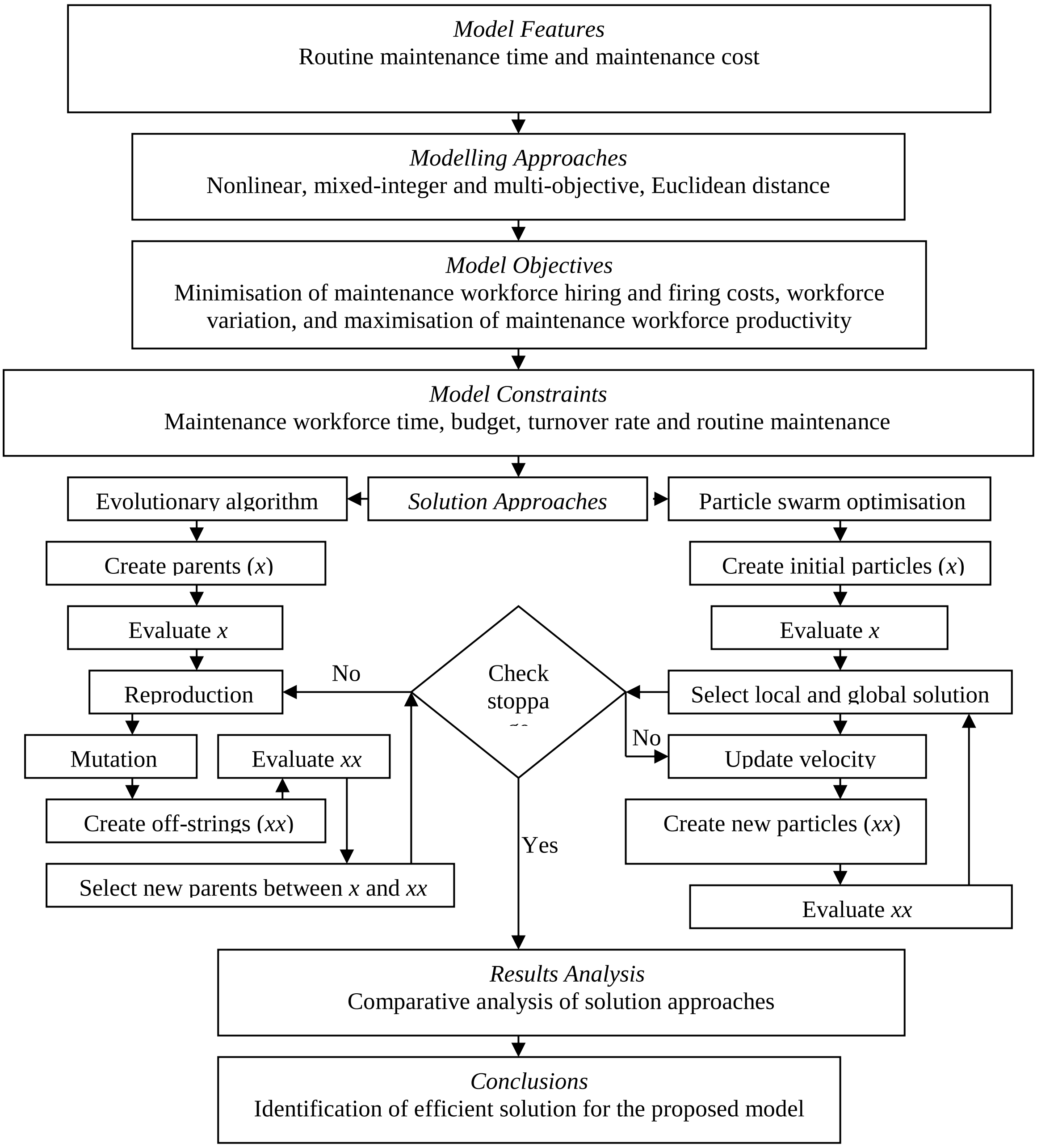

Figure 1 Research methodology [15].

Phase I: Formulation of nonlinear optimisation model

This phase involves the selection of model objective functions, decision variables and modelling techniques for maintenance workforce variable optimisation. This study adopts the optimisation model proposed by Ighravwe *et al*. (2015) [15] in generating a Pareto solution for workforce salaries, productivity, size variation, and hiring and firing costs. The notations used in presenting the adopted nonlinear optimisation model are presented in Appendix A. The structure of the selected model is as follows (Equations 1 to 16):

Model goals:

$$\text{Min } Z_1 = \sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T} c_{ijt}x_{ijt} \tag{1}$$

$$\text{Minmax } \mathrm{Z}_2 = \sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T} (PD_{ijt} - r_{ijt}x_{ijt}) \tag{2}$$

$$\text{Minmax } Z_3 = \sum_{i=1}^{M}\sum_{t=1}^{T} E(x_{i1t} - \frac{\sum_{t=1}^{T} x_{i1t}}{T-1})(x_{i2t} - \frac{\sum_{t=1}^{T} x_{i2t}}{T-1}) \quad (3)$$

$$\text{Min } Z_4 = \sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T}\left(hc_{ijt}h_{ijt} + fc_{ijt} f_{ijt}\right) \quad (4)$$

Subject to:

$$w_{i1t} \le R_i w_t \qquad \forall t \in T \quad (5)$$

$$x_{i1t}w_{i1t} + x_{i2t}w_{i2t} \le \mu + \theta^{-1}(1-\alpha_t) * \sigma_t \qquad \forall t \quad (6)$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N} x_{ijt}w_{ijt} \le W_t \qquad \forall t \quad (7)$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N} c_{ijt}x_{ijt} \le (\vec{b}_t - \vec{a}_t)(1-\hat{\alpha}_t) + \vec{a}_t \qquad \forall t \quad (8)$$

$$\sum_{j=1}^{N} x_{i1kt} \ge f_t \sum_{j=1}^{N} x_{i2kt} \qquad \forall i,t \quad (9)$$

$$u_{ijt}\overline{w}_{ijt} \le x_{ijt}w_{ijt} \qquad \forall i,j,t \quad (10)$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N} x_{ijt} \le X_t \qquad \forall t \quad (11)$$

$$x_{i1t} + x_{i2t} \le x_{\max,i} \qquad \forall i,t \quad (12)$$

$$x_{ijt} \ge x_{ij,\min} \qquad \forall i,j,t \quad (13)$$

$$\frac{a_{ijt}x_{ijt}}{\hat{a}_{ijt}x_{ijt}} * \frac{p_{ijt}x_{ijt}}{\hat{p}_{ijt}x_{ijt}} * \frac{q_{ijt}x_{ijt}}{\hat{q}_{ijt}x_{ijt}} \ge WOE_t \qquad \forall i,j,t \quad (14)$$

$$x_{ijt} + f_{ijt} = (1-TR_{ijt})x_{ijt-1} + h_{ijt} \qquad \forall i,j,t \quad (15)$$

$$\frac{\sum_{i=1}^{M}\sum_{j=1}^{N} SR_{ijkt}x_{ijkt}}{\sum_{i=1}^{M}\sum_{j=1}^{N} \hat{a}_{ijkt}x_{ijkt}} \le SR_t \qquad \forall t \quad (16)$$

The first objective function of the model deals with the minimisation of workforce salaries (Equation 1), with the second being the maximisation of workforce productivity (Equation 2). Minimisation of variation in workforce size is the third objective function (Equation 3), and the fourth is the minimisation of workforce hiring and firing costs (Equation 4). The generation of a Pareto solution for these objective functions is constrained by the maintenance workload for full-time workers (Equation 5) and total workload in a given maintenance section (Equation 6). Other sets of constraints in Ighravwe *et al*.'s (2015) model include the total workload for a maintenance system (Equation 7) total workers' salaries (Equation 8), ratio of full-time workers to casual workers (Equation 9), actual amount of work done (Equation 10), total workforce size (Equation 11), sectional workforce size (Equation 12), minimum number of workers for each worker category (Equation 13), workforce overall effectiveness (Equation 14), change in workforce level (Equation 15), and workers' severity rate (Equation 16) [15].

Using equations (17) to (24), the weighted goal programming version of Ighravwe *et al.*'s (2015) model [15] is expressed as follows:

$$Min = D_o \tag{17}$$

Subject to:

$$f_2 - Z_2 \leq 0 \tag{18}$$

$$f_3 - Z_3 \leq 0 \tag{19}$$

$$Z_o - d_o^- + d_o^+ \leq 0 \qquad o = 1,2,3,4 \tag{20}$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T}\left(c_{ijt}x_{ijt}\right) \leq Z_1 \tag{21}$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T}\left(PD_{ijt} - r_{ijt}x_{ijt}\right) \leq Z_2 \tag{22}$$

$$\sum_{i=1}^{M}\sum_{t=1}^{T}E(x_{i1t} - \frac{\sum_{t=1}^{T}x_{i1t}}{T-1})(x_{i2t} - \frac{\sum_{t=1}^{T}x_{i2t}}{T-1}) \leq Z_3 \tag{23}$$

$$\sum_{t=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T}\left(hc_{ijt}h_{ijt} + fc_{ijt}f_{ijt}\right) - d_4 \leq Z_4 \tag{24}$$

Equations (5) to (16)

$$x_{ijt} \geq 1,\ f_{ijt} \geq 0,\ h_{ijt} \geq 0,\ w_{ijt} \geq 0,\ u_{ijt} \geq 0,\ SR_{ijt} \geq 0$$

The ideal value for each of the objective functions is determined based on the concept of normalised Euclidean distance analysis (Equation 25). This concept involves specifying the minimum and maximum expected values of each objective function. The ideal solution of the model is taken as the smallest summation of D_o and constraint violations [17].

$$D_o = \sqrt{\sum_{o=1}^{4}\kappa_o\left[\left(\frac{Z_o(x) - Z_{o,\min}}{Z_{0,\max} - Z_{o,\min}}\right)S - \bar{Z}_o^*\right]^2} \tag{25}$$

where S is a parameter and its value lies between (0,1) or (1,100); κ_o, $Z_{o,\max}$ and $Z_{o,\min}$ are the weight, maximum, and minimum value of objective function o, respectively; and $\bar{Z}_o$ is the normalised Pareto optimal point for solution set o.

Phase II: Meta-heuristics

Stochastic and population-based algorithms were employed as solution methods. A PSO algorithm, Differential evolution (DE) algorithm, and GA are the three meta-heuristics that are used. The PSO algorithm was designed to mimic the characteristics of birds' social behaviour. The basic operation involved in PSO algorithmic implementation is updating particles' velocity and position [19]. A particle's velocity is updated based on its social and cognitive knowledge as well as its previous velocity and position (Equation 26).

$$V_{jj}(tt) = wV_{jj}(tt-1) + c_1R_1\left(pbest_{tt-1}^{jj} - x_{jj}(tt-1)\right) + c_2R_2\left(gbest_{tt-1} - x_{jj}(tt-1)\right) \quad (26)$$

where $V_{jj}(tt)$ and $x_{jj}(tt)$ are velocity and position, respectively, of particle *jj* at iteration *tt*; $pbest_{tt}^{jj}$ and $gbest_{tt}$ are personal best and global position, respectively, at iteration *tt*; R_1 and R_2 are uniform random numbers; c_1 and c_2 are parameters; and *w* is inertial weight.

Velocity clapping is used to control the velocity value of each particle based on the minimum and maximum velocity of a given decision variable (Equation 27). The new position of the particle is expressed as Equation (28).

$$\begin{cases} v_{jj}(tt) > v_{\max} & \text{then} \quad v_{jj}(tt) = v_{\max} \\ v_{jj}(tt) < v_{\min} & \text{then} \quad v_{jj}(tt) = v_{\min} \end{cases} \quad (27)$$

$$x_{jj}(tt) = V_{jj}(tt) + x_{jj}(tt-1)) \quad (28)$$

where $v_{\min}$ and $v_{\max}$ are the minimum and maximum velocity of a particle, respectively.

Since real coding GA (RCGA) outperformed binary coded GA [20], it was selected as the GA for this optimisation model. The mutation operation in RCGA is carried out based on Equation (29). A simulation of an unbiased coin flip is used to determine the direction in which a mutant vector will move [20], [21].

$$v_{gg}(tt-1) = \begin{cases} x_{gg}(tt-1) + \delta^{tt}\left(Max\left(x_{gg}\right) - x_{gg}(tt-1)\right) & \text{Head} \\ x_{gg}(tt-1) - \delta^{tt}\left(x_{gg}(tt-1) - Min\left(x_{gg}\right)\right) & \text{Tail} \end{cases} \quad (29)$$

$$\delta^{tt} = R\delta^{tt-1}(1 - tt/TT)^{B} \quad (30)$$

where v_{gg} is mutant vector *gg*, $Min(x_{gg})$ and $Max(x_{gg})$ are the minimum and maximum values of decision variable *gg*, respectively, *R* is a uniformly distributed random number, *TT* is the maximum generation obtainable, and *B* is a parameter.

During the RCGA crossover operation, two parents are randomly selected from a reproduction pool (P_1 and P_2) and used to generate two $(O_1 \text{ and } O_2)$ offspring (Equations 31a and 31b).

$$O_{1,i} = (1-\gamma)P_1 + \gamma P_2 \quad (31a)$$

$$O_{2,i} = \gamma P_1 + (1-\gamma)P_2 \quad (31b)$$

$$\gamma = (1-2\alpha)\eta - \alpha \quad (32)$$

where η , α , and γ are parameters.

This study used the Boltzmann selection operation to determine which parents and offspring would comprise the reproduction pool. When Equation (33) holds, the offspring is selected. Otherwise, a parent is selected [22].

$$U(0,1) > \frac{1}{1+e^{(f_{\psi}(x_{gg}(tt)) - f_{\psi}(x_{gg}^{O'}(tt))/T(tt)}} \quad (33)$$

where $f_{\psi}(x_{gg}(tt))$ and $f_{\psi}(x_{gg}^{o}(tt))$ are the fitness functions of the parents and offspring, respectively, and $T(tt)$ is the temperature at generation *tt*.

The operation of the DE algorithm is different from that of RCGA. The DE mutation operation is based on three randomly selected parents, such that $gg \neq \overline{r}_1 \neq \overline{r}_2 \neq \overline{r}_3$ (Equation 34).

$$v_{gg}(tt) = x_{\overline{r}1}(tt-1) + MR\left(x_{\overline{r}2}(tt-1) - x_{\overline{r}3}(tt-1)\right) \quad (34)$$

where $x_{\overline{r}1}$, $x_{\overline{r}2}$, $x_{\overline{r}3}$ are first, second, and third randomly selected parent, respectively and *MR* is the mutation rate.

A Crossover operation for the DE algorithm is carried out based on randomly generated numbers (R_{gg} and I_{gg}). The values of the generated numbers are used to determine whether or not a mutant or target vector will be considered a trail vector (Equation 35).

$$u_{gg} = \begin{cases} v_{gg}(tt) & \text{If } R_{gg} \leq CR \text{ or } gg = I_{gg} \\ x_{gg}(tt\text{-}1) & \text{If } R_{gg} > CR \text{ or } gg \neq I_{gg} \end{cases} \quad (35)$$

where u_{gg} is trial vector gg, *CR* is crossover rate, and *D* is number of decision variables [22]

3. Case study

The optimisation model presented in this study was used to determine the optimal values for various maintenance workforce variables at a brewery plant located in southwest Nigeria. The company specialises in manufacturing both alcoholic and non-alcoholic beverages. This study assumed a six-year planning period for the implementation of the optimisation model.

The company currently operates three production lines. Two of the production lines are used for the production of bottled drinks, while the other is used for the production of canned drinks. The company operates three shifts per day, with an average of 25 production days per month. Based on the information obtained from the case study, workforce analysis workforce was limited to section-wise and class-wise workforce distribution. At the sectional level, the company's maintenance workforce was grouped into mechanical, electrical, and janitorial workers. The company does not employ casual mechanical or electrical workers. Other information used to implement the model is presented in Table 1. The parametric settings for the PSO, DE, and genetic algorithm are presented in Table 2.

4. Discussions of Results

The best parametric settings were found to be *P* = 50, *F* = 0.30, *C* = 0.20 when the GA was used as a solution; *P* = 20, *F* = 0.3, *C* = 0.15 when the DE algorithm was used; and *P* = 30, c_1 = 1.1, c_2 = 0. when the PSO algorithm was employed. The meta-heuristics showed quick convergence during implementation (Figure 2). The penalty function values of the meta-heuristics were used to identify the best parametric settings. Based on this, the GA was selected as the most suitable meta-heuristic for the model (Figure 2). This finding is consistent with that of Mansour (2011) [4], who reported a GA to be a suitable solution method for maintenance optimisation models.

4.1 Objective functions

The values for the model objective function vary according to situation (Figures 2 and 3). The results illustrated in Figure 3 show that the workforce cost increased as a result of changes in the workforce structure from one period to the next [23]. The total workforce expense for the six periods was ₦115, 556,057.20. The total workforce salary was about ₦112, 250,994.00, and total hiring and firing costs were ₦3, 305,063.20. The difference between the maximum (₦56, 351,196.00) and minimum (₦16, 814,058.00) workforce salary was ₦39, 537,138.00. A value of ₦1, 544,422.40 was obtained as the difference between the maximum (₦1, 834,599.60) and minimum (₦290, 177.20) hiring and firing costs. The company requires an average of ₦18,708,499.00 per year for workforce salary and ₦550,843.87 per year for hiring and firing (Figure 3). The results obtained from the model showed that the average workforce productivity for the company was 3,675, while total maintenance workforce productivity was 22,050. The difference between the maximum and minimum workforce productivity values was 122 (Figure 4).

Table 1 Maintenance workforce data

Parameters	Full-time janitorial workers	Casual janitorial workers	Electrical workers	Mechanical workers
Unit cost (₦)	63,6042	49,8042	72,8364	80,3712
Unit hiring cost (₦)	42,402.8	33,202.8	48,557.6	53,580.8
Unit firing cost (₦)	106,007	83,007	121,394	13,3952
Category productivity (₦)	1,500	2,000	1,500	1,500
Unit productivity (₦)	150	200	150	150
Minimum workload (hr)	2,175	725	1,450	1,450
Maximum workload (hr)	3,900	2,925	2,925	2,925
Minimum worker’s availability	0.742	0.742	0.742	0.742
Maximum worker’s availability	1	1	1	1
Minimum worker’s performance	0.80	0.80	0.80	0.80
Maximum worker’s performance	1	1	1	1
Minimum quality of workdone	0.60	0.60	0.60	0.60
Maximum quality of workdone	1	1	1	1
Minimum number of workers that can be hired	0	4	0	0
Maximum number of workers that can be hired	1	8	1	2
Minimum number of workers that can be fired	0	2	0	0
Maximum number of workers that can be fired	2	6	1	2
Minimum use factor for workers	0.85	0.85	0.85	0.85
Maximum use factor of workers	1	1	1	1
Turnover rate	0.02	0.02	0.02	0.02

Table 2 Meta-heuristics parametric settings

Parameters	DE algorithm	GA	PSO algorithm
Population size (*P*)	50	50	50
Generations/iterations	200	200	200
Mutation rate (*MR*)	10 - 30%	10 - 30%	-
Crossover rate (*CR*)	10 - 45%	10 - 30%	-
Cognitive knowledge (c_1)	-	-	0.1 - 1
Social knowledge (c_2)	-	-	0.1 - 1
Inertia weight range (*w*)	-	-	0.10 - 0.50

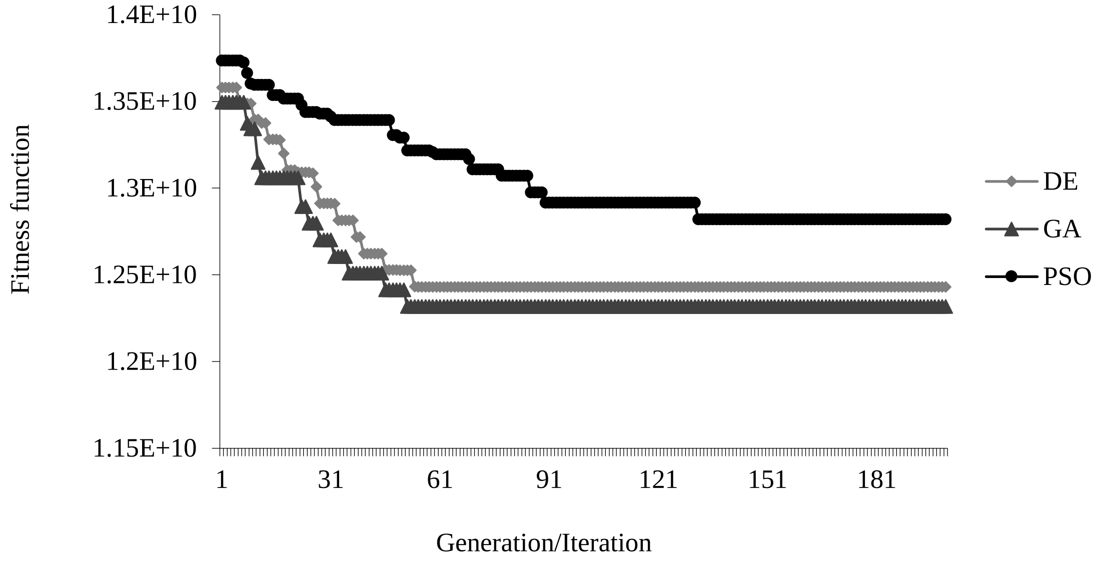

Figure 2 Convergence curve for the model of the different meta-heuristics.

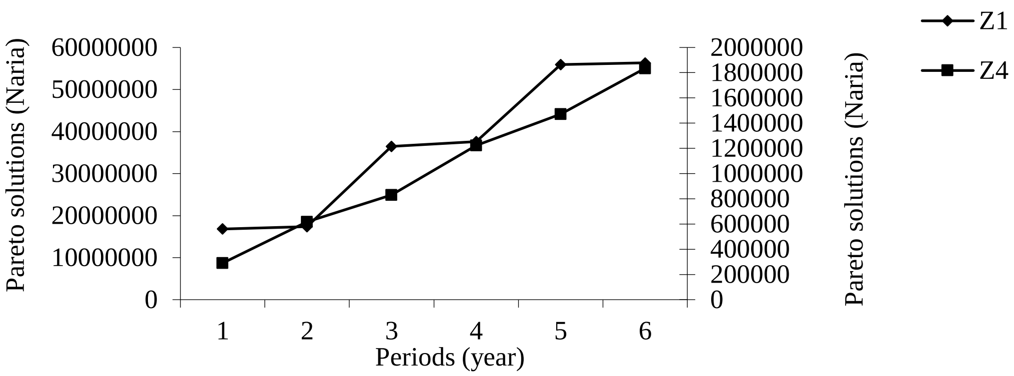

Figure 3 Total maintenance workforce costs for the different periods.

4.2 Model's Constraints

The results obtained from each of the decision variables are discussed in the following sections.

4.2.1 Maintenance workforce size

The minimum and maximum number of workers required at a given period were found to be 24 and 30 workers, respectively (Table 3). The company required an average of seven full-time and four casual janitorial maintenance workers, ten electrical workers and eight workers for mechanical maintenance activities.

A total of 48 mechanical maintenance workers were required over the course of the six periods (Table 3). Four maintenance workers are expected to be hired and five fired over the six periods. The company's electrical maintenance section required a total of 55 maintenance workers for the six-year planning period. Two electrical workers are expected to be hired and four fired. A total of 42 maintenance workers are required for the janitorial maintenance section, and four full-time janitorial maintenance workers will be hired and at least six will be fired. A total of 20 casual janitorial workers are expected to work for the company. The company will hire 37 casual janitorial maintenance workers and fire 28 (Table 3).

The differences between the maximum (nine) and minimum (seven) numbers of mechanical electrical maintenance, and casual janitorial maintenance workers were two (min=7, max=9), three (min=7, max=10), and three (min=2, max=5), respectively. There was no difference between the maximum and minimum number of full-time janitorial maintenance workers (Table 3).

The difference between the maximum (one) and minimum (zero) values for the full-time janitorial, electrical, and mechanical maintenance workers predicted to be hired were the same (one maintenance worker). The difference between the minimum and maximum number of casual janitorial maintenance workers to be hired was two (min=5, max=7). There is no difference between the maximum and minimum number of full-time janitorial or electrical maintenance workers predicted to be fired. There was a difference of one between the maximum and minimum number of mechanical maintenance workers to be fired (Table 3).

According to the data presented in Table 3, the average number of existing maintenance workers required in each section of the maintenance system varies from one period to another. The average number of maintenance workers fired varies by section, while the average number hired remained the same throughout all periods (Figure 5). The difference among the average number of existing, hired, and fired workers in Period 1 was 14 workers and that in Period 2 was 16. The difference was seven for Periods 3 and 5. The differences in Periods 4 and 6 were eight and 12 workers, respectively.

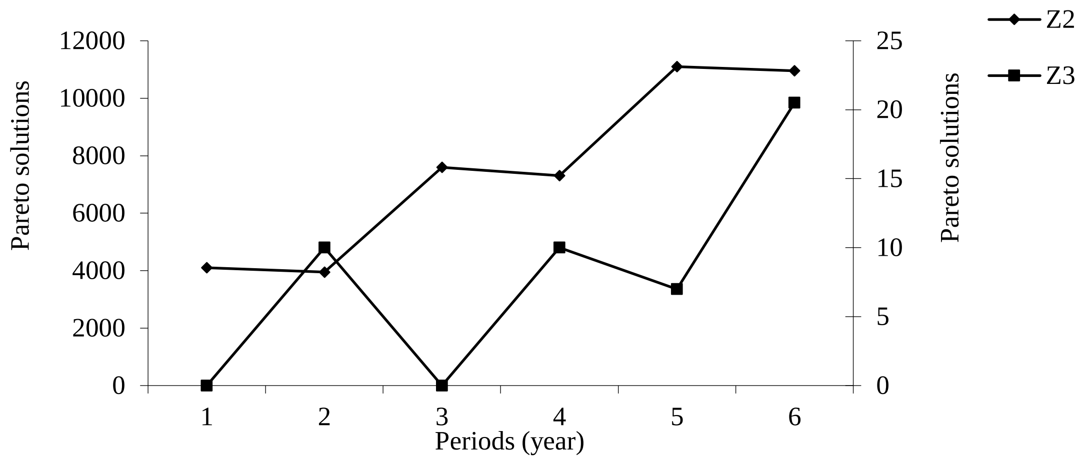

Figure 4 Total maintenance workforce productivity and co-variance for the different periods.

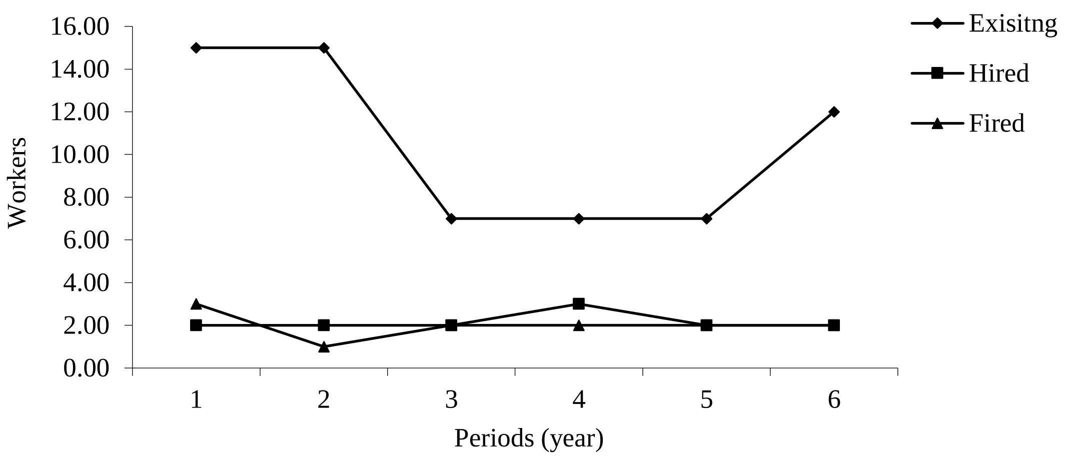

Figure 5 Average maintenance workforce distribution for the different periods.

Table 3 Maintenance workforce distribution for the different periods

Parameters	Variables	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
	x_{110t}	7	7	7	7	7	7
	x_{120t}	5	4	2	3	4	2
Existing workers	x_{210t}	10	10	9	10	9	7
	x_{220t}	0	0	0	0	0	0
	x_{310t}	8	9	9	7	7	8
	x_{320t}	0	0	0	0	0	0
	h_{110t}	0	1	1	1	1	0
	h_{120t}	5	6	7	7	6	6
Hired workers	h_{210t}	0	0	0	1	0	1
	h_{220t}	0	0	0	0	0	0
	h_{310t}	1	1	0	1	1	0
	h_{320t}	0	0	0	0	0	0
	f_{110t}	1	1	1	1	1	1
	f_{120t}	6	3	6	4	5	4
Fired workers	f_{210t}	1	0	0	1	1	1
	f_{220t}	0	0	0	0	0	0
	f_{310t}	1	0	1	1	0	2
	f_{320t}	0	0	0	0	0	0

4.2.2 Maintenance workloads

The total maintenance time required from a full-time janitorial maintenance worker over the six periods was about 17,911.57 hr., about twice the amount of time (9,226.73 hr.) required from a casual janitorial maintenance worker (Table 4). The difference between the total maintenance time required from an electrical (12,680.02 hr.) and mechanical maintenance worker (13,170.90 hr.) was 490.88 hr. (Table 4). Among the various worker categories, the mechanical maintenance workers had the highest difference between the maximum (2,572.63 hr.) and minimum (1,812.80 hr.) total maintenance time per period (757.84 hr.), the electrical maintenance worker category had the least (min=1,961.90 hr., max=2,396.63 hr., difference=334.45 hr. The difference between the casual janitorial maintenance workers had a maximum of 1,738.42 hr. and minimum of 1,278.37 hr., for a difference of 460.05 hr. (Table 4). The model generated a value of 684.69 hr. as the difference between the maximum (3,363.90 hr.) and minimum (2,679.21 hr.) values for full-time janitorial maintenance workers (Table 4). Period 4 had the highest total maintenance time required from a given worker in each section (9,492.72 hr.), Period 5 had the lowest. The difference between the total unit maintenance time in Period 1 (8,923.67 hr.) and Period 6 (8,362.97 hr.) was 560.70 hr. The model's result for the total unit maintenance time was 9,079.86 hr. for period 2 and 8,800.15 hr. for period 3. The results obtained showed that a maintenance workers will work for an average of 2,207.88 hr. annually (Table 4).

4.2.3 Maintenance workers' use factors

The average use factor for maintenance workers was above 90%. The casual janitorial maintenance workers had the highest average use factor at 93.54%. The difference between the average use factor for full-time and casual maintenance workers was about 0.31%. There was a difference of 0.39% (Table 4) between the average use factor for electrical maintenance workers and that of a mechanical worker. As the results in Figure 6 show, there was no direct relationship between average values for workload and use factor for the worker categories. This is a result of changes in the size of the workforce, which affects the workload and use factor values (Equation 10). When the values of two or more parameters are affected by an optimised variable, the relationships among the parameters are often indirect [18, 23 & 24] In a study conducted by He et al. (2014) [23], an indirect relationship was found between workforce reliability and cost. The casual janitorial maintenance workers had the lowest average workload value, but highest average use factor when compared with other worker categories. The average required use factor for a worker was about 93.16% (Figure 6).

Table 4 Maintenance workload and use factor distribution by period

Parameters	Variables	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
Maintenance workload (hr.)	w_{110t}	2807.9604	3277.1763	3363.9038	3064.0009	2719.3144	2679.2127
	w_{120t}	1482.2746	1705.9414	1470.3348	1738.4267	1551.3796	1278.3738
	w_{210t}	2060.7979	1961.8995	2153.1170	2396.6253	2045.4021	2062.1751
	w_{220t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	w_{310t}	2572.6337	2134.8445	1812.7985	2293.6667	2013.7498	2343.2054
	w_{320t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Use factor (%)	u_{110t}	0.9189	0.9449	0.9418	0.9377	0.9409	0.9094
	u_{120t}	0.9247	0.9267	0.9167	0.9421	0.9643	0.9377
	u_{210t}	0.9454	0.9383	0.9558	0.9283	0.8889	0.9313
	u_{220t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	u_{310t}	0.9399	0.9345	0.9203	0.8832	0.9287	0.9578
	u_{320t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

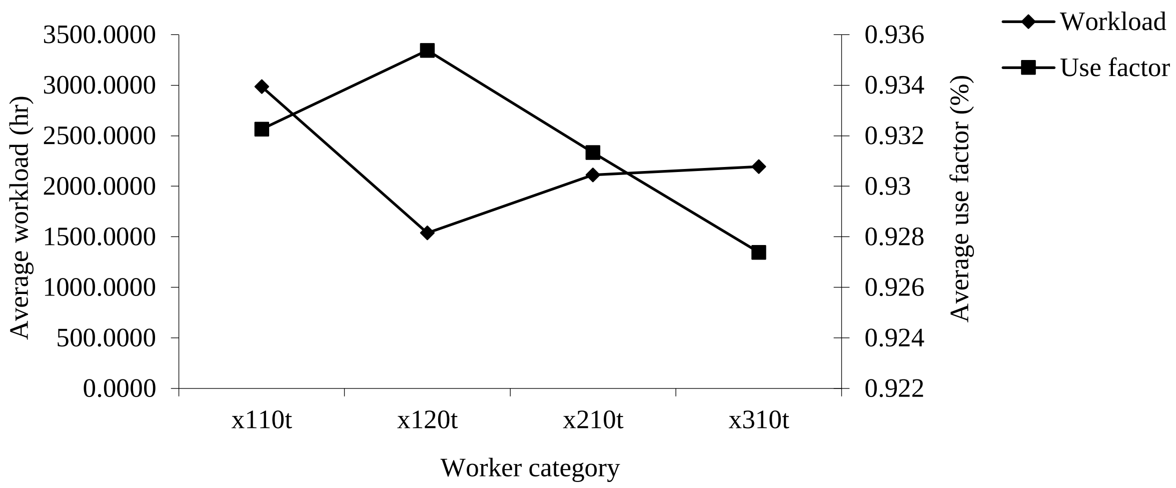

Figure 6 Average maintenance workload and use factor of maintenance workers.

Table 5 Maintenance workforce performance by period

Parameters	Variables	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
Worker efficiency (%)	p_{110t}	0.8553	0.8800	0.9185	0.8819	0.9045	0.8802
	p_{120t}	0.8796	0.8724	0.9413	0.8991	0.8977	0.9447
	p_{210t}	0.9061	0.8791	0.9158	0.9257	0.8498	0.8603
	p_{220t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	p_{310t}	0.8881	0.9319	0.9284	0.8790	0.9165	0.8725
	p_{320t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Quality of workdone (%)	q_{110t}	0.7980	0.7527	0.7216	0.8422	0.7531	0.8255
	q_{120t}	0.7190	0.7755	0.8656	0.7704	0.7174	0.7387
	q_{210t}	0.7924	0.7783	0.7553	0.8283	0.8295	0.8525
	q_{220t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	q_{310t}	0.8167	0.7412	0.8167	0.8861	0.7719	0.8880
	q_{320t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

4.2.4 Maintenance worker's performance

All the worker categories had at least one efficiency value greater than 90%, as shown in Table 5. The electrical and mechanical maintenance workers had an equal number of worker efficiency values over 90% (Table 5). The average mechanical maintenance worker's efficiency value was greater that of the average electrical maintenance worker (Figure 7). The model results revealed that the expected minimum value for the maintenance workers was above 85% (Table 5). The difference between the minimum (0.8725) and maximum (0.9319) values for mechanical maintenance workers was 0.0528, compared to 0.0466 (min=0.8791. max=0.9257) for electrical maintenance worker.

The casual janitorial maintenance workers had the lowest average value for quality of work done according to this model. There was an inverse relationship between the average worker efficiency and quality of work done for casual janitorial maintenance workers (Figure 7). In electrical maintenance workers, as the average value of workers' efficiency decreases, the average value of the quality of work done by the increases.

None of the full-time worker categories had worker availability value above 90% (Table 6). The difference in maximum worker availability between electrical (0.8868) and mechanical (0.8993) workers was about 1.25%. Workers in the casual janitorial maintenance category had the highest worker availability values for every period except Period 5, in which full-time janitorial maintenance workers had the highest value.

The maximum worker availability value of the mechanical workers was 1.79% higher than of the full-time janitorial maintenance workers. The difference between the minimum and maximum severity rates of electrical and mechanical maintenance workers was 0.59%. This shows that that the category with the worst worker availability is full-time janitorial maintenance workers. As shown in Table 6, the only maintenance worker category that had a rate of more than 10% was the casual janitorial maintenance workers. The full-time janitorial maintenance workers had the lowest severity rate when compared with the other categories. The mechanical maintenance workers had the highest average severity rate, while the full-time janitorial maintenance workers had the lowest (Figure 8).

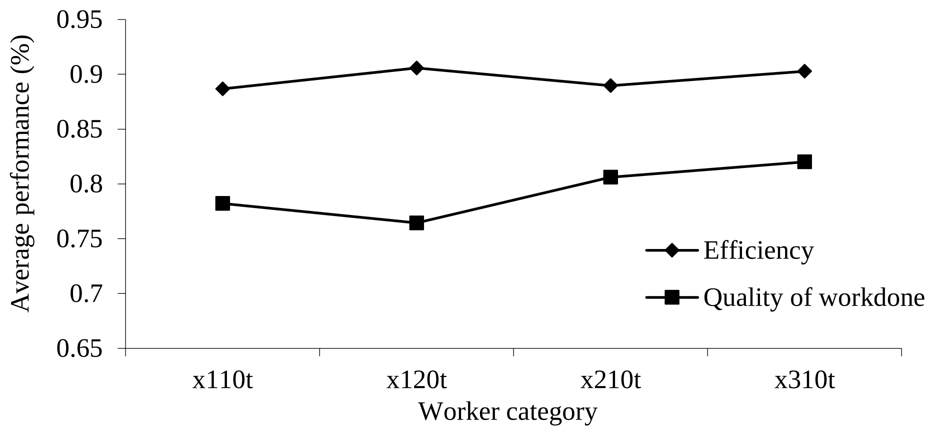

Figure 7 Average values for maintenance workers' efficiency and quality of work done.

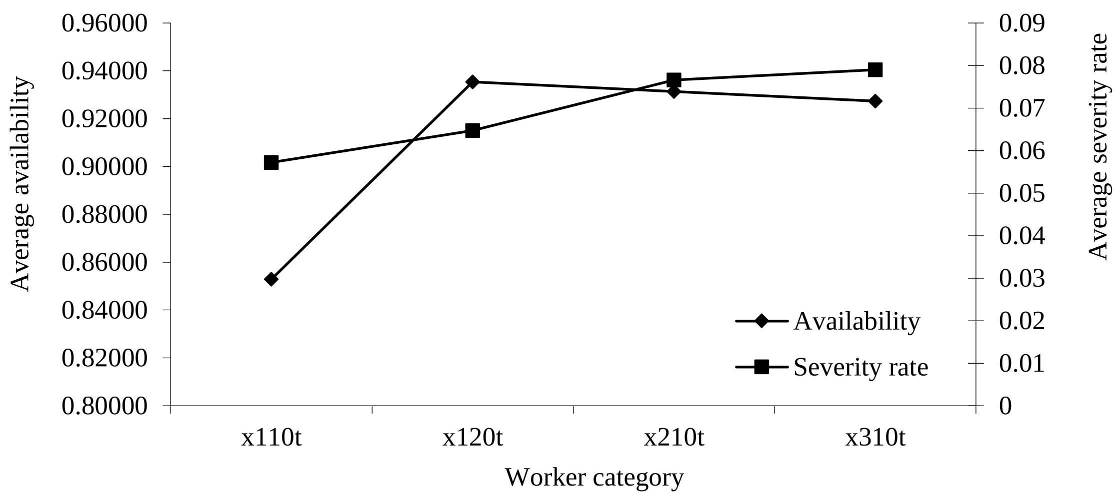

Figure 8 Average maintenance workforce availability and severity rate by period.

Table 6 Maintenance workforce availability and severity rate for the different periods

Parameters	Variables	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
Worker's availability (%)	a_{110t}	0.8835	0.8705	0.7937	0.8414	0.8653	0.8629
	a_{120t}	0.9319	0.8868	0.8849	0.9211	0.8609	0.9057
	a_{210t}	0.8868	0.8840	0.8754	0.8691	0.8341	0.8797
	a_{220t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	a_{310t}	0.8473	0.8529	0.8694	0.8993	0.8626	0.8397
	a_{320t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Worker's severity rate (%)	SR_{110t}	0.0606	0.0440	0.0255	0.0925	0.0788	0.0418
	SR_{120t}	0.1016	0.0653	0.0559	0.0637	0.0551	0.0468
	SR_{210t}	0.0798	0.0823	0.0643	0.0912	0.0663	0.0759
	SR_{220t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	SR_{310t}	0.0767	0.0823	0.0728	0.0751	0.0702	0.0970
	SR_{320t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

5. Conclusions

This study proposes the use of weighted goal programming, Euclidean distance, and a GA as solution methods for an existing mixed-integer nonlinear programming model. The applicability of our approach was tested using information that was obtained from a Nigerian brewery plant. Comparative analysis was carried out to examine PSO, genetic, and DE algorithmic results as solution methods for the formulated model. The results obtained showed that the GA was the most suitable solution method. The GA generated satisfactory results in terms of maintenance workforce costs, productivity, and variation. Furthermore, optimal values for maintenance workforce budget, workload, availability, quality of work done, and efficiency values were generated using the selected optimisation model [15].

Based on the results obtained from the GA, the maximum number of maintenance workers for the system was 30 per year, and an average workers' salary of ₦18, 708,499 was required. The hiring and firing costs over six years was ₦3, 305,063.20. The average productivity of maintenance workers was 3,675, and the total routine maintenance time was 17,911.57 hr. In addition, all of the worker categories had at least one worker efficiency value that was greater than 90%.

Further research should examine whether or not this method could also be used for other type of maintenance activities that are not purely machine-based such as road maintenance. Future studies should also attempt to account for the influence of individual factors (personality, attitude, and skills), environmental factors (noise level, room temperature, and humidity) and operational planning (delivery date, subcontracting, and product quality) on the proposed models.

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