Asia-Pacific Journal of Science and Technology: Volume: 24. Issue: 01. Article ID.: APST-24-01-09. Research Article

APST

Asia-Pacific Journal of Science and Technology

https://www.tci-thaijo.org/index.php/APST/index

Published by the Research and Technology Transfer Affairs Division,
Khon Kaen University, Thailand

Maintenance workforce optimisation in a process industry using differential evolution

Desmond Eseoghene Ighravwe[1], Sunday Ayoola Oke[2, *], Kazeem Adekunle Adebiyi[3]

[1] Department of Mechanical and Biomedical Engineering, Bells University of Technology, Ota, Nigeria
[2] Department of Mechanical Engineering, Faculty of Engineering, University of Lagos, Akoka-Yaba, Lagos, Nigeria
[3] Department of Mechanical Engineering, Faculty of Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria
*Correspondent author: sa_oke@yahoo.com

Received 23 April 2016
Revised 29 December 2017
Accepted 17 January 2019

Abstract

In the past few years, differential evolution (DE) algorithms have been applied to solve system optimisation problems. Optimisation of workforce variables is a necessary requirement to make maintenance workforce planning. Since the effective control and monitoring of major system losses is tied to maintenance, the competent historical performance and potential of DE to optimise maintenance workforce variables has strongly inspired this work. The workforce optimisation structure depends on computations involving the following performance parameter: Production line availability, workforce size changes, cost of service rate improvement, workforce bonuses as well as penalty costs and then cost of spare parts. The developed framework used DE algorithm to optimise workforce including production and maintenance variables in an integrated framework. The model incorporates nonlinear integer model and weighted additive fuzzy goal programming model. The DE algorithm was used in generating Pareto solution for maintenance and production variables. The reliability as well as the effectiveness of the presented method was verified using practical real-life data from a process industry operating in a developing country. The obtained results showed that DE algorithm can generate accurate results with a fast convergence rate and good stability as genetic algorithm and particle swarm optimisation algorithm. The study could be replicated in other process industries such as drinks manufacturing.

Keywords: Maintenance costs, production volume, meta-heuristics, process industry, weighted additive fuzzy goal programming

1. Introduction

Maintenance workforce analysis is a series of mathematical calculations embarked by the maintenance manager in which maintenance variables and parameters are used to evaluate the threshold of resources to be utilised for maintenance activities, and also how such resources are to be employed. Although modelling maintenance workforce may have been initiated several years ago, the advent of optimisation into the workforce area spring up a few years ago, and tends to open up several exciting and outstanding possibilities for the concept to play out. Consider the work by Ighravwe *et al*. [1] in which the authors were faced with the challenge of developing a workforce system that considered fatigue and training, it was the application of optimisation techniques that aided such progress. This and other literature cases raise interesting queries for maintenance researchers to probe and find solution to in advancing an understanding on the optimisation of maintenance workforce crew performance in a situation of uncertainty and in a circumstance where multiple goals exist for the smooth running of the maintenance system. An essential theoretical gap which appears at the intersection of production research and studies related to spare parts as well as outsourcing research is addressed.

Particularly, new insights are advanced on what level to ensure the smooth operation of production lines. It is also sought to know how exploring novel and innovative workforce practices in routine maintenance ordering would impact on the performance of various production lines availability. A third aspect of enquiry is the need to probe into what level of spare parts should be retained within a production system such that routine maintenance will run smoothly? Furthermore, an understanding is sought on how much quantities of goods should be produced from each of the production line in a production system? It may also be interesting to probe into what should be the production route at which each production line should run. Finally, enquiries are made to know what amounts of production activities should be outsourced? The gyration of optimal solutions for the above mentioned problems may involve the use of optimisation models, prioritisation tools and meta-heuristics (genetic algorithm (GA), differential evolution (DE) and particle swarm optimisation (PSO)).

The evolutionary algorithm literature portrays the idea that these studies have highlighted that optimisation of process parameters could be conveniently relied upon based on the potential attributes of DE in generating accurate outcomes, having fast convergence rate as well as demonstrating good stability in performance. DE has now emerged as a saving tool to aid optimisation of maintenance resources with special focus on maintenance workforce. DE have long been recognised as principal triggers of process optimisation whose outcomes could help in making reliable decisions that could sustain the organisation both in the short and long terms. Sitkin *et al*. [2] argued that systems can be guaranteed prolonged activities and lifespan through good performance now while placing itself for enhanced performance in the future that remains uncertain in nature.

Now from agriculture and medicine to manufacturing, researchers are garnering many insights into the potentials of DE to demonstrate outstanding optimal values for manufacturing. Although pockets of studies appear to have been carried out, using DE in manufacturing, majority of contribution have been restricted to production system. Knowledge is yet to extend to areas such as maintenance, logistics and even marketing and distribution. Keeping in mind the current global depression, the declining need for more process efficiency, the declining profit margins of industries, the more intense pressure on maintenance for optimisation, time has come to radically transform the maintenance performance assessment and improvement schemes. There is a great need to analyse and optimise every bit of maintenance resource.

In this paper, it is acknowledged that the maintenance workforce, after being scheduled for maintenance activities needs to be monitored, assessed and controlled for the most advantageous performance threshold in the process industry of concern. It was observed that evaluating the maintenance workforce at the best performance levels and maintaining them at such thresholds is crucial for effective control. Consequently, it becomes essential to document data concerning the workforce and evaluate the same at the optimum parametric levels of the maintenance workforce process variable monitoring, by the unique approach of differential evolution for the forthcoming control purpose that offers the essential weight-age to the current investigation.

The process industry has the target to offer the best maintenance services to the production department and the company at large in a largely minimal time period. Particularly in a situation of high competitive activities among the rival industries, the maintenance service period becomes essentially predominant to achieve the goal of minimum downtime while indirectly optimizing the profit and/or moving it to lucrative threshold. Optimisation tools are employed in many of the several operations in the process industry, for instance, the quality control function, the production scheduling activities, the machining processes. Optimisation has an outstanding record of compressing the process accomplishment time, enhancing the product quality and providing maximum profit thresholds for industries. The optimization of maintenance workforce parameters is necessary to attain the best values of process activities. The differential evolution method of optimisation is largely a significantly embraced method for outstanding assurance as well as optimisation of system processes. Previous research have offered merely restricted ideals concerning the impacts of maintenance process optimisation on the parameters of the system for maintenance systems in the process industry, using significantly selective parameters of production line availability, workforce size changes, the cost of service rate improvement, the workforce bonuses, the cost of spare parts as well as the penalty cost. Consequently, actual field investigation in the industry, coupled with laboratory computational experimentation using aid software, was embarked upon in this research, with the objective of optimising the workforce, including production as well as maintenance variable in an integrated structure.

This paper contributes in the subsequent manners: First, the presented framework supplements currently existing methods of maintenance workforce performance evaluation. By revealing the working systems of the non-linear integer model, the weighted additive fuzzy goal programming and the differential evolution, and the differential evolution, and the manner in which they affect one another in a maintenance workforce system, the framework presented aids in explaining the non-linear parametric relationships of components of the maintenance workforce system. Among others, while the cost of service rate improvement, penalty costs as well as cost of spare parts remains significant components of consideration in maintenance workforce evaluations, the current frameworks for evaluations influence the manner in which these considerations are appraised and incorporated into the maintenance workforce algorithms as these components of often neglected in analysis. Furthermore, through the maintenance management may be unaware of the influence of omitting these variables in his/her decision framework, the negative influence of their omissions could be serious. Second, through drawing from as well as integrating concepts of production as well as maintenance to provide an explanation on how parent solution for the declared variables could be generated, the paper heed the call to shed more light on hour Pareto solutions are generated in maintenance workforce decision making. Third, this paper sheds light on the weaknesses of conventional solution methods, including the simplex method and the method of Big-M, as they are deficient in generating attractive outcomes for non-linear models [1], as those considered in this paper. It therefore shows the way to developing satisfactory models for maintenance managers for decision making. Fourth, current maintenance-production optimization frameworks are multi-objectives in nature. Hence, a framework beyond this multi-objective scope may be an outstanding contribution to the maintenance workforce literature. An additional contribution is this: the current work incorporates decision makers' desired values into a multi-objective in a maintenance-production framework, and this contribution to knowledge is work while.

The above-mentioned issues motivated the need for the current study. Thus, an application-based framework is developed for analysis of maintenance-production variables in manufacturing systems. This is carried out using a nonlinear integer model [1], weighted additive fuzzy goal programming (WAFGP) model and DE. Based on the proposed framework, this study contributes a WAFGP approach to maintenance-production problem. Furthermore, a non-dominated sorting approach for multi-objective maintenance planning problem is contributed. Finally, DE is contributed as a solution method for maintenance-production problem.

2. Literature Review

2.1 General literature overview

In the past few years, consistent with the perspectives of a number of theorist and practitioners, DE has been applied in diverse areas such as agriculture [3], manufacturing [4-6], energy systems [7], structures [8], medicine [9, 10]. Now a brief summary of these contributions to literature revealed the gaps that exist in literature.

For agriculture, Sethanan and Piakaso [3] contributed a report in which a DE was applied in providing solution to a route minimisation of total cost in the collection of raw milk. It was reported that enhancement in total costs was obtained using the differential evolution algorithm. In manufacturing, Yildiz [6] proposed a DE amalgamated with Taguchi method in solving the multi-pass problems in turning operations. From the case investigations, it was concluded that the DE amalgamated with Taguchi method showed more outstanding performance than other metaheuristics such as algorithms of particle swarm optimisation, integrated harmony search, integrated genetic, immune, scatter search as well as the fused simulated annealing as well as Hooke-Jeeves pattern method of searching.

Yet another study in manufacturing, Zeng *et al*. [5] integrated Pareto utility discrete differential evolution (PUDDE) algorithm as well as embedded discrete event simulated model as a solution methodology for solving a complex problem in manufacturing plant devoted to apparel sewing. Noktehdan *et al*. [4] studied the grouped differential evolution and hybrid grouped differential evolution algorithms by considering an application to cellular manufacturing. The framework was applied to solve a group problem. It was concluded that the introduced algorithm meets up or out-performed the results exhibited by using literature test examples. Raza and Al-Turki [11] evaluated the performance of heuristic and meta-heuristics as solution methods for the maintenance scheduling problem. An implicit enumerative algorithm performance was compared with Tabu search and simulated annealing. They observed that the heuristic computational time was less than these meta-heuristics, while the solution quality form these meta-heuristics were better than that of the heuristic.

Fetanat and Shafipour [12] addressed the problem of economy effect and reliability of a power plant during maintenance scheduling. A binary optimisation model that used ant colony optimisation was presented in the study. Li and Pan [13] considered flexible job-shop scheduling problem that incorporated maintenance activities. Tabu search was used to generate Pareto solution for the multi-objective in the study. Li et al. [14] also studied flexible job-shop scheduling and maintenance problem using meta-heuristic. They used artificial bee colony algorithm to generate Pareto solution for workload size, machine complexity and makespan. Nourelfath *et al*. [15] used a combined GA and Tab search approach to generate Pareto solution for imperfect preventive maintenance activity. Chaoqui et al. [16] combined Johnson's algorithm and GA in addressing the flow job-shop maintenance and production activities problem. Johnson's algorithm created the window for production activity scheduling, while GA used to incorporate maintenance activity into tolerance interval during production activities.

In the energy domain, DE has been applied by Atif and Al-Sulaiman [7] to optimise a heliostat field in a solar central receiver system, using two methods. The feasibility of the methods was demonstrated using practical data from Dhahran, Saudi Arabia and the parameters were reported to have been optimally computed. Le-Anh et al. [8] applied DE as a solution technique for composite plate optimisation problem in which the static and fundamental frequencies were candidates for optimisation. The DE framework utilised coupled the commonly used DE and a classical method that handles discrete integer variables as well as mutation strategy. It was concluded that the tested framework produced robust results comparable with literature outputs.

The outstanding contributions of DE in medicine are notably discussed here two concrete studies involving Ghosh [10] as well as De Falco [9]. In the case of Ghosh [10] analysed and developed an approach to judge the value of insulin in diagnosis and clinical enquires. It was reported that a global solution was attained using DE. De Falco [9] used DE in medical databases with a focus on continuous grouping of items unaided by operators. The fuzzy 'If-Then' rules were applied and found to successfully yield desired outputs. The first part of the literature review showed that a number of studies have been documented on manufacturing with the use of differential evolution algorithm and that no single account of the algorithmic application to workforce issues has been found. The second part of the survey of literature re-affirms the search experience stated here. The workforce literature is relatively at the growing stage and has account of classic work on planning [17], capacity [18], allocation [19], scheduling [20] and optimisation [21].

An account on workforce was given by Starkey et al. [22] that examined a multi-objective genetic type-2 fuzzy logic-oriented framework for use in optimising workforce area. The presented results revealed strong enhancement at the application of the model in industries with huge numbers of non-static field engineers. A next contribution is attributed to Monra et al. [23]. The authors examined a Bayesian method with population variability to approximate the distributions of accident rates as well as recovery. The authors concluded that the model was validated with a case study oriented on hydro-power production and located in Brazil. Furthermore, Firat et al. [24] assigned skill competent technicians to job hierarchically using a branch and price method. A computational investigation revealed the efficiency of the method. In addition, Ighravwe et al. [25] demonstrated the potential genetic algorithm (GA) and DE as potential methods for solving maintenance workforce planning problem. Their study considered optimisation model and fuzzy goal programming method. The findings revealed that DE was a more suitable solution method than GA and PSO.

The investigations reviewed in two parts (DE and studies associated with workforce) revealed several important gaps in the scientific literature relevant to the current study. It is clear that very little information is available relating to workforce studies on maintenance systems. It is also known from the literature study that there are little details on work that captures the integration of production and maintenance exists, under the umbrella of workforce studies. Furthermore, available investigations on maintenance workforce seem to have downplayed uncertainties in modelling elements of the system. In addition, there seems that there is no recognition of the fact that maintenance system is very complex and that modelling workforce in such a system involves clear definitions of the important goals of the system and its properly formulated goals. Hence tools such as goal programming have been sparsely applied to maintenance workforce modelling. In order to clearly reveal the contribution specific to the workforce and metaheuristics arena related to maintenance, a few studies are presented in Table 1.

2.2 Literature summary

Specifically, in the past six years, researchers have consciously pursued extensive research in maintenance workforce coupled with metaheuristics and the scope of coverage is expanding. The following insights could be drawn from the available literature:

- While the transportation area as well as the process industry have been the major interests of scholars, the bias of researchers have been towards the process industry and more calls for papers in this industry are being released through the interesting debates of their contributions. Thus, the current research is strongly motivated to explore this research arena and contribute to the debate on workforce.
- More recent papers have seen interests in expanding the conceptualization of the human aspect or the human-driven workforce. For instance, the reliability concept adaptation to humans is a deviation of previous perceptions to equipment alone, and is now established in workforce debates on maintenance. Also, the consciousness in limiting the number of experimental trials through the use of Taguchi methods has been established in the workforce debates [26]. Furthermore, authors have argued on the consideration of maintenance period, workforce size and life-cycle cost in maintenance work force communications.
- A substantial number of authors have considered the workforce while there is a growing attention in merging maintenance workforce and production workforce into a unifying scheme.
- Attention of researchers has been drawn to practically-oriented studies as pure theoretical studies are being downplayed.
- The maintenance problems associated with workforce is complicated; it contains a substantial number of interacting variables identified and models to improve the existing frameworks is also expanding.

Table 1 Some articles related to maintenance workforce and meta-heuristics

S/No.	Research focus	Researcher(s)	Details of the research	Comments
1	Transportation	Markovic et al. [26]	Comparison of maintenance optimization (metaheuristics) for refuse gathering automobiles using Taguchi and degradation system	The work fails to consider unique workforce attributes The research was carried out outside manufacturing environment but service Local data with peculiar African setting framework is missing
2	Process industry	Ighravwe et al. [25]	Human reliability centered workforce planning	The potential of reliability in capturing human performance is demonstrated with the aid of fuzzy programming while being aided with differential evolution. However, differential evolution is not the controlling model for the work but a support
3	Optimization of a process industry	Ighravwe and Oke [27]	A principal contribution of the study is the introduction of rest periods compared with no-rest periods for a mixed-integer multi-objective maintenance and production workforce	The potentials of differential equation to enhance optimization is not exploited
3	Optimization of industrial processes	Ighravwe et al. [28]	Three solution techniques of weighted goal programming, genetic algorithm and Euclidean distance were put forward to a mixed-integer non-linear programming model	No elements of differential evolution introduced as a major driver but a minor transformation agent
4	Process (manufacturing) optimization	Ighravwe et al. [29]	Establishment of optimal maintenance period as well as size of workforce, life-cycle cost	Differential evolution used to enhance the accomplishment of fuzzy inference system and not as the main tool for transformation
5	Technicians workload optimization	Ighravwe et al. [1]	Reliability-centered approach to technicians' workloads optimization Stochastic nature of work as well as the management of the workloads identified	No elements of differential evolution considered in the analysis

3. Meta-heuristics

Brief discussions on the two groups of the meta-heuristics used as solution methods for the WAFGP model are presented as follows:

3.1 Swarm optimisation algorithms (SA)

The modelling of social behaviour of bird flocking and fish schooling led to the development of SA. The basic characteristics of SA involve updating of swarms velocity and position in order to generate improved solutions for numerical problems [30]. PSO algorithm is an algorithm that was designed to mimic the characteristic of bird's social behaviour. Global solution for combinatorial problems is generated by updating particle positions and velocity at each epoch (iteration). During position and velocity updating, the social and the cognitive knowledge of particles in a swarm are used in controlling the search capacity of PSO algorithm [31]. PSO algorithms have been used in optimising parameters in maintenance systems, common among these parameters are system availability [32], maintenance crew size [30], maintenance and repair costs [33], preventive maintenance cost, the corrective maintenance cost and the penalty cost of lost load [34] and system reliability [35].

3.2 Evolutionary algorithms (EA)

EA are population and stochastic search meta-heuristics algorithms that were designed to mimic natural evolution processes in living organisms. Three basic operations (mutation, reproduction and selection) are required for most EA implementation generation of off-springs is based on mutation and reproduction operations. The maximum (x_{max}) and minimum (x_{min}) values of decision variables as well as random number (RN) which lies between (0, 1) are used in generating the initial population to a problem. This will allow search for optimal value to cover decision plane as much as possible. The widely used expression for initialisation of decision variables values during the application of meta-heuristics is expressed as Equation (1) in literature [31].

$$x(0) = x_{\min} + RN(0,1)(x_{\max} - x_{\min}) \tag{1}$$

where x represents decision variable, $x_{\min}$ represents the minimum value of x, and $x_{\max}$ represents the maximum value of x.

In AI domain, fitness function $(f_{\psi}(x(tt))$ is used in evaluating the quality of solutions for optimisation problems. The value of $f_{\psi}(x(tt))$ is the aggregation of objective $f(x(tt))$ and penalty ($p(x(tt))$) functions. The value of $p(x(tt))$ is the aggregation of level of violation of constraints in an optimisation problem. Several studies on how to compute $p(x(tt))$ exist in literature. A commonly used penalty evaluation approach in literature was proposed by Joines and Houck [36]. Their approach has the advantage of improving exploration [31]. Joines and Houck [36] pointed out that the value of $p(x(tt))$ is expressed as Equation (2).

$$p(x(tt)) = (\gamma'_{tt})^{\alpha'} \sum_{m'''=1}^{n_g+n_h} p_{m'''}^{\beta'}(x) \tag{2}$$

where

γ'_{tt} represents parametric value at generation or iteration step tt, m''' represents constraint,

α' represents a parameter, β' represents a constant parameter, n_g represents the number of inequality constraints, n_k represents the number of equality constraints, and $p_{m'''}^{\beta'}(x)$ represents violation value of a constraint.

The transfer of genotypic features from parents (x') to off-springs (x'') is done using reproduction operation, while phenotypic features are transferred using mutation operation. The decision on whether to use crossover operation, mutation operation or both depends on the type of EA been used in generating solution to a problem. The difference between GA and DE is the approach used in generating off-springs. In GA, at least two parents are required to generate off-springs while standard DE requires a minimum of three parents [31]. In an attempt to actualise the current research, the investigators are required to formulate the problem rooted on the framework of an optimisation model in an applicable manner to the maintenance workforce situation. To achieve this set goal, the investigators have selected the differential evolution framework for effectiveness as it has record merits of performance in a wide range of industrial applications. The differential evolution has been adapted from the original framework by Storn and Price. The DE pseudo code for multi-criteria is henceforth described.

Algorithm: Pseudo code for multi-criteria DE

Initialize the mutation rate, crossover rate, stoppage criteria, number of generations (t) and population size
Formulated a weighted fuzzy goal for the objective functions
Create the initial population
Evaluate the parents' fitness
    While stoppage condition not met do
        For each individual do
        Mutation operator to the trial vector
        Crossover operator to the offspring
        Evaluate the offspring fitness
        Use non-dominated sorting to select the individual for the next population [37]
        end
    end
Return the fitness individual as the Pareto solution;

4. Research Methodology

The research methodology that are used in this study considered the use of an existing nonlinear mixed-integer model [38], weighted fuzzy goal programming (WFGP) model and meta-heuristics in generating Pareto solution for maintenance and production variables. The notations used in presenting the mixed-integer nonlinear model are presented in Appendix A, while the model (Equations 3 to 22) is presented as follows [38]:

Model goals

$$\text{Max}G_1 = \frac{\sum_{l=1}^{L}\sum_{t=1}^{T} P_{lt} - \rho}{\sum_{l=1}^{L}\sum_{t=1}^{T} P_{lt}} \cdot 100\ \% \tag{3}$$

$$\text{Min } G_2 = \sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T}\left(\delta_{ijt}^{1} h_{ijt} + \delta_{ijt}^{2} f_{ijt}\right) + \sum_{t=1}^{T}\sum_{i=1}^{M}\left(a_i + (1+\lambda_i)\right)\sum_{j}^{N} x_{ijt} \tag{4}$$

$$\text{Min } G_3 = \sum_{l=1}^{L}\sum_{t=1}^{T}\sum_{s=1}^{S}\left(\beta_l\left(\left[\left(\max\left(\overline{\chi}_{lst},0\right)\right)\right]\right) + \left(\hat{\beta}_l\left[\left(\min\left(\overline{\chi}_{lst},0\right)\right)\right]\right)\right) R_{lts}\sum_{i=1}^{M}\sum_{j=1}^{N} x_{ijt} \tag{5}$$

$$\text{Min } G_4 = \sum_{l=1}^{L}\sum_{i=1}^{N}\left(C_{il}^{1}\sum_{t=1}^{T} Q_{ilt} + \sqrt{C_{il}^{1}C_{il}^{2}C_{il}^{3}\sum_{t=1}^{T} Q_{ilt}}\right) \tag{6}$$

Subject to :

$$\sum_{s=1}^{S} R_{lst} \geq 1 \qquad \forall(l,t) \tag{7}$$

$$\sum_{l=1}^{L} R_{lst} \geq 1 \qquad \forall(s,t) \tag{8}$$

$$\sum_{l=1}^{L} PV_{lt} + I_{t-1} + \xi_t - I_t - (1 \pm r)d_t = 0 \qquad \forall t \tag{9}$$

$$I_T \leq I_{\max} \tag{10}$$

$$x_{ijt} + f_{ijt} = (1 - TR_{ij})x_{ijt-1} + h_{ijt} \qquad \forall i, j, t \tag{11}$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N} c_{ijt}x_{ijt} \leq B_t \qquad \forall t \tag{12}$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N} \delta_{ijt}^{1} h_{ijt} \leq \hat{B}_t \qquad \forall t \tag{13}$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N}\delta_{ijt}^{2} f_{ijt} \le \overline{B}_t \qquad \forall t \qquad (14)$$

$$\sum_{t=1}^{T} INV_{clt} C_{cl}^{1} C_{cl}^{2} \le Bq_{cl} \qquad \forall (c,l) \qquad (15)$$

$$\mathrm{MWE_t} + \mathrm{SPC_t} \le (Mb - Ma)(1-\alpha_t) + Ma \qquad \forall t \qquad (16)$$

$$\lambda \sum_{i=1}^{M} x_{i1t} \ge \sum_{i=1}^{M} x_{i2t} \qquad \forall t \qquad (17)$$

$$\sum_{j=1}^{N}\sum_{s=0}^{S}\omega_{1jlst} \ge \sum_{j=1}^{N}\sum_{s=0}^{S}\omega_{2jlst} \qquad \forall (l,t) \qquad (18)$$

$$INV_{cl(t-1)} + q_{clt} - (1+FSP)\left(TOT_{lt} - \sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{s=0}^{S}\omega_{ijlst} \Big/ MN \right) \Big/ MTTF_{cl} = INV_{clt} \quad \forall (c,l,t) \qquad (19)$$

$$q_{\min,cl} \le q_{clt} \le q_{\max,cl} \qquad \forall (c,l,t) \qquad (21)$$

$$\frac{1}{T}\sum_{t=1}^{T} INV_{clt} \le Aq_{cl} \qquad \forall (c,l) \qquad (20)$$

$$\sum_{c=1}^{C} a_c INV_{clt} \le \Psi_{lt} \qquad \forall (l,t) \qquad (22)$$

The first goal deals with maximisation of production line availability (Equation 3), while the second goal considered minimisation of change in maintenance workforce size and service rate improvement costs (Equation 4). The third goal deals with minimisation of maintenance workforce bonuses and penalty costs (Equation 5) and the last goal considered the minimisation of cost of spare parts (Equation 6). Routine maintenance schedules (Equations 7 and 8), product demand (Equation 9), finished goods inventory (Equation 10) and change in worker's level (Equation 11) are considered as constraints in generating Pareto solution for the above mentioned goals. Also, workers' salaries (Equation 12), hiring cost (Equation 13), firing cost (Equation 14), spare parts inventory cost (Equation 15) and maintenance budget (Equation 16) are other constraints that were considered by Ighravwe et al., [38]. The relationships between worker categories (Equation 17), workloads relationships (Equation 18), spare parts ordering, usage and wastage relationships (Equation 19) and spare parts ordering limits are other sets of constraints that were considered by Ighravwe et al., [25]. Average spare parts inventory (Equation 21) and spare parts storage areas (Equation 22) were also considered as constraints by Ighravwe et al., [38].

Weighted additive fuzzy goal programming (WAFGP) approach is used in handling the multi-objective in model [38]. The aspiration level (b_o) for each of the fuzzy goal are considered [39]. The membership function for the maximisation goal is shown in Figure 1. Minimisation goals membership function is shown in Figure 2. The fuzzy goal for minimisation objective function is defined with Equation (24). The fuzzy goal for maximisation objective function is expressed as Equation (25).

$$\mu_o = \begin{cases} 1 & \text{If } G_o \le b_o \\ 1 - \dfrac{G_o - b_o}{\Delta_{oR}} & \text{If } b_o \le G_o \le \Delta_{oR} + b_o \\ O & \text{If } G_o \ge \Delta_{oR} + b_o \end{cases} \qquad (24)$$

$$\mu_o = \begin{cases} 1 & \text{If } G_o \geq b_o \\ 1 - \dfrac{b_o - G_o}{\Delta_{oL}} & \text{If } b_o \text{ -}\Delta_{oL} \leq G_o \leq b_o \\ O & \text{If } G_o \leq \Delta_{oR} - b_o \end{cases} \tag{25}$$

where b_o represents aspiration level for *o-th* fuzzy goal, Δ_{oR} represents quantity of a tolerance for minimisation of fuzzy goal, and Δ_{oL} represents quantity of a tolerance for maximisation case of fuzzy goal.

The complete WAFGP model is presented as follows:

$$\text{Min } \bar{f} = \kappa_1 \frac{\delta_1}{\Delta_{1L}} + \kappa_2 \frac{\delta_2}{\Delta_{2r}} + \kappa_3 \frac{\delta_3}{\Delta_{3R}} + \kappa_4 \frac{\delta_4}{\Delta_{4R}} \tag{26}$$

Subject to:

$$Z_1 + \delta_1 \geq b_1 \tag{27}$$

$$Z_o - \delta_o \leq b_o \qquad o = 2,3,4 \tag{28}$$

$$\mu_1 + \frac{1}{\Delta_{1L}} \leq 1 \tag{29}$$

$$\mu_0 + \frac{1}{\Delta_{oR}} \leq 1 \qquad o = 2,3,4 \tag{30}$$

Equations (7) to (22)

where δ_o represents deviation value of objection function *o*, μ_o represents the degree of membership function for fuzzy goal *o*, κ_o represents the weight for fuzzy goal *o*.

The expressions for the objective functions and constraints in the WAFGP model are obtained from the work of Ighravwe *et al.*, [38].

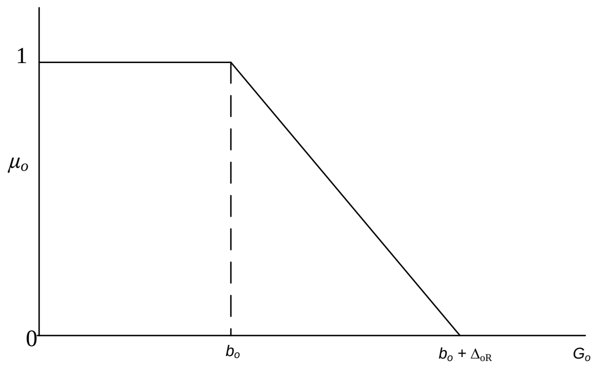

Figure 1 Linear membership function for the minimisation objective [39]

5. Model Application

According to the international labour organisation (ILO), the organisation considered with a staff of about 250 is classified as a medium-sized organisation (MSO). Thus, an MSO was chosen to examine the efficacy of the advanced methodological framework. The MSO that is subjected to test operates from one of the towns in the

Western part of Nigeria. It has a production system, which focuses on beer production, using three production lines (1, 2 and 3). The maintenance system that serves production is centralise with operations carried out at different centres in the MSO being directed from the centre. In Production Lines 1 and 2, bottle drinks are produced, while Production Line 3 is used for the production of canned drinks.

The minimum rate per hour of Production Line 1 is 250 packs (cartons), while its maximum production rate per hour is 270 packs (cartons). Production Line 2 has a minimum production rate of 207 packs (cartons) per hour and a maximum production rate of 230 packs (cartons) per hour. The minimum and maximum production rates for Production Line 3 are 195 and 210 packs (cartons) per hour. An extensive discussion and interview was granted to the process engineer in order to have insights into the production as well as maintenance system and further, to zero-in on the most important aspects of the system related to the current study. Some attributes of the system are displayed in Table 2. The company's maintenance department has three main maintenance sections (cleaning, electrical and mechanical). Apart from the cleaning section which had full-time and part-time workers, the other sections have only full-time workers. Other information used during the implementation of the WAFGP model is presented in Table 2.

The GA and DE mutation probability was set as 0.15, while their crossover probability was 0.20. The cognitive knowledge of the PSO algorithm was 0.3, while the PSO algorithm social knowledge was 0.35. A population size of 50 individuals or particles was used in implementing the model for 200 generations. The results obtained during the implementation of model showed that the DE is the most suitable algorithm for solving the formulated model for the case study (Figure 3). By using the DE as a solution method for the formulated model, the values of the decision variables were generated for six planning periods.

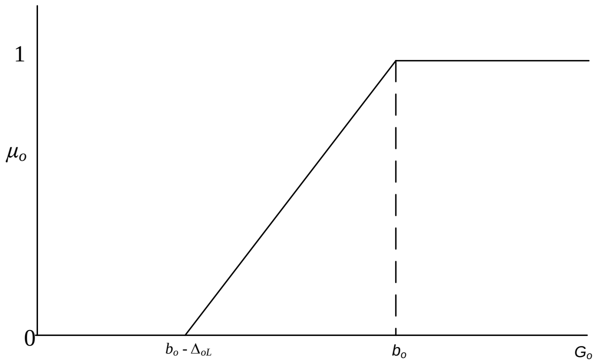

Figure 2 Linear membership function for the maximisation objective [39]

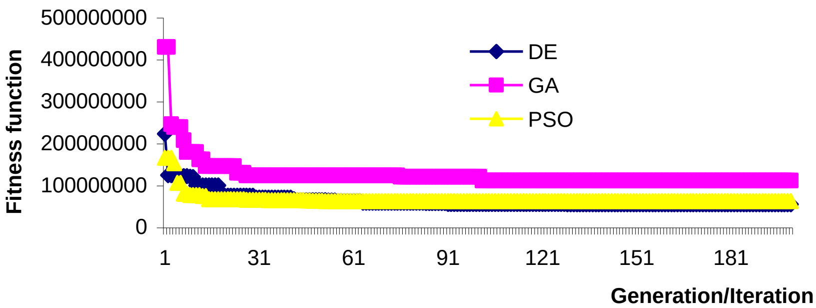

Figure 3 Meta-heuristics solutions for model

Table 2 Maintenance workforce information

Parameters	Full-time cleaning workers	Part-time cleaning workers	Full-time electrical workers	Full-time mechanical workers
Unit cost (₦)	636,042.00	498,042.00	728,364.00	803,712.00
Unit hiring cost (₦)	42,402.80	33,202.80	48,557.60	53,580.80
Unit firing cost (₦)	106,007.00	83,007.00	121,394.00	133,952.00
Penalty cost (₦)	1,000.00	1,000.00	1,000.00	1,000.00
Bonus (₦)	1,500.00	1,500.00	1,500.00	1,500.00
Minimum number of workers	6	2	8	8
Maximum number of workers	8	6	12	12
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 (%)	70	70	70	70
Maximum use factor of workers (%)	100	100	100	100
Minimum workload for line 1(h)	761.25	253.75	507.50	507.50
Maximum workload for line 1 (h)	1,365.00	1,023.75	1,023.75	1,023.75
Minimum workload for line 2 (h)	761.25	253.75	507.50	507.50
Maximum workload for line 2 (h)	1,365.00	1,023.75	1,023.75	1,023.75
Minimum workload for line 3 (h)	652.50	217.50	435.00	435.00

6. Results and Discussions

This section presents the results obtained from the formulated model as well as discussions of the results obtained.

6.1 Model objective functions

The fitness function for formulated model was 47,384,848.23. The result for production line availability (Z_1) showed that its membership function value was close to a complete membership function value. This implies that the interruption caused by routine maintenance activity does not affect the company's production plan. The model results showed that the membership function for minimisation of change in workforce size and service rate improvement costs had a complete membership function (Z_2). This implies that the soft constraint for Z_2 was not violated (Table 3). Based on the DE results, the company required an average of ₦3, 429,585,052.00 per period for the maintenance workforce bonuses and penalty expenses (Z_3). This amount is more than the expected expenses for the maintenance workforce bonuses and penalty because the membership function value obtained for Z_3 was zero. The membership function value for the cost of spare parts (Z_4) showed that the DE result for Z_4 was within an acceptable range. The organisation requires ₦1, 428,442.62 annually as spare parts cost (Table 3).

Table 3 Optimal crisp and membership functions values for model objective functions

Objective functions	Crisp values	Membership function values
Z_1	99.8755	0.9751
Z_2	₦ 31,738,235.9760	1.0000
Z_3	₦ 205,77,510,309.7559	0.0000
Z_4	₦ 8,570,655.7131	0.2825

6.2 Model decision variables

The discussions of the DE solutions for the decision variables in model are presented as follows:

(i) Routine maintenance schedule

For Schedule 1 on Production Line 1 and Schedule 3 on Production Line 3, the model was unable to generate work-orders for only one-period schedule. Furthermore, the model results showed that at least one standard work-order of carrying out routine maintenance on the basic production rate priority was obtained for each of the schedules (Table 4). In order to break ties when two or more production lines have the same work-order, a criterion that the routine maintenance should be carried out on a production line with a higher production rate was considered. Based on the results for routine maintenance activity for Schedule 1 (morning), the work-order of routine maintenance activities for the production lines in Periods 1 and 2 was 1-3-2. For Periods 3 and 4, the work-order of routine maintenance activity for Schedule 1 was 1-2-3. During Schedule 1, routine maintenance activity commenced first on Production Line 1 for all the periods considered (Table 4)

The routine maintenance activity for Schedule 2 (afternoon) from Periods 1 to 3 had a work-order of 1-2-3. A work-order of 2-3-1 was obtained for the production lines at Period 4 for Schedule 2. In Period 5, the routine maintenance activity work-order for Schedule 2 was 1-3-3, while a work-order of 3-2-1 was obtained for the production lines at Period 6 for Schedule 2. The number of times which routine maintenance activities started at Production Line 1 (Periods 1, 2, 3 and 5) was more than those of Production Lines 2 and 3 during Schedule 2. The work-order for routine maintenance activity at Period 1 for Schedule 3 (evening) was 2-3-1, while Period 2 had a work-order of 1-3-2. The work-order for Schedule 3 at Periods 3 and 6 were the same (3-2-1), while Periods 4 and 5 had the same work-order (1-2-3) for Schedule 3. For Schedule 3, routine maintenance activity on Production Line 1 commenced first for three periods (2, 4 and 5) when compared with those of Production Lines 2 and 3 (Table 4).

(ii) Production rates

The average production rate for Production Line 1 was 260 units/h, while Production Line 2 had an average production rate of 218 units/h. A value of 203 units/h was obtained as the average production rate for Production Line 3. The production rate for the production lines had two periods that they were the same. For instance, the production rate for Production Line 1 was the same at Periods 2 and 4 (257 units/h). Production Line 2 results showed that the production rate for Periods 4 and 5 were the same (218 units/h). In Periods 3 and 5, Production Line 3 had the same production rate (202 units/h). The production rate for Production Line 3 exhibited an alternating increasing and decreasing pattern (Figure 4). In Period 1, Production Lines 2 and 3 had the same amount of production rate (201 units/h).

Production Line 3 had the lowest difference between the maximum (208 units/h) and minimum (200 units/h) production rate among the three production lines. The difference between the maximum (270 units/h) and minimum (253 units/h) production rate for Production Line 1 was 17 units/h. A value of 29 units/h was obtained as the difference between the maximum (230 units/h) and minimum (201 units/h) production rate of Production Line 3. The DE results generated the minimum production rate for the three production lines as 660 units/h (Period 1), while their maximum production rate was 692 units/h. In Periods 3 and 5, the values of average production rates for the three production lines were the same (231 units/h). For the six periods, the average production rate for the three production lines was 681 units/h.

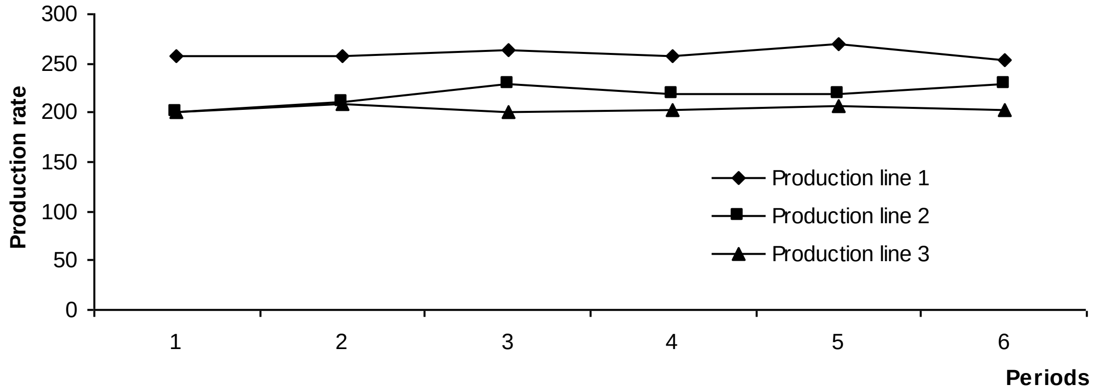

Figure 4 Production rates for the production lines

Table 4 Maintenance schedule for the different production lines

Schedules	Periods	Production Line 1	Production Line 2	Production Line 3
	$t = 1$	1	0	1
	$t = 2$	1	0	1
Schedule 1	$t = 3$	0	0	0
(Morning)	$t = 4$	1	0	0
	$t = 5$	1	1	1
	$t = 6$	1	1	1
	$t = 1$	1	1	1
	$t = 2$	1	0	0
Schedule 2	$t = 3$	1	1	0
(Afternoon)	$t = 4$	0	1	1
	$t = 5$	1	0	1
	$t = 6$	0	0	1
	$t = 1$	0	1	1
	$t = 2$	1	0	1
Schedule 3	$t = 3$	0	0	1
(Evening)	$t = 4$	1	1	1
	$t = 5$	1	0	0
	$t = 6$	0	0	1

(iii) Maintenance workforce distribution

The workforce structure for the existing full-time cleaning maintenance workers showed that it attained stability after an initial decrease from Periods 1 to 3. The company is expected to maintain an average of seven full-time cleaning maintenance workers in a period. The average number of casual cleaning maintenance workers that were required to exist in the maintenance system per period was four maintenance workers. The casual cleaning maintenance workers workforce structure attained stability after the first four periods (Table 5). The average workforce size for the full-time electrical and mechanical maintenance workers for the maintenance system was the same (nine maintenance workers). The full-time mechanical maintenance workers structure assumed a trapezoidal form, while the of the full-time electrical maintenance workers structure did not follow any regular pattern (Table 5).

The minimum number of maintenance workers that can be hired at any period by the company was four maintenance workers. Apart from Period 2, the minimum number of workers which can be fired was four maintenance workers. Furthermore, during the six planning periods, a maintenance worker must be fired in at least a period for any of the maintenance worker categories. The minimum number of maintenance workers that can be fired for any of the maintenance worker class was three maintenance workers (Table 5). The maximum number of maintenance workers required for the maintenance system was 30 maintenance workers, while a minimum of 27 maintenance workers was required for the maintenance system (Period 3). Based on model results, equal values of total number of hired and fired maintenance workers were required in Periods 1, 5 and 6 (Figure 5).

The total number of full-time cleaning maintenance workers (42 maintenance workers) that will exist in the maintenance system was about twice the total number of part-time cleaning maintenance workers (22 maintenance workers). The total number of full-time mechanical maintenance workers required for the maintenance system was more than that of full-time electrical maintenance workers (52 maintenance workers) by two maintenance workers (Table 5). The total number of hired maintenance workers for Periods 2, 3 and 5 were the same (Figure 5). In Period 1, the total number of hired and fired maintenance workers was the same (four maintenance workers). Also, Periods 5 had equal number of hired and fired maintenance workers (seven maintenance workers). Furthermore, Period 6 had the same number of hired and fired maintenance workers (five maintenance workers).

Table 5 Workforce distribution for the different periods

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

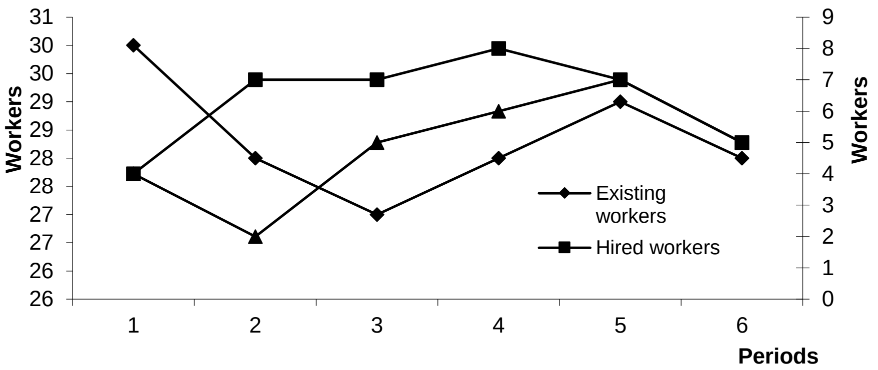

Figure 5 Maintenance workforce distribution

(iv) Maintenance workloads

None of the maintenance worker categories had a routine maintenance workload that was less than 40 h per period for Schedule 1 on Production Line 1 for any of the periods. The amount of routine maintenance workloads for the full-time and casual cleaning maintenance workers was about 1.5 times greater than those of the full-time electrical and mechanical maintenance workers on Production Lines 1 and 2. The highest amount of routine maintenance time for Schedule 1 on the different production lines was assigned to the full-time cleaning maintenance workers (Table 6). For Schedule 1, the amount of maintenance workloads for the various maintenance categories in Period 2 was greater than those of other periods. For the first four periods, the model was able to create an avenue for other type of maintenance activities that can be carried out on Production Line 2 (Table 6). The total amount of routine maintenance time in Period 6 (564.0811 h) for the maintenance workers was greater than that of Period 5 (509.8730 h).

The results for Schedule 1 routine maintenance workloads on Production Line 3 generated the highest amount of routine maintenance workloads in Periods 2. The casual cleaning maintenance workers had the lowest amount of total routine maintenance workloads for the six periods. Furthermore, the lowest amount of routine maintenance workloads for a maintenance worker category during Schedule 1 on the production lines occurred at Period 5 on Production Line 3 (Table 4). The number of times in which the model schedule routine maintenance activities on Production Line 2 was less than those of Production Lines 1 and 3. Although, the total amount of routine maintenance workloads on Production Line 2 (2,155.7831 h) was more than the total amount of routine maintenance workloads on Production Lines 1(1,204.7189 h) and 3 (943.4758 h) during Schedule 2 (Table 6).

During routine maintenance in Schedule 2, the difference between the total amount of routine maintenance workload for the full-time cleaning maintenance workers for the six periods on Production Lines 1 (441.379 h) and 2 (444.315 h) was less than 1%. The total amount of routine maintenance workloads on Production Line 2 for Schedule 2 (1,059.87 h) was less than the total amount of routine maintenance workloads for the casual maintenance workers (1,095.91 h). The total amount of routine maintenance workloads for the different periods on Production Line 2 during Schedule 2 were above 600 h. Furthermore, the total amount of routine maintenance workloads on Production \Line 2 for Schedule 2 in Period 5 was the highest when compared with other maintenance worker classes (Table 7).

None of the periods had a value of total routine maintenance workloads of up to 300 h on Production Line 3 during Schedule 2. The full-time mechanical workers had the lowest amount of routine maintenance workloads when compared with other maintenance worker classes for Production Line 3 during Schedule 2. Furthermore, the difference between the total routine maintenance workloads in Periods 1 (222.754 h) and 3 (222.92 h) was less than 1%. Apart from the full-time cleaning maintenance workers, the routine maintenance workloads for the other maintenance worker categories followed an alternating increasing and decreasing patterns during Schedule 3 on Production Line 1. The routine maintenance workloads pattern for Production Line 2 at Schedule 3 followed an increasing pattern except that of the full-time mechanical maintenance workers. On Production Line 3 at Schedule 3, it was only the routine maintenance workloads for the full-time mechanical maintenance workers that did not follow an alternating increasing and decreasing pattern (Table 8). In Periods 2, 5 and 6, the amounts of routine maintenance workloads for the production lines for the different maintenance worker categories were less than 100 h. Furthermore, on Production Line 1 it was only on Schedule 3 that the amount of routine maintenance workload was more than 100 h. On Production Lines 2 and 3, it was only the full-time and casual cleaning maintenance workers that had a period in which routine maintenance workloads were more than 100 h (Table 8).

Apart from Production Line 2 at Period 4 total amount of routine maintenance workloads, none of the total amount of routine maintenance workloads in any period was more than 500 h during Schedule 3. Production Line 2 had the least number of times in which routine maintenance activities were scheduled during Schedule 3. Production Line 3 had the highest sum of total routine maintenance workloads for the six periods when compared with those of the other production lines. This was because Production Line 3 had the highest number of times in which routine maintenance activities was scheduled during Schedule 3 (Table 8). The model results for maintenance schedules showed that Period 4 was the only period in which routine maintenance activities were scheduled for all the production lines. In Period 4, the sum of the total routine maintenance workloads on Production Lines 1(313.0410 h) and 3 (274.8675 h) was less than Period 2 total routine maintenance workloads (769.1160 h).

(v) Use factor for maintenance workloads

Since the use factor of the maintenance worker categories was employed in computing the actual amount of routine maintenance workloads, the level at which each maintenance worker category was actually busy becomes their use factor. Based on the model results for the routine maintenance schedules, no maintenance worker category had a use factor that was less than 65% during Schedules 1 and 3 on the production lines.

Table 6 Amount of maintenance workloads for Schedule 1 (h)

Schedules	Maintenance workloads	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
Production Line 1	ω_{1111t}	95.4736	103.5691	0.0000	91.6241	104.3832	87.7798
	ω_{1211t}	65.6841	78.8942	0.0000	74.4685	43.7314	40.5870
	ω_{2111t}	42.5105	41.0017	0.0000	46.2390	58.7976	47.9697
	ω_{2211t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ω_{3111t}	49.1649	53.4024	0.0000	41.2407	42.9156	44.2391
	ω_{3211t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 2	ω_{1112t}	0.0000	0.0000	0.0000	0.0000	149.6356	181.8058
	ω_{1212t}	0.0000	0.0000	0.0000	0.0000	149.0519	179.1717
	ω_{2112t}	0.0000	0.0000	0.0000	0.0000	103.1780	122.9527
	ω_{2212t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ω_{3112t}	0.0000	0.0000	0.0000	0.0000	108.0075	80.1509
	ω_{3212t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 3	ω_{1113t}	82.1669	98.7530	0.0000	0.0000	92.8197	69.9307
	ω_{1213t}	41.9572	71.2138	0.0000	0.0000	32.9549	41.7986
	ω_{2113t}	28.2841	69.2785	0.0000	0.0000	57.5861	45.9891
	ω_{2213t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ω_{3113t}	71.1242	45.1210	0.0000	0.0000	48.9060	57.7553
	ω_{3213t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 7 Amount of maintenance workloads for Schedule 2 (h)

Schedules	Maintenance workloads	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
Production Line 1	ω_{1121t}	70.7166	91.1553	110.9542	0.0000	80.7726	0.0000
	ω_{1221t}	65.4507	58.1676	81.8328	0.0000	39.9130	0.0000
	ω_{2121t}	47.0405	59.1089	47.5026	0.0000	46.6510	0.0000
	ω_{2221t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ω_{3121t}	51.7255	46.3894	39.2243	0.0000	47.5383	0.0000
	ω_{3221t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 2	ω_{1122t}	105.6285	0.0000	231.0733	107.6130	0.0000	0.0000
	ω_{1222t}	266.9625	0.0000	304.9067	524.0390	0.0000	0.0000
	ω_{2122t}	94.4305	0.0000	100.6424	97.3133	0.0000	0.0000
	ω_{2222t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ω_{3122t}	133.5323	0.0000	94.8208	94.8208	0.0000	0.0000
	ω_{3222t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 3	ω_{1123t}	61.1158	0.0000	0.0000	96.4146	84.8609	74.7601
	ω_{1223t}	51.5189	0.0000	0.0000	95.0378	47.5852	41.7017
	ω_{2123t}	55.1418	0.0000	0.0000	48.6306	37.3909	58.5968
	ω_{2223t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ω_{3123t}	54.9771	0.0000	0.0000	36.6255	51.2608	47.8573
	ω_{3223t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 8 Amount of maintenance workloads for Schedule 3 (h)

Schedules	Maintenance workloads	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
Production Line 1	ω_{1131t}	0.0000	86.4432	0.0000	85.5642	89.5211	0.0000
	ω_{1231t}	0.0000	85.6231	0.0000	120.8611	32.6758	0.0000
	ω_{2131t}	0.0000	48.7662	0.0000	52.9888	42.3349	0.0000
	ω_{2231t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ω_{3131t}	0.0000	51.9446	0.0000	53.6271	44.6655	0.0000
	ω_{3231t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 2	ω_{1132t}	116.7101	0.0000	0.0000	176.5280	0.0000	0.0000
	ω_{1232t}	175.9939	0.0000	0.0000	414.4585	0.0000	0.0000
	ω_{2132t}	88.6060	0.0000	0.0000	89.5090	0.0000	0.0000
	ω_{2232t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ω_{3132t}	96.7433	0.0000	0.0000	88.6201	0.0000	0.0000
	ω_{3223t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 3	ω_{1133t}	87.4506	59.5182	114.1973	95.7342	0.0000	79.1057
	ω_{1233t}	45.445	75.2421	72.702	106.4894	0.0000	34.7912
	ω_{2133t}	53.5745	57.5203	53.4957	37.965	0.0000	51.0021
	ω_{2233t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ω_{3133t}	72.3045	48.153	41.8782	34.6789	0.0000	56.3352
	ω_{3233t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

(The minimum value of use factor for a maintenance worker category during Schedule 2 was about 53% (Table 9). During Schedule 1 in Period 1 and 2, the most busy maintenance worker category was the casual cleaning maintenance workers, while the full-time mechanical maintenance workers were the least busy maintenance worker class (Table 9). The casual cleaning maintenance workers were the least busy maintenance worker category (Production Line 3) at Period 5. During Schedule 1, it was only the full-time cleaning and mechanical maintenance workers which had a use factor value of 100%. Furthermore, Periods 2 to 5 did not have maintenance workers' use factor value which were up to 100%. The lowest average use factor values for the maintenance workers during Schedule 1 occurred on Production Line 3 at Period 2. When the different average maintenance workers' use factor for the various periods were compared, Period 6 had the highest average maintenance workers' use factor value during Schedule 1 on Production Line 3 (Table 9).

For Schedule 2, Period 3 (Production Line 2) had the highest average maintenance workers' use factor value when compared with other periods. Furthermore, Period 1 (Production Line 3) had the least average maintenance workers' use factor value during Schedule 2. Apart from Periods 2 and 6, the other periods had at least a maintenance workers' use factor value that was 100%. In terms of the number of maintenance workers' use factor values that was 100%, Period 1 had the highest number (Table 10). The maintenance workers' use factor value for Schedule 2 on Production Line 1 showed that none of the maintenance worker categories had use factors that were less than 70%. Furthermore, the minimum maintenance workers' use factor for Production Line 2 was about 55%, Production Line 3 minimum maintenance workers' use factor was about 74% (Table 10).

During routine maintenance on Production Line 1 at Schedule 2, the casual cleaning maintenance workers had the lowest (Period 2) and highest (Period 1) values when compared with the other maintenance worker categories. The maintenance workers' use factor value for Production Lines 2 and 3 at Schedule 2 results showed that the full-time cleaning maintenance workers had the least use factor value (Table 10). The average maintenance workers' use factor results showed that Periods 3 to 6 had a use factor value above 80% at Schedule 2. In terms of the production lines maintenance workers' use factor values, each of the production lines had maintenance workers' use factor of more than 70%. The expected average value for the maximum maintenance use factor was 91.4% (Production Line 2 at Period 3), while the minimum average maintenance use factor value for the production line during Schedule 2 was 73.13% (Production Line 3 at Period 1).

The minimum average maintenance workers' use factor for Schedule 3 was 73.13% (Production Line 2 at Period 1), while the maximum average maintenance workers' use factor was 95.14%. The maintenance workers' use factor for Schedule 3 had at least a period in which a maintenance workers' use factor was 100%, except in Production Line 2. Furthermore, each of the periods had a minimum of one maintenance workers' use factor that was 100%. Also, it was only Production Line 3 that had a maintenance worker classes with 100% maintenance workers' use factor in a period (Table 11). Based on the Schedule 3 results (Table 11), Production Line 1 did not have any maintenance worker category whose maintenance workers' use factor was up to 100%. The number of times in which the casual cleaning workers' use factor was about 90% on Production Lines 2 and 3 were the same (Table 11). Production Line 3 was the only production line with equal number of maintenance use factor value that was about 60% in a period.

Table 9 Use factor for maintenance workloads for Schedule 1 (%)

Schedules	Use factor	*t* = 1	*t* = 2	*t* = 3	*t* = 4	*t* = 5	*t* = 6
Production Line 1	u_{1111t}	0.9877	0.9419	0.0000	0.8497	0.9807	0.8354
	u_{1211t}	1.0172	0.9239	0.0000	0.5871	0.8782	0.8271
	u_{2111t}	0.8212	0.7153	0.0000	0.8282	0.9503	0.7812
	u_{2211t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	u_{3111t}	0.7574	0.9417	0.0000	0.8206	0.7768	0.7199
	u_{3211t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 2	u_{1112t}	0.0000	0.0000	0.0000	0.0000	0.7842	0.96317
	u_{1212t}	0.0000	0.0000	0.0000	0.0000	0.7436	0.9054
	u_{2112t}	0.0000	0.0000	0.0000	0.0000	0.8216	0.9949
	u_{2212t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	u_{3112t}	0.0000	0.0000	0.0000	0.0000	0.9722	0.6423
	u_{3212t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 3	u_{1113t}	0.9760	0.7535	0.0000	0.0000	0.8456	1.0324
	u_{1213t}	0.9408	0.7073	0.0000	0.0000	0.6565	0.8550
	u_{2113t}	0.6915	0.7873	0.0000	0.0000	0.6809	0.7438
	u_{2213t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	u_{3113t}	0.6604	0.5368	0.0000	0.0000	0.8106	1.0263
	u_{3213t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 10 Use factor for maintenance workers for Schedule 2 (%)

Schedules	Use factor	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
Production Line 1	u_{1121t}	0.7268	0.8330	0.8789	0.0000	0.7604	0.0000
	u_{1221t}	1.0136	0.6831	0.9713	0.0000	0.8032	0.0000
	u_{2121t}	0.8212	0.7153	0.7731	0.0000	0.9503	0.0000
	u_{2221t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	u_{3121t}	0.7965	0.8165	0.7790	0.0000	0.8678	0.0000
	u_{3221t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 2	u_{1122t}	0.6031	0.0000	1.0243	0.5546	0.0000	0.0000
	u_{1222t}	1.0276	0.0000	0.8982	1.0425	0.0000	0.0000
	u_{2122t}	0.9069	0.0000	0.7899	0.8682	0.0000	0.0000
	u_{2222t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	u_{3122t}	1.0254	0.0000	0.9435	0.9435	0.0000	0.0000
	u_{3222t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 3	u_{1123t}	0.6677	0.0000	0.0000	0.9232	0.8056	0.9599
	u_{1223t}	0.6699	0.0000	0.0000	0.8206	0.8442	0.8217
	u_{2123t}	0.84710	0.0000	0.0000	0.7996	0.7859	0.9894
	u_{2223t}	0.0000	0.0000	0.0000	0	0.0000	0.0000
	u_{3123t}	0.7405	0.0000	0.0000	0.8814	1.0031	0.8418
	u_{3223t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 11 Use factor for maintenance workers for Schedule 3 (%)

Schedules	Use factor	*t* = 1	*t* = 2	*t* = 3	*t* = 4	*t* = 5	*t* = 6
Production Line 1	u_{1131t}	0.0000	0.7876	0.9385	0.8011	0.8456	0.0000
	u_{1231t}	0.0000	1.0110	0.9479	0.9700	0.6565	0.0000
	u_{2131t}	0.0000	0.8632	0.7618	0.9566	0.6809	0.0000
	u_{2231t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	u_{3131t}	0.0000	0.9171	1.0777	1.0777	0.8106	0.0000
	u_{3231t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 2	u_{1132t}	0.6677	0.0000	0.0000	0.9232	0.0000	0.0000
	u_{1232t}	0.6699	0.0000	0.0000	0.8206	0.0000	0.0000
	u_{2132t}	0.8471	0.0000	0.0000	0.7996	0.0000	0.0000
	u_{2232t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	u_{3132t}	0.7404	0.0000	0.0000	0.8814	0.0000	0.0000
	u_{3223t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Production Line 3	u_{1133t}	0.9019	0.6956	0.8314	0.8963	0.0000	0.8526
	u_{1233t}	0.6988	0.8187	0.8436	0.8538	0.0000	1.0985
	u_{2133t}	1.0000	0.7158	0.7479	0.6811	0.0000	0.5853
	u_{2233t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	u_{3133t}	1.0000	0.8236	0.8814	0.6909	0.0000	0.7941
	u_{3233t}	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

(vi) Spare parts results

Based on the formulated model and the generated results (Figure 4), the maximum amounts of the spare parts order for routine maintenance on Production Lines 1 and 2 was at Period 6. Production Line 3 had its maximum spare parts order quantities at Period 1. At Period 3, Production Lines 1 and 3 had the minimum amount of quantity of spare parts order, while Production Line 2 had its minimum amount of quantity of spare parts order at Period 4 (Figure 6). The difference between the maximum (807 units) and minimum (279 units) spare parts order qualities used for maintenance activity on Production Line 1 was 528 units. The DE generated 4,905 units as the difference between the maximum (7,903 units) and minimum (3,098 units) of spare parts order quantity used for routine maintenance activity on Production Line 2. A value of 237 units of the selected spare parts used for routine maintenance activities on Production Line 3 was observed as the difference between the maximum (360 units) and minimum (123 units) spare parts order quantities (Figure 6).

For Production Line 1, the company required an average of 561 units of the selected spare parts to be order per period. For the six periods, the total quantities of the selected spare parts that was required to be ordered for Production Line 2 was 30,295 units, while Production Line 3 required 1,619 units (Figure 6). The minimum amount of the sum of the three selected spare parts that can be ordered in a period was 3,904 units (Periods 4), while the maximum sum of the three selected spare parts to be ordered was 9,064 units (periods). Based on the information in Figure 6, as the quantity of spare parts order for Production Line 1 increases, Production Line 2 spare parts order quantity decreases and verse-visa. However, this observation does not hold at Period 6. The characteristic of the spare parts order quantity for Production Line 3 showed that there was a steady decrease in the quantity of spare parts order for the first three periods, while a steady increase began from Period 4 (Figure 6).

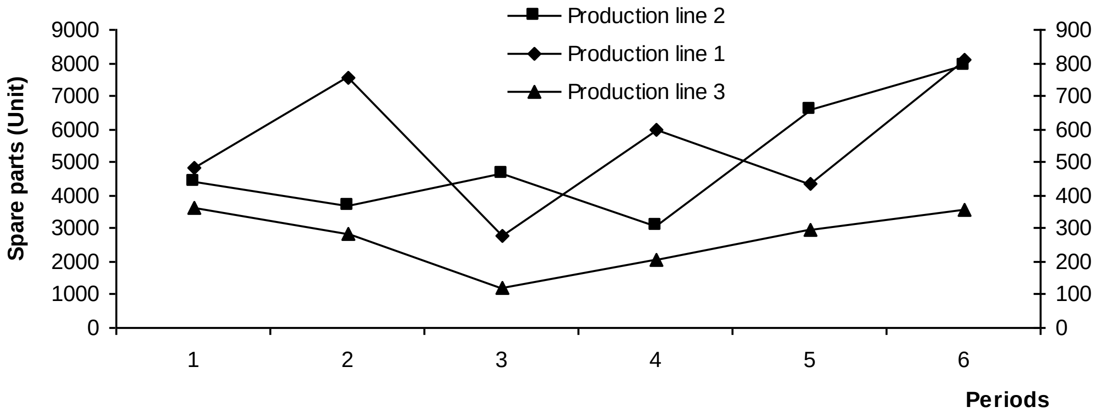

Figure 6 Quantity of spare parts order at different periods

7. Conclusions

Maintenance workforce analysis in process industry as gained more attention in recent times due to the increased level of automation of installed facilities. To aid maintenance workforce analysis in process industry, this study proposed a WAFGP model for Ighravwe et al. [38] model for the generation Pareto solution for maintenance and production variables. A case study of a brewery plant was presented to demonstrate the model applicability. Also, comparative analysis of GA and PSO with DE results was presented. The results from a formulated WAFGP model for a process industry revealed that the DE results performed satisfactory when compared with the PSO and GA results for the case study.

Although this study considered a brewery plant as a case study, the proposed WAFGP application can be extended to other maintenance systems. For example, the application of the proposed WAFGP model in addressing the problem of maintenance workforce sizing in hospitality industry and military maintenance department can be considered a further study. The use of grey relation and goal programming for dealing with multi-objective maintenance workforce models can be considered as a further study. Further investigation can be carried to statistically justify the parametric settings of the selected meta-heuristics for maintenance planning problem.

8. References

[1] Ighravwe D.E., Oke S.A., Adebiyi K.A., A reliability based maintenance technicians' model loads optimization model with stochastic consideration, J Ind Eng Int. 2016; 12: 171-183.

[2] Sitkin, S.B., See, K.E., Miller, C.C., Lawless, M.W. and Carton A.M. The paradox of stretch goals: Organisations in pursuit of the seemingly impossible. Acad Manag Rev. 2011; 36(3): 544-566.

[3] Sethanan, K. and Pitakaso, R. Differential evolution algorithms for scheduling raw milk transportation. Comp Electr Agric. 2016; 121: 245-259.

[4] Noktehdan, A., Karimi, B. and Kashan, A.H., A differential evolution algorithm for the manufacturing cell formation problem using group based operators. Exp Syst Appl. 2010; 37(7): 4822-4829.

[5] Zeng, X., Wong, W-K. and Leung, Y.-S., An operator allocation optimisation model for balancing control of the hybrid assembly lines using Pareto utility discrete differential evolution algorithm. Comp Operat Res. 2012; 39(5): 1145-1159.

[6] Yildiz, A.R. Hybrid evolutionary systems for manufacturing processes. Appl Soft Comp. 2013; 13(3): 1433-1439.

[7] Atif, M. and Al-Sulaiman, Optimisation of heliostat field layout in solar central receiver systems on annual basis using differential evolution algorithm. Ener Conser Manag. 2015; 95: 1-9.

[8] Le-Anh L., Nguyen-Thoi, T., Hottw, U., Dang-Trung H., and Bui-uan T., Static and frequency optimisation of folded laminated composite plates using an adjusted differential evolution algorithm and a smoothed triangular plate element. Comp Struct. 2015; 127: 382-394.

[9] De Falco, I., Differential evolution for automatic rule extraction from medical databases. Appl Soft Comp. 2013; 13(2): 1265-1283.

[10] Ghosh, S., A differential evolution based approach for estimating minimal model parameters from IVGTT data. Comp Bio Med. 2014; 46: 57-60.

[11] Raza S.A. and Al-Turki U.M. A comparative study of heuristic algorithms to solve maintenance scheduling problem. J Qual Maint Eng. 2007; 13(4): 398-410.

[12] Fetanat A. and Shafipour G., Generation maintenance scheduling in power systems using ant colony optimization for continuous domains based 0–1 integer programming, Exp Syst Appl. 2011; 38: 9729-9735.

[13] Li, J-Q., and Pan, Q-K., Chemical-reaction optimization for flexible job-shop scheduling problems with maintenance activity. Appl Soft Comp. 2012; 12: 2896–2912.

[14] Li, J-Q., Pan, Q-K. and Tasgetiren, M.F., A discrete artificial bee colony algorithm for the multi-objective flexible job-shop scheduling problem with maintenance activities. App Math Mod. 2014; 38: 1111-1132.

[15] Nourelfath M., Chatelet E. and Nahas N. Joint redundancy and imperfect preventive maintenance optimization for series–parallel multi-state degraded systems. Reliab Eng Sys Saf.2012; 103: 51-60.

[16] Chaoqui M., Benhra J. and Zakari A. Agile Approach for Joint Scheduling of Production and Maintenance in Flow Shop. Int J Comp Appl. 2014; 59(11): 29-36.

[17] Alba, E., Luque, G., and Luna, F., Parallel meta-heuristic for workforce planning. J Mathem Alg. 2007; 6(3): 509-528.

[18] Hargaden, V., and Ryan, S., Workforce analytics: Matching supply and demand in professional service firms. In: Manufacturing and Service Operations Management (MSOM) Annual Conference; 2011.

[19] Haque, N., Virginas, B., Kern, M., and Owusu, G., An auction-based system for workforce resource allocation. New Frontiers in App Artificial Intel -Lecture Note in Comp Sci. 2008; 5027: 845-854

[20] Alfares, H.K., Aircraft maintenance workforce scheduling: A case study. J Qua Maint Eng. 1999; 5(2): 78-88.

[21] April, J., Better, M., Glover, F., Kelly, J.P., and Kochenberger, G., Strategic workforce optimisation: Ensuring workforce readiness with optforce [Internet].2010 [cited 2015 April 1]. Available from http://www.opttek.com/sites/default/files/OptForce%20White%20Paper%202012.pdf

[22] Starkey, A., Hagrasa, H., Shakya S. and Owusu G., A multi-objective genetic type-2 fuzzy logic based system for mobile field workforce area optimisation. Inform Sci. 2016; 329: 390-411.

[23] Monra, M. Azevedo, R.V., Droguett, E.L., Chaves, L.R. Lins, I.D., Vilela, R.F., Estimation of expected number of accidents and workforce unavailability through Bayesian population variability analysis and Markov-based model, Reliab Eng Sys Saf.2016; 150: 136-146

[24] Firat, M., Briskron, D., and Laugier, A., A branch and price algorithm for stable workforce assignment with hierarchical skills. Euro J Oper Res. 2016; 251(2): 679-685.
[25] Ighravwe, D.E., Oke S.A., and Adebiyi, K.A., An enhanced reliability-oriented workforce planning model for process industry using combined fuzzy goal programming and differential evolution approach. J Ind Eng Int. 2017b; doi: 10.1007/s40092-017-0223-9.
[26] Markovic, D., Petrovic, G., Cojbasic, Z. and Marinkovic, D., A comparative analysis of metaheuristic maintenance optimization of refuse collection vehicles using the Taguchi experimental design. Trans Famena. 2012;36(4): 25-38.
[27] Ighravwe D.E and Oke S.A., A mixed-integer multi-objective maintenance and production workforce planning model, Process Integr Optim and Sus. 2017c; 1: 251-267.
[28] Ighravwe D.E., Oke S.A., Adebiyi K.A., A weighted goal programming model for maintenance workforce optimization for a process industry, Asia-Pacific J Sci Tech. 2017d; 22(4): 1-18
[29] Ighravwe D.E, Oke S.A., Adebiyi K.A., A surrogate model for optimal maintenance workforce cost determination in a process industry, Eng Appl Sci Res. 2017e; 44(4): 202-207.
[30] Yare, Y. and Venayagamoorthy, G.K., Optimal scheduling of generator maintenance using modified discrete particle swarm optimisation. Symposium-Bulk Power System Dynamics and Control-VII, Revitalising Operational Reliability 2007 August 19-24; Charleston, SC. USA; 2007.
[31] Engelbrencht, A.P., Artificial Intelligence: An Introduction. England: John Wiley and Sons Limited; 2007.
[32] Pereira, C.M.N.A., Lapa, C.M.F., Antonio, C.A., Mol, A.C.A. and da Luz, A.F., A particle swarm optimisation (PSO) approach for non-periodic preventive maintenance scheduling programming. Prog Nuclear Ener. 2010; 52: 710-714.
[33] Heo, J-H., Lyu, J-K., Kim, M-K. and Park, J-K., Application of particle swarm optimisation to the reliability centred maintenance method for transmission Systems. J Electrical Eng Tech. 2012; 7(6): 814-823.
[34] Wang, J., Lu, J., Bie, Z., You, S. and Cao X., Long-term maintenance scheduling of smart distribution system through a PSO-TS algorithm. J Appl Math. 2014; 1-12.
[35] Samuel, G.G. and Rajan, C.C.A., Hybrid particle swarm optimisation: Evolutionary programming approach for solving generation maintenance scheduling problem. Scien Res and Ess. 2013; 8(35): 1701-1713.
[36] Joines, J.A., and Houck, C.R., On the use of non-stationary penalty functions to solve nonlinear constrained optimisation problems with genetic algorithms. In: Proceedings of the IEEE Congress on Evolutionary Computation. 1994; 579-584.
[37] Deb, K. Agrawal, S. Pratap A. and Meyarivan, T., A Fast Elitist Nondominated sorting genetic algorithm for multi-objective optimization: NSGA-II, Proceedings of the Parallel Problem Solving from Nature VINSGA-II," Proceedings of the Parallel Problem Solving from Nature VI Conference;2000 September 16-20; Paris. France; p. 849-58.
[38] Ighravwe, D.E., Oke, S.A., and Adebiyi, K.A., Preventive maintenance task balancing with spare parts optimisation via big-bang big-crunch algorithm. Int J Sys Assu Eng Manag. 2017a; 8(2): 811-822.
[39] Mekidiche, M., Belmokaddem, M., and Djemmaa, Z., Weighted additive fuzzy goal programming approach to aggregate production planning. Int J Intell Sys Appl. 2013; 4: 20-29.

Appendix A

x_{ijt} number of maintenance technicians in maintenance section *i* belonging to technician category *j* at period *t*

h_{ijt} number of maintenance technicians hired for maintenance section *i* belonging technician category *j* at period *t*

f_{ijt} number of maintenance technicians fired from maintenance section *i* belonging to technician category *j* at period *t*

ω_{ijlst} amount of maintenance workload (h) for a technician in maintenance section *i* belonging to technician category *j* during preventive maintenance tasks on production line *l* for schedule *s* at period *t*

R_{lst} binary variable to whose value is 1 if preventive maintenance is carried out on line *l* during schedule *s* at period *t*, otherwise 0

p_{lt} production time on production line *l* at period *t*

I_t quantity of finished goods inventory at period *t*

INV_T quantity of spare parts inventory at period *T*

ξ_t quantity of goods expected from subcontractors at period *t*

Q_{ilt}	quantity of spare part *i* ordered for production line *l* at period *t*
d_t	quantity of goods demanded at period *t*
PR_l	production rate of production line *l*
δ^1_{ijt}	unit cost for hiring a technician for maintenance section *i* belonging to technician category *j* at period *t*
δ^2_{ijt}	unit cost for firing a technician from maintenance section *i* belonging to technician category *j* at period *t*
T_{ijt}	unit training cost for a technician in maintenance section *i* belonging to technician category *j* at period *t*
β_l	penalty for releasing a production line *l* beyond due date
$\hat{\beta}_l$	bonus for releasing a production line *l* before due date
λ_i	rate of change of cost of technicians' service rate improvement in maintenance section *i*
χ_{lst}	amount of time for maintenance tasks that cause stoppages in the production activities
C^1_{il}	unit cost for spare part *i* used in line *l*
C^2_{il}	is the spare part *i* inventory carrying rate on line *l*
C^3_{il}	is the cost order for spare *i* used on line *l*
$I_{\max}$	expected maximum value of the finished goods at a period *T*
T_{ij}	turnover rate of technicians in maintenance section *i* belonging to technician category *j*
B_t	amount of budgeted funds for technicians' salaries
$\hat{B}_t$	amount of budgeted funds for technicians' hiring cost
$\overline{B}_t$	amount of budgeted funds for technicians' firing cost
Aq_{il}	expected number of spare part *i* for production line *l*
Bq_{il}	budgeted fund for spare part *i* for production line *l*
MTTF	mean time to failure
TOT	total time of equipment usage
FSP	expected amounts of the fraction of spare parts that will damage out of *x* units that are successfully used during maintenance activities
ρ	total proportion of time required for routine maintenance tasks
a_i	represents initial training cost of maintenance workers in maintenance section *i*
d_t	quantity of goods demanded at period *t*
Mb	maximum budget for maintenance cost
Ma	minimum budget for maintenance cost
MWE_t	maintenance workforce expenses at period *t*
SPC_t	spare parts cost at period *t*
Ψ_{lt}	total storage area for spare parts used for maintenance activities on production line *l* at period *t*
a_c	unit area of spare part *c*
r	random number
α_t	positive random number for maintenance cost at period *t*
$\hat{\lambda}$	priority factor for worker category