

# An enhanced reliability-oriented workforce planning model for process industry using combined fuzzy goal programming and differential evolution approach

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**Abstract** This paper draws on the “human reliability” concept as a structure for gaining insight into the maintenance workforce assessment in a process industry. Human reliability hinges on developing the reliability of humans to a threshold that guides the maintenance workforce to execute accurate decisions within the limits of resources and time allocations. This concept offers a worthwhile point of deviation to encompass three elegant adjustments to literature model in terms of maintenance time, workforce performance and return-on-workforce investments. These fully explain the results of our influence. The presented structure breaks new grounds in maintenance workforce theory and practice from a number of perspectives. First, we have successfully implemented fuzzy goal programming (FGP) and differential evolution (DE) techniques for the solution of optimisation problem in maintenance of a process plant for the first time. The results obtained in this work showed better quality of solution from the DE algorithm compared with those of genetic algorithm and particle swarm optimisation algorithm, thus expressing superiority of the proposed procedure over them. Second, the analytical discourse, which was framed on stochastic theory, focusing on specific application to a

process plant in Nigeria is a novelty. The work provides more insights into maintenance workforce planning during overhaul rework and overtime maintenance activities in manufacturing systems and demonstrated capacity in generating substantially helpful information for practice.

**Keywords** Returns-on-workforce investment · Fuzzy goal programming · Meta-heuristics · Maintenance workforce planning · Manufacturing system

## Introduction

The promise of human reliability as a principal determinant of risk evaluation success in human-managed systems has since been acknowledged (Boring et al. 2004; Boring and Bye 2008). Notwithstanding, human reliability has potentials of deepening and changing our insights of maintenance workforce optimisation. However, the literature is awaiting this fulfilment (see Shahriari et al. 2016).

A great deal of the theory of maintenance is inclined to underestimate the outstanding worth of the return-on-investment concept of the human aspect of maintenance (see Raza and Al-Turki 2007). The purpose of this article is to delve into the potentialities for an innovative analysis of a reliability-oriented maintenance workforce optimisation model. The work breaks new grounds in maintenance theory and practice from novel perspectives, drawing inspiration from the outstanding capabilities of fuzzy goal programming, differential evolution and the return-on-investment concept. This work draws extensively from the foundational research by Ighravwe et al. (2016b). The concept of return-on-investment is arguably of several decades ago, and has been employed widely in hardware evaluation of maintenance resources.

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Here, we set up this structure to signify a human resource term that quantifies the ratio of profit compared to the total workforce value. The arena of maintenance engineering has as its mainstay a yearning for a superior understanding of how the human reliability concept with respect to return-on-investment, can influence the performance of workforce as a whole. Up till now, the maintenance engineering field has been limited by its orientation towards the hardware aspect of reliability (see also Sarker and Yu 1995). There is a great deal to achieve from a superior inclusion of return-on-investment as an influencing factor in maintenance optimisation structural development. Maintenance investigations are positioned to an advantage from a more powerful commitment with return-on-investment concept, as an avenue of bringing modelling into reality, in a manner hitherto largely under-explored. Through this approach, fresh knowledge will be developed and new insights will emerge.

Hybridisation (see De et al. 2016), which is a biological concept, transferred to mathematical modelling of real-life problems, is a division of science that transfers down positive traits from individual components of the hybrid into a whole that is better than the characteristics of the individuals, separately. In mathematical modelling, hybridisation of fuzzy goal programming (FGP) and differential evolution (DE) (De et al. 2017) is pursued for the combined advantageous characteristics of having an hybridised model capable of: (1) achieving membership values concerning goals to the likely degree, having the uppermost extent, by reducing beneath divergence, which is deemed fit in an answer search procedure; (2) ability of the model to perform in the absence differentiable optimisation problem, and (3) optimisation of a problem through maintenance of population of candidate explanation. The ability of FGP and DE to perform excellently in the demonstration of the above attributes qualifies the hybrid FGP–DE as a high-quality candidate to handle the multi-objective and multi-criteria optimisation problem in maintenance workforce modelling.

In this communication, a hybrid approach where, in addition to the defined multi-objective problem in Ighravwe et al. (2016b), a novel concept of return-on-investment is considered. The original work of Ighravwe et al. (2016b) was strongly laid on the foundation of technicians' reliability wherein technicians' productivity as well as earned values was considered. Motivated by the literature deficiency, limitations in maintenance literature as well as gaps in existing knowledge and practices in maintenance engineering, the proposed approach on return-on-workforce investment is an innovative addition to literature. This approach discards the restricted application of the age-long concept of return-on-investment (ROI) to physical assets in maintenance and offers a fresh look at the

human side of this novel idea. ROI measures the ratio of profit compared to the total workforce value. Although it is applauded to be more beneficial in providing detailed information on workers' performance than workers' productivity in financial terms (Visier 2015), the realisation and beneficial application of ROI in maintenance practice has not been fulfilled until this present communication. Yet, another novel contribution of this paper is the distinctly insightful manner in which the fuzzy goal programming is formulated for the maintenance workforce problem. This has never been conceptualised in this form till the present research output. Coupling the DE and FGP in a new manner is also completely an addition to the literature.

The proposed model, as in the foundation model by Ighravwe et al. (2016b), permits the incorporation of essential elements of training, fatigue and workers' experience into a structure. This is a rare approach in maintenance workforce literature. Thus, the hybrid FGP–DE in the current approach supports decision-making by maintenance managers with the optimisation of variables as the main intent since global optimum is sought. In this paper, the principal aim is to search for a fast, easily transformable model to different maintenance systems in manufacturing, and a framework that is effective in solving the human reliability maintenance workforce optimisation problem. The advanced method employs optimisation principles coupled with maintenance tenets and principles to practically solve real-life problem in maintenance, which is stochastic in nature (Maiti and Roy 2016). The principal benefit of the proposed approach in this work is declared in providing a reliable optimum fact on return-on-workforce investment. Additional benefit of the approach entails: provision of a more effective tool of combined application of differential evolution and particle swarm optimisation algorithms.

## Literature review

### Survey of literature

Workforce optimisation has received considerable attention of several researchers. A wide range of research areas are available on workforce optimisation problem, ranging from lot-sizing consideration (Judice et al. 2004; Ighravwe and Oke 2014) to workforce modelling using artificial intelligence tools such as simulated annealing, genetic algorithms and some defined metrics (Safaei et al. 2008; Ighravwe and Oke 2014; Ighravwe et al. 2015, 2016a, b). Nonetheless, studies are rare on the maintenance workforce optimisation problem. There is no report that exclusively considers maintenance workforce optimisation problem in association with return-

**Table 1** A brief of maintenance workforce-associated studies accounted for in literature field

Article no.	Article accounting for maintenance workforce-associated studies	Number of principal terms recognised, revealing article's focus	Principal words/terms indicating key focus of articles
1	Javanmard and Koraeizadeh (2016)	3	Genetic algorithm, cost, reliability
2	Ighravwe and Oke (2016a)	3	Fuzzy goal programming model, simulated annealing, differential evolution
3	Kozanidis et al. (2012a)	4	Flight load's allotment, capability of maintenance, aircraft's long-term availability, mixed-integer nonlinear model
4	Gavranis and Kozanidis (2015)	3	Mixed-integer programming, exact solution algorithm, valid inequalities
5	Alba et al. (2007)	4	Equivalent amalgam genetic procedure equivalent meta-heuristics, equivalent genetic procedure, equivalent scatter seek
6	Ahmed et al. (2015)	5	Availability, reliability, maintenance cost, goal programming, risk
7	Lei (2013)	2	Job shop scheduling, multi-objective artificial bee colony.com
8	Azadeh et al. (2015)	5	Non-dominated sorting genetic algorithm-II (NSGA-II), multi-objective scheduling, response surface methodology, multi-objective particle swarm optimisation
9	Yulan et al. (2008)	8	Machine availability, near-Pareto optional solutions, total weighted percent deviation, multi-objective genetic algorithm, maintenance cost, total weighted tardiness, makespan, total weighted completion of time of jobs
10	Ling et al. (2011)	3	Pairwise distance cost expected mission capability of equipment
11	Kleenman and Lamont (2005)	3	Multi-objective evolutionary algorithms, variable length chromosome, multi-criterion optimisation
12	Azzouz et al. (2016)	6	Test functions, dynamic optimisation, statistical tests, multi-objective optimisation, evolutionary algorithms, performance metrics
13	Piasson et al. (2016)	4	Fuzzy reliability index, reliability-centred maintenance, NSGA-II
14	Nie (2016)	4	Fuzzy random time window, makespan, average timeliness level, expected value
15	Pant et al. (2017)	3	Reliability, particle swarm optimisation, optimisation
16	Ebrahimipour et al. (2015)	4	Multi-objective optimisation, reliability, effective age, cost

on-investment where the human side of reliability is accounted for. There is further no literature study that has considered the innovativeness of fuzzy goal programming, the superb power of differential evolution as well as the super potential global optimisation potentials of integrated fuzzy goal programming and differential evolution (FGP–DE) in the optimisation of maintenance workforce variables. “In several earlier studies, investigators usually exclude important elements of training, fatigue and some core human side of reliability as the maintenance workforce was evaluated (see Khalili-Damghani et al. (2013b)). The algorithms advanced by these researchers are opened to tremendous challenges in the long-run consideration of maintenance outputs as sub-optimal solutions were at the risk of being obtained.

In an attempt to have a representative view of literature, ensuring the inclusion of recent and relevant publications on workforce planning, maintenance modelling, and optimisation approaches adopted in related research, the authors

prepared tables to reveal in detail what are lacking in the already published papers and in what respect the current paper is filling the gap (Tables 1, 2). The tables are innovative and have important parts. In achieving the set goal of a comprehensive and representative literature review, the authors consulted peer-reviewed journals in major publishers, including Springer, Science-direct, Taylor and Francis, among others, and searched through to conclude on the relevant articles to include in the literature review.

In addition, the following reviews are documented. FGP has helped to overcome the problem of simultaneous optimisation of goals and the expression of goal's aspiration level in mathematic terms which is not feasible using goal programming model (Moradgholi et al. 2016). When dealing with multi-objective maintenance model, goal programming and mixed-integer programming techniques have been successfully applied used to obtain Pareto solution for maintenance variables (Ramirez-Hernandez

**Table 2** Articles detailing out relevant maintenance workforce optimisation studies and brewing industrial research

S/ no.	Aspect/industry studied in the research	Author(s)	Study detailed in this article	Remarks
1	Brewery	Wyld and Pugh (2010) Dale and Plunkett (1984) Nnobi-Okoye et al. (2016) Kubule et al. (2016) Eiholzer et al. (2017) Orlikowski and Krakowiak (2013) Sturm et al. (2012)	Assessment of influence of beer duty on small breweries Audits, inspection and quality costs in the process plant industry Assessment of multi-input–single-output (MISSO) production process of a brewery Energy efficiency improvements in a brewery A methodology to optimise a medium-sized Scottish brewery from a direct heat recovery viewpoint then by the integration of a solar thermal system The paper treats the issue of appearance of corrosion in various levels of the brewing process, and with the approaches of management and prevention of corrosion Considered the possibility of the sustainable energy provision arising from bio-wastes for a miniature level brewery	This brewery literature has not considered plant maintenance The important information concerning return-on-investment is missing There is only one paper that considered uncertainty capturing in study Necessary details about fuzzy goal programming and differential evolution is missing Consideration not given to maintenance workforce optimisation Uncertainty not considered. The concept of return-on-investment was ignored Maintenance workforce optimisation not considered. Fuzzy goal programming-cum-differential evolution not considered Uncertainly in the framework was ignored Maintenance workforce optimisation not given attention Attention was not devoted to uncertainty Return-on-investment was not found in the paper Return-on-investment not considered Uncertainly in maintenance activities ignored Practical example involving a brewery not documented
2	Airline	Kozanidis et al. (2012b) Gavranis and Kozanidis (2015)	Built-up a mixed-integer nonlinear procedure to allocate flight load as well as capability for maintenance Developed an integer programming framework to maximise aircraft availability based on an exact solution procedure	No identified information on return-on-investment covered Return-on-investment not considered Uncertainly in maintenance activities ignored Practical example involving a brewery not documented
3	Workforce planning	De Bruecker et al. (2015) Alba et al. (2007)	Review of literature pertaining to workforce planning problems and skills Developed three parallel meta-heuristic methods that could locate high-quality solutions	No identified information on return-on-investment covered Return-on-investment not considered Uncertainly in maintenance activities ignored Practical example involving a brewery not documented



**Table 2** continued

S/ no.	Aspect/industry studied in the research	Author(s)	Study detailed in this article	Remarks
4	Maintenance optimisation	Knapp and Mahajan (1998) Flage (2013) Ahmed et al. (2015) Azadeh and Zadeh (2016) Nie (2016) Pant et al. (2016)	Formulated a model for optimising the allocation of manpower Deliberated on the execution of the ALARP theory, associated with risk acceptance criteria, incorporating maintenance optimisation An integrated analytic hierarchy process AHP-fuzzy MCDM method is contributed to perform a comprehensive comparison between different maintenance policies Developed a model to solve scheduling problem on parallel machines under the influence of fuzzy random time windows The work elaborates on the progress of PSO as well as its application to reliability optimisation	Return on-investment not considered The imprecise nature of maintenance activities not captured in modelling Return on-investment not captured The imprecise nature of maintenance activities not discussed Uncertainty in maintenance activities not considered Return-on-investment ignored Maintenance workforce parameters not considered, return-on-investment ignored Fuzzy goal programming and differential evolution not considered Did not consider return-on-investment of maintenance workforce Integrated FGP and DP was not considered The issue of return-on-investment not discussed The concept of uncertainty not considered The fusion of FGP and DE not allowed Return-on-investment not treated.
5	Maintenance workforce modelling	Ighravwe and Oke (2016a)	A fuzzy goal programming model was employed to formulate a single objective function for maintenance workforce optimisation	
6	Bi-objective problems	Rabbani et al. (2017) Ghezavati and Beigi (2016) Amiri and Khajeh (2016)	A bi-objective location-routing problem was formulated and solved by an NSGA-II combined with clustering method A location-routing problem formulated and solved using a new bi-objective mathematical programming Bi-objective optimisation of the availability allocation problem in a series-parallel system with repairable components was formulated and solved	Return-on-investment ignored Return-on-investment ignored Return-on-investment ignored
7	Differential evolution algorithm	Beji et al. (2012)	Enhanced system reliability without changing its nature employing differential evolution algorithm	Return-on-investment ignored
8	Fuzzy goal programming	Khalili-Damghani et al. (2013a) Khalili-Damghani and Shahrokh (2014)	Advanced a fuzzy goal programming model for the choice of project portfolio A novel multi-product multi-period multi-objective aggregate production planning problem was solved employing multi-objective mixed-integer mathematical programming	Return-on-investment ignored Return-on-investment ignored

Table 2 continued

S/ no.	Aspect/industry studied in the research	Author(s)	Study detailed in this article	Remarks
9	Multi-objective models	Kozanidis (2009) Lei (2013) Azadeh et al. (2015) Pirasson et al. (2016) Yulan et al. (2008) Ling et al. (2011) Kleenman and Lamount (2005) Azzouz et al. (2016) Ebrahimipour et al. (2015) Dolatshahi-Z and Khalili- Damghani (2015) Khalili-Damghani et al. (2013a) Khalili-Damghani and Amiri (2012) Khalili-Damghani et al. (2014) Rabbani et al. (2016) Shahriari (2016)	Development a multi-objective optimisation model to maximise availability of aircraft over the planning horizon A multi-objective artificial bee colony algorithm was suggested for scheduling problem having non-resumable jobs as well as flexible maintenance Investigation was based on reliability and model involved multi-objectives Contributed a multiobjective procedure to solve reliability-centred-maintenance setup problem Developed an associated optimisation problem based on multi-objectives Developed a multi-objective particle swarm optimisation algorithm A multi-objective algorithm containing adjusted job shop and flow shop problem is presented Conducted literature review on dynamic multi-objective optimisation problems A multi-objective preventive maintenance scheduling problem for multi-production system is developed A multi-objective redundancy allocation problem was formulated and solved with a multi-objective particle swarm optimisation model A novel non-static self-adaptive multi-objective particle swarm optimisation solution approach was proposed to solve binary-state multi-objective reliability redundancy allocation problems A scheme established on an efficient epsilon-constraint approach and data envelopment analysis (DEA) was advanced for solving binary-state multi-objective reliability redundancy allocation series-parallel problem Redundancy allocation problem was solved with an efficient $\epsilon$ -constraint approach to generate non-dominated solutions on the Pareto front coupled with data envelopment analysis A novel mathematical representation was contributed in which the simultaneous balancing a mixed-model U-line and human-related issues were considered A two-objective mathematical representation for balancing compressing the project time was presented	Uncertainty in maintenance activities not considered Return-on-investment ignored Maintenance workforce parameters not considered return-on-investment ignored Fuzzy goal programming and differential evolution not considered. Did not incorporate uncertainty in modelling Omission of return-on-investment of maintenance workforce Fuzzy goal programming-cum-differential evolution absent Uncertainty characteristics of model not considered Combined effects of FGP and DE not appreciated Return-on-investment not given consideration Did not consider return-on-investment concept Uncertainty not considered FGP and DE not considered Did not consider uncertainty Return-on-investment not considered Integration of FGP and DE omitted in discussions Did not consider uncertainty Ignored the fusion of FGP and DE Avoided the use of return-on-investment of maintenance workforce Model did not incorporate uncertainty Ignored the association between FGP and DE Did not consider return-on-investment of maintenance workforce Ignored uncertainty in model Did not discuss return-on-investment of maintenance workforce The merging of FGP and DE not considered Did not contain elements of return-on-investment of maintenance workforce Offered the least attention to the union of FGP and DE Uncertainty in model tracking was not recognised Did not elaborate on the return-on-investment of maintenance workforce The merging of FGP and DE not mentioned Ignored return-on-investment of maintenance workforce Did not consider return-on-investment of maintenance workforce Ignored return-on-investment concept Did not account for return-on-investment Did not account for return-on-investment



et al. 2007; Mansour 2011; Ighravwe and Oke 2014). Due to the nonlinearity of some multi-objective maintenance models, the use of branch-and-bound technique, genetic algorithm (GA) and tabu-search as solution methods for maintenance workforce models are common in literature (Safaei et al. 2008; Mansour 2011). Also, production planning which is related to maintenance planning has also benefited from the use of some of above-mentioned solution methods (Amiri and Khajeh 2016). See Duffuaa et al. (2001), Sergaki and Kalaitzakis (2002) and Meisels and Kaplansky (2004) for more insights in related literature to this research.

### Summary of literature review, research gaps and contributions

Arising from literature review is an understanding that optimisation offers several benefits in the effective control of maintenance workforce. The following details are some helpful quantities of enlightenment uncovered from the above debate:

1. While several studies on maintenance parametric optimisation have used different maintenance performance measures as objective functions (productivity, cost, reliability, earned-value), none has considered return-on-workforce investment.
2. Many multi-objective maintenance workforce planning models are limited to the use of goal programming (Mansour 2011; Ighravwe and Oke 2014; Ighravwe et al. 2016b). Thus, the problem of evaluating the degree of attainment of maintenance goals has not been addressed.
3. Most applications of meta-heuristics in maintenance parametric optimisation literature are limited to GA (Mansour 2011). Currently, sparse information is available on empirical studies that have applied DE and PSO algorithm as solution methods for maintenance models.
4. The accounted studies mainly centred on nonlinear models and effective maintenance has been a significant criterion to ascertain operations that are safe and also aids in the attainment of production targets.
5. In the formulation of models, the optimal determination of costs often emerged in computations.
6. Very large numbers of papers have displayed significant experience in formulating, solving and practically applying models based on optimisation to a wide suit of workforce problems.
7. Interests of researchers have been very scanty in respect of reliability concepts in workforce consideration. Despite the scanty interests, the direction of research has been limited to the physical asset consideration while the human aspect has been ignored.
8. Only one study was reported on the human-side reliability relevant to workforce optimisation in maintenance.
9. Much literature focused on modelling while practical collection of data from maintenance departments has been less.
10. Fuzzy goal programming and differential evolution have not been previously reported in literature concerning applications of optimisation tools to maintenance workforce.
11. Optimisation models have been applied in maintenance workforce evaluation with an accompanying result of saving some money. This action has significant influence in making the company's product brands to maintain competitiveness in the market. Also, the prolonged existence of the organisation is guaranteed.
12. Many investigators have dealt with multi-objectives and multi-criteria problems, but very less researchers considered bi-objectives or single objective. The application of multi-objectives aided in evolving the most acceptable trade-off among the important variables of the maintenance models.
13. Researchers in maintenance workforce have evolved feasible and the largely realistic solutions for implementation in practice.
14. Very few researchers have recognised uncertainty presence in maintenance optimisation and have accordingly embedded that factor in formulations. However, none has considered the uncertainty tracking ability of fuzzy goal programming in maintenance workforce optimisation modelling.

Consequently, the current research approaches this scientific investigation in a systematic manner to investigate the influence of two adjoining variables (including machining time and workforce performance), the effect of return-on-investment, as well as the influence of a new optimisation procedure, fuzzy goal programming and differential evolution on the outcome and decision-making in maintenance.

To elaborate on the research gaps that this article is focusing, we need to assert that till date scholars see the reliability theory through the lenses of equipment assessment alone. For decades most reliability scholars have focused on the hardware aspect of maintenance. The maintenance literature has unconsciously omitted the reliability of the human element in the system, though the literature worldwide acclaim the significance and controlling influence of the human element in maintenance. While this idea has been scantily recognised by a few discerning authors, there have not been any intensive debate on this philosophy. Also, scholars have not really

operationalised this idea in any serious manner to the best of our knowledge. It is only recently that a pocket of facts started emerging from the literature about this. Thus, there is a necessity for a deeper appreciation of the human reliability concept in maintenance workforce evaluations. There is an urgent need to also understand the scientific consequences of how this visualisation of human elements in maintenance will affect our world of industrial practices.

In the present communication, we went beyond the proposal of a reliability-oriented model for the technicians manning the maintenance system but also built on the stochastic assumption of the modelling conditions with foundations laid by Ighravwe et al. (2016b). That is, the extensively advocated and admitted theories of reliability employed age-long on equipment, has been transferred to the assessment of the human performance. The stochastic theory of systems, a commonly applied concept was also employed. This is a rare contribution offered by Ighravwe et al. (2016b) in the area of maintenance. Our viewpoint in this work swerves from the foundation laid by this earlier author in this research area. While a mixed-integer model for the development of optimisation sense, advanced by Ighravwe et al. (2016b) has been based on the sizes of technicians in the work-system, the workload availability of the technicians, their reliability as well as performance and quality of work done served as a stepping stone for us, the work added two elegant adjustments. Maintenance time and workforce performance became attractive variables that will fully explain the results of our own influence. We suggest the combination of fuzzy goal programming and differential evolution as a solution method for the nonlinear optimisation model generated in the optimal value deformation for the model considering the maintenance workforce variables.

### Research methodology

This section presents information on the selected nonlinear mixed-integer optimisation model, FGP model and the meta-heuristics which are well thought-out as solution approaches for the formulated FGP procedure.

#### Ighravwe et al.’s (2016b) model

The notations used in presenting Ighravwe et al. (2016b) model are contained in “Appendix A”. Ighravwe et al. (2016b) model addresses two main maintenance workforce problems (maintenance time and workforce performance) using the concept of stochastic programming. Their model was a bi-objective model. The first objective function of

their model was maximisation of maintenance workforce earned-value (Eq. 1), while maximisation of average maintenance workforce reliability (Eq. 2) was considered as the second objective function.

$$\text{Max } G_1 = \sum_{i=1}^M \sum_{j=1}^N \sum_{k=2}^K \sum_{t=1}^T (v_{ijkt} w_{ijkt} x_{ijkt}) \tag{1}$$

$$\text{Max } G_2 = \frac{1}{T} \sum_{t=1}^T \left[ \prod_{i=1}^M 1 - \left( 1 - \prod_{j=1}^N \left( \prod_{k=2}^K [1 - (1 - RR_{ijkt})^{x_{ijkt}}] \right) \right) \right] \tag{2}$$

The two objective functions were subjected to several constraints. First, the issue of overhaul maintenance activities was considered (Eqs. 3a and 3b). When  $t = 1$ , Eq. (3a) is considered, otherwise Eq. (3.b) is considered.

$$W_{i2}^L \leq \sum_{j=1}^N \left( W_{ij2t} - \int_{\hat{b}_{ij21}}^{\hat{b}_{ij22}} \hat{b}.f(\hat{b})d\hat{b} \right) x_{ij2t} \leq W_{i2}^U \quad \forall(i, t) \tag{3a}$$

$$W_{i2}^L \leq \sum_{j=1}^N \left( \left( W_{ij2(t-1)} + \int_{\hat{a}_{ij21}}^{\hat{a}_{ij22}} \hat{a}.f(\hat{a})d\hat{a} - \int_{\hat{b}_{ij21}}^{\hat{b}_{ij22}} \hat{b}.f(\hat{b})d\hat{b} \right) \right) x_{ij2t} \leq W_{i2}^U \quad \forall(i, t). \tag{3b}$$

The modelling of overtime (Eqs. 4a and 4b) and rework (Eqs. 5a and 5b) maintenance activities constraints are similar to that of overhaul maintenance activities constraint.

$$W_{i3}^L \leq \sum_{j=1}^N \left( W_{ij3t} - \int_{\hat{b}_{ij31}}^{\hat{b}_{ij32}} \hat{b}.f(\hat{b})d\hat{b} - \int_{\hat{c}_{ij31}}^{\hat{c}_{ij32}} \hat{c}.f(\hat{c})d\hat{c} \right) x_{ij3t} \leq W_{i3}^U \quad \forall(i, t) \tag{4a}$$

$$W_{i3}^L \leq \sum_{j=1}^N \left( W_{ij3(t-1)} + \int_{\hat{a}_{ij31}}^{\hat{a}_{ij32}} \hat{a}.f(\hat{a})d\hat{a} - \int_{\hat{b}_{ij31}}^{\hat{b}_{ij32}} \hat{b}.f(\hat{b})d\hat{b} - \int_{\hat{c}_{ij31}}^{\hat{c}_{ij32}} \hat{c}.f(\hat{c})d\hat{c} \right) x_{ij3t} \leq W_{i3}^U \quad \forall(i, t) \tag{4b}$$

$$W_{i4}^L \leq \sum_{j=1}^N \left( W_{ij4t} - \int_{\hat{e}_{ij41}}^{\hat{e}_{ij42}} \hat{e}.f(\hat{e})d\hat{e} + \int_{\hat{b}_{ij41}}^{\hat{b}_{ij42}} \hat{b}.f(\hat{b})d\hat{b} \right) x_{ij4t} \leq W_{i4}^U \quad \forall i, t \tag{5a}$$



$$\begin{aligned}
 W_{i4}^L \leq & \sum_{j=1}^N \left( W_{ij4(t-1)} - \int_{\tilde{a}_{ij41}}^{\tilde{a}_{ij42}} \tilde{a}.f(\tilde{a})d\tilde{a} - \int_{\tilde{e}_{ij41}}^{\tilde{e}_{ij42}} \tilde{e}.f(\tilde{e})d\tilde{e} \right. \\
 & \left. + \int_{\tilde{b}_{ij41}}^{\tilde{b}_{ij42}} \tilde{b}.f(\tilde{b})d\tilde{b} \right) x_{ij4t} \leq W_{i4}^U \\
 & \forall i, t.
 \end{aligned} \tag{5b}$$

Another limitation in their model was average number of worker category (Eq. 6). This constraint controls the expected number of a particular worker category in a system.

$$\frac{\sum_{t=1}^T x_{ijkt}}{T} \leq x_{ijk,ave} \quad \forall(i, j, k). \tag{6}$$

To further constrain the number of worker in a category, limitation on maintenance workforce size (Eq. 7), workforce cost for each maintenance activity (Eq. 8) and total maintenance workforce budget are other sets of constraints in their model (Eq. 9) that were considered.

$$xx_{\min,t} \leq \sum_{j=1}^N \sum_{k=2}^K x_{ijkt} \leq xx_{\max,t} \quad \forall(i, t) \tag{7}$$

$$\sum_{i=1}^M \sum_{j=1}^N C_{ijkt} w_{ijkt} x_{ijkt} \leq \chi_{kt} \quad \forall(i, t) \tag{8}$$

$$\sum_{i=1}^M \sum_{j=1}^N \sum_{k=2}^K C_{ijkt} w_{ijkt} x_{ijkt} \leq \bar{\chi}_t \quad \forall t. \tag{9}$$

Other constraints in Ighravwe et al. (2016b) model are workforce availability (Eq. 10), workers’ efficiency (Eq. 11) and quality of work done (Eq. 12) as well as workers’ overall effectiveness (Eq. 13) and reliability (Eq. 14) (see Raza and Al-Turki 2010).

$$\frac{\sum_{j=1}^N a_{ijkt} x_{ijkt}}{\sum_{j=1}^N \hat{a}_{ijkt} x_{ijkt}} \geq (\bar{b}_k - \bar{a}_k)(1 - \bar{\alpha}_{kt}) + \bar{a}_k \quad \forall(i, j, k) \tag{10}$$

$$\frac{\sum_{j=1}^N p_{ijkt} x_{ijkt}}{\sum_{j=1}^N \hat{p}_{ijkt} x_{ijkt}} \geq (\hat{b}_k - \hat{a}_k)(1 - \hat{\alpha}_{kt}) + \hat{a}_k \quad \forall(i, j, k) \tag{11}$$

$$\frac{\sum_{j=1}^N q_{ijkt} x_{ijkt}}{\sum_{j=1}^N \hat{q}_{ijkt} x_{ijkt}} \geq (\tilde{b}_k - \tilde{a}_k)(1 - \tilde{\alpha}_{kt}) + \tilde{a}_k \quad \forall(i, j, k) \tag{12}$$

$$\begin{aligned}
 & \frac{\sum_{i=1}^M \sum_{j=1}^N a_{ijkt} x_{ijkt}}{\sum_{i=1}^M \sum_{j=1}^N \hat{a}_{ijkt} x_{ijkt}} * \frac{\sum_{i=1}^M \sum_{j=1}^N p_{ijkt} x_{ijkt}}{\sum_{i=1}^M \sum_{j=1}^N \hat{p}_{ijkt} x_{ijkt}} * \frac{\sum_{i=1}^M \sum_{j=1}^N q_{ijkt} x_{ijkt}}{\sum_{i=1}^M \sum_{j=1}^N \hat{q}_{ijkt} x_{ijkt}} \geq \mu_k''' \\
 & + \Phi^{-1}(1 - \alpha_{kt}''') \sigma_k''' \\
 & \forall(k, t)
 \end{aligned} \tag{13}$$

$$1 - \prod_{j=1}^N \left( \prod_{k=1}^K [1 - (1 - RR_{ijkt})^{x_{ijkt}}] \right) \geq r_{kt} \quad \forall i, t \tag{14}$$

The new objective function (returns-on-workforce investment) that is added to Ighravwe et al. (2016b) model is expressed as Eq. (15). Return-on-workforce investment measures the ratio of profit with respect to total workforce costs. It provides a more detailed information on workers’ performance when compared with workers’ productivity (Visier 2015).

$$\text{Max } G_3 = \frac{\sum_{t=1}^T S_t - C_t}{\sum_{i=1}^M \sum_{j=1}^N \sum_{k=1}^K \sum_{t=1}^T C_{ijkt} x_{ijkt}}, \tag{15}$$

where  $S_t$  represents the value of goods sold at period  $t$  and  $C_t$  represents the cost of goods sold at period  $t$ .

Based on personal communication with the Ighravwe et al. (2016b), the actual expression for workforce reliability is given as Eq. (16).

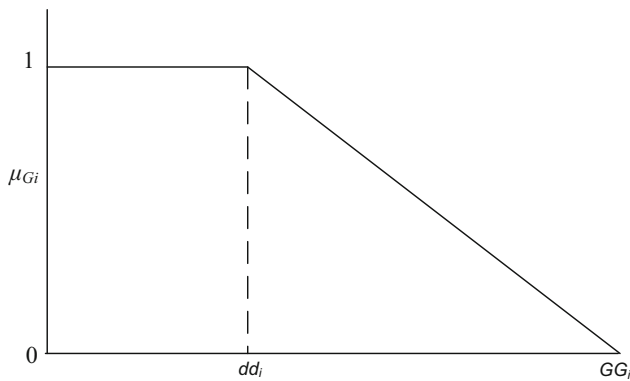
$$\prod_{j=1}^N \left( \prod_{k=1}^K [1 - (1 - RR_{ijkt})^{x_{ijkt}}] \right) \geq r_{kt} \quad \forall i, t. \tag{16}$$

### Fuzzy goal programming model

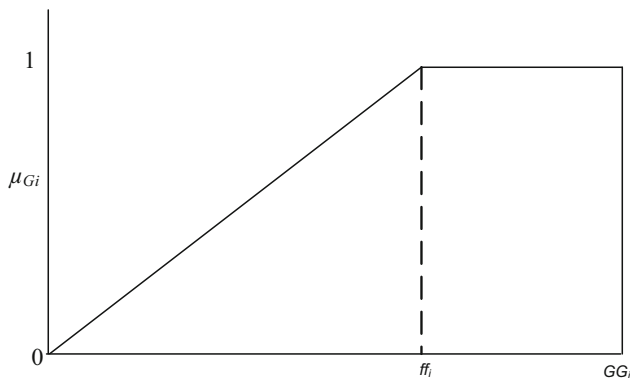
In order to combine the various objective functions into a single function, this study adopts FGP (Belmokaddem et al. 2009). First, the membership functions ( $\mu_i$ ) for the minimisation (Fig. 1) and maximisation (Fig. 2) objective functions are designed. The characteristic equation for converting minimisation objective functions into fuzzy goals is expressed as Eq. (17), while Eq. (18) is used to convert maximisation objective function into fuzzy goal.

$$\mu_{G_o} = \begin{cases} 1 & G_o \leq dd_{lo} \\ 1 - \frac{dd_{uo} - GG_o}{GG_o} dd_{lo} \leq G_o \leq dd_{uo} & \\ 1 & G_o > dd_{uo} \end{cases} \tag{17}$$

$$\mu_{G_o} = \begin{cases} 0 & ff_o G_o \\ 1 - \frac{GG_o - dd_{lo}}{GG_o} dd_{lo} \leq G_o \leq dd_{uo} & \\ 1 & ff_o > G_o, \end{cases} \tag{18}$$



**Fig. 1** Linear membership function for the minimisation objective (Belmokaddem et al. 2009)



**Fig. 2** Linear membership function for the maximisation objective (Belmokaddem et al. 2009)

where  $dd_{lo}$  represents the lower bound for objective  $\Delta$  function  $o$ ,  $dd_{uo}$  represents the upper bound for objective function  $o$ ,  $\mu_{G_o}$  represents the membership function for objective function  $o$ ,  $gg_o$  represents the boundary between partial and complete membership functions for minimisation objective functions, and  $ff_o$  represents the boundary between partial and complete membership functions for maximisation objective function.

By defining the expressions for minimum and maximum goals, the complete structure of the enhanced maintenance workforce optimisation model is presented as follows:

$$\text{Max } \bar{f} = \sum_{o=1}^3 \mu_o \tag{19}$$

Subject to:  
Equations (3a–14).

Equation (16).

$$\mu_o \leq \mu_{z_o} \quad \forall o \tag{20}$$

$$\mu_o \leq \bar{\alpha}_o \quad \forall o, \tag{21}$$

where  $\mu_{z_o}$  represents the optimised membership function for  $o$ th goal,  $\mu_o$  represents the degree of membership

function for  $o$ th goal, and  $\bar{\alpha}_i$  represents the desirable achievement level for the  $o$ th fuzzy goal (Belmokaddem et al. 2009).

### Meta-heuristics

The brief descriptions of the selected PSO and evolutionary (GA and DE) algorithms are presented in as follows.

#### Particle swarm optimisation algorithm

PSO algorithm indicates a population-oriented stochastic meta-heuristic that was designed to mimic the characteristic of birds’ social behaviour (Kennedy and Eberhart 1995). Its operations consist of two steps (velocity and position updating) (De et al. 2015). The velocity of a particle is updated using its prior velocity and position as well as social and cognitive knowledge (Eq. 22). The function of  $w$  is to ensure that the particles in a swarm are able to exploit and explore solution search space (Engelbrencht 2007).

$$V_{jj}(tt) = wV_{jj}(tt - 1) + c_1R_1(pbest_{tt-1}^{jj} - x_{jj}(tt - 1)) + c_2R_2(gbest_{tt-1} - x_{jj}(tt - 1)), \tag{22}$$

where  $V_{jj}(tt)$  represents the velocity of particle  $jj$  at iteration  $tt$ ,  $x_{jj}(tt)$  represents the position of particle  $jj$  at iteration  $tt$ ,  $pbest_{tt}^{jj}$  represents the personal best position of particle  $jj$  at iteration  $tt$ ,  $gbest_{tt}$  represents the global solution of the swarm at iteration  $tt$ ,  $R_1$  and  $R_2$  are uniform random number between 0 and 1 while  $c_1$  as well as  $c_2$  are parameters, and  $w$  represents inertial weight.

A huge value of  $w$  supports exploration and a little value of  $w$  supports exploitation (Engelbrencht 2007; Ouadfel et al. 2010). The variation of the inertia weight in the PSO algorithm is based on the minimum and maximum expected weights as well as the current and maximum iteration step (Eq. 23).

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{tt_{\max}} tt, \tag{23}$$

where  $tt_{\max}$  represents maximum iteration or generation,  $w_{\max}$  signifies the utmost value of inertia weight, and  $w_{\min}$  represents the least value of inertia weight.

The value of velocity for each particle at each iteration step  $tt$  is controlled using velocity clapping concept (Eq. 24). This entails specifying the minimum and maximum velocity for each decision variable (Kennedy and Eberhart 2001).

$$\begin{cases} v_{jj}(tt) > v_{\max} & \text{then } v_{jj}(tt) = v_{\max} \\ v_{jj}(tt) < v_{\min} & \text{then } v_{jj}(tt) = v_{\min} \end{cases}, \tag{24}$$

where  $v_{\max}$  signifies the utmost velocity of a particle, and  $v_{\min}$  signifies the least velocity of a particle.

The decision on whether a particle will move towards a local or global optimal solution is controlled using  $c_1$  and  $c_2$ . A particle's ( $x_{ji}(tt)$ ) new position is based on its current velocity and previous position (Eq. 25).

$$x_{ji}(tt) = V_{ji}(tt) + x_{ji}(tt - 1) \tag{25}$$

*Real coding genetic algorithm (RCGA)*

The concept of survival of the fittest in natural selection process was used to develop GA (Holland 1975; Sadeghi et al. 2011). Most studies on GA application often consider the use of either RCGA or binary coding methods (Javanmard and Koraeizadeh 2016). In this study, RCGA is selected over binary coded GA, the reason for selecting RCGA is that it performed better than binary-coded GA. This assertion was reported when Cormier et al. (2001) used RCGA to optimise Bragg grating parameters.

During RCGA implementation, two parents are randomly selected and allowed to undergo mutation (Eq. 26). The direction which a mutant vector will move towards is determined by simulating a flopped unbiased coin (Cormier et al. 2001; Chen and Wang 2011). The  $\delta^t$  helps in improving the search ability of GA, its value decreases as number of generation increases (Eq. 27).

$$v_{gg}(tt - 1) = \begin{cases} x_{gg}(tt - 1) + \delta^t(\text{Max}(x_{gg}) - x_{gg}(tt - 1)) & \text{Head} \\ x_{gg}(tt - 1) - \delta^t(x_{gg}(tt - 1) - \text{Min}(x_{gg})) & \text{Tail} \end{cases} \tag{26}$$

$$\delta^t = R\delta^{t-1}(1 - tt/t_{\max})^B, \tag{27}$$

where  $v_{gg}$  represents mutant vector  $gg$ ,  $\text{Min}(x_{gg})$  represents minimum value of decision variable  $gg$ ,  $\text{Max}(x_{gg})$  represents maximum value of decision variable  $gg$ ,  $\delta^t$  represents a parameter,  $R$  represents uniformly distributed random number, and  $B$  represents constant parameter.

During crossover operation, two off-springs are generated ( $O_1$  and  $O_2$ ) using the two selected parents ( $P_1$  and  $P_2$ ) from a reproduction pool. The value of the first off-spring is expressed as Eq. 28a, while Eq. 28b represents the value of the second off-spring (Chen and Wang, 2011).

$$O_{1,i} = (1 - \gamma)P_1 + \gamma P_2, \tag{28a}$$

$$O_{2,i} = \gamma P_1 + (1 - \gamma)P_2, \tag{28b}$$

$$\gamma = (1 - 2\alpha)\eta - \alpha, \tag{29}$$

where  $\eta$ ,  $\alpha$  and  $\gamma$  are parameters.

During selection process, parents and off-springs are considered. The individuals that will survive to the next generation are determined using Boltzmann selection operation (Eq. 30). If the condition holds, an off-spring is accepted, else it is rejected (Engelbrencht 2007).

$$U(0, 1) > \frac{1}{1 + e^{(f_{\psi}(x_{gg}(tt)) - f_{\psi}(x_{gg}^o(tt)))/T(tt)}}, \tag{30}$$

where  $f_{\psi}(x_{gg}(tt))$  represents the fitness function of a parent,  $f_{\psi}(x_{gg}^o(tt))$  represents the fitness function of an off-spring, and  $T(tt)$  represents temperature at generation  $tt$ .

This study determines the value of  $T(tt)$  using a linear cooling annealing scheme (Engelbrencht 2007), as expressed with Eq. (31).

$$T(tt + 1) = T(tt) - \Delta T, \tag{31}$$

$$\Delta T = T(0) - T(f), \tag{32}$$

where  $T(0)$  signifies initial temperature, and  $T(f)$  signifies final temperature.

*Differential evolution algorithm*

This section is devoted to the application of differential evolution to the maintenance workforce optimisation problem. Differential evolution is the seminal idea of Ken Price in collaboration with Raissar Storn, launched in the period 1994–1996. From an elementary stage, DE has developed into a robust instrument with much versatility in use for engineering-based problems. In searching for the tool to apply in this work, our target was to employ a tool for the complicated maintenance workforce problem, which has global optimal attainment capacity, stochastic in nature, and one that solves the maintenance workforce optimisation problem fast as it is very challenging to solve it analytically. Fortunately, we narrowed our search to DE as it has records of being used to solve such problems using approximate solutions (Beji et al. 2012; De et al. 2017). DE has been found to be very simple, stochastic and with the ability for the most excellent genetic mode of method for the solution of genuine priced analysis function collection fundamentally, as will be seen shortly, DE appends the weighted disparity flanked by two population vectors towards a third vector. DE algorithm is a member of evolutionary algorithm. In DE algorithm, mutation operation is carried out by randomly selecting three parents such that  $qq \neq \bar{r}_1 \neq \bar{r}_2 \neq \bar{r}_3$ . Mutant vectors are based on Eq. (33).

$$v_{gg}(tt) = x_{\bar{r}_1,gg}(tt - 1) + \text{MR} \left( x_{\bar{r}_2,gg}(tt - 1) - x_{\bar{r}_3,gg}(tt - 1) \right), \tag{33}$$

where  $x_{r1,gg}$  represents the first randomly selected parent,  $x_{r2,gg}$  represents the second randomly selected parent,  $x_{r3,gg}$  represents the third randomly selected parent, and MR represents mutation rate.

The decision on whether to accept the value of a mutant vector or target vector as a trial vector depends on comparison of crossover rate with a random number as well as a selected random integer from the dimension of a problem (Eq. 34). A flowchart for DE algorithm is presented in "Appendix B".

$$u_{gg} = \begin{cases} v_{gg}(tt) & \text{If } R_{gg} \leq CR \text{ or } gg = I_{gg} \\ x_{gg}(tt-1) & \text{If } R_{gg} > CR \text{ or } gg \neq I_{gg} \end{cases}, \quad (34)$$

where  $u_{gg}$  represents trial vector  $gg$ ,  $CR$  represents crossover rate,  $R_{gg}$  represents random number for decision variable  $gg$ ,  $I_{gg}$  represents random integer number from  $(1, 2, \dots, D)$ , and  $D$  represents the dimension of a problem (Engelbrecht 2007).

## Model application

The FGP model was implemented in a plant located in South West Nigeria. The company manufactures alcoholic and non-alcoholic products. Engineering judgments from key personnel in the organisation's maintenance and production departments were sought during the implementation of the FGP model. Six planning periods were considered during the implementation of the FGP model. Currently, the company operates three production lines. The first production line is used for production of canned alcoholic and non-alcoholic products, while the other production lines are used for the production of bottled drinks. The company operates an average of 25 days per month using three shifts per day. The company's maintenance workforce was grouped into cleaning, mechanical and electrical workers. Two categories of workers are considered for the cleaning maintenance workers (full-time and part-time), while only one worker category was considered for the mechanical and electrical maintenance workers (full-time). The maximum number of maintenance workers for the company's maintenance system was 38 workers maintenance, while the minimum number of maintenance workers was 24 maintenance workers. Other maintenance workforce information used during the implementation of the model is presented in Table 3.

During the implementation of the model, different parametric settings were considered for the selected meta-heuristics (Table 4). The range for the mutation and crossover rates are based on possible values for these parameters in literature (Cormier et al. 2001; Ighravwe et al. 2016b). In this study, we did not use commercially

available software to solve the formulated model. This made us to limit the selection of the most suitable meta-heuristic to quality of solution. The computational time of each meta-heuristic was not considered because it depends on programming skill of a programmer as well the programming language used for coding a meta-heuristic. Thus, it is possible for different programmers to report different computational time for the same problem, with the same quality of solution. The selected meta-heuristics were coded using VB Net programming language.

The most suitable value of the cognitive knowledge constant for the PSO algorithm was 0.30, while the social knowledge constant value was 0.35. The range for the inertia weight was between 0.09 and 0.5. The results obtained for the most suitable parametric settings for the DE algorithm showed that the value for mutation rate was 0.15, while a crossover rate value of 0.20 was obtained. The GA parametric setting results for the model showed that the most suitable value for the GA mutation rate was 0.15, while the crossover rate value was 0.30. Based on the fitness values of the selected meta-heuristics, the most suitable meta-heuristic for the formulated model was the DE algorithm (Fig. 3).

The ranges for the selected meta-heuristics fitness values were determined using the concept of confidence interval (Engelbrecht 2007). To compute the range of a meta-heuristic solution range, Eq. (35) was considered. A confidence interval of 99% was used to generate the results in Table 5. Based on the information in Table 5, the most suitable meta-heuristic for the formulated problem is DE algorithm. By using the DE algorithm as a solution method for solving the model, the values for the different objective functions and decision variables at different periods were generated.

$$q_{\text{range}} = \mu_q^* \pm t_{\alpha, n-1}^* \delta_q^*, \quad (35)$$

where  $\mu_q^*$  represents the mean value of meta-heuristic  $q$  solution,  $\delta_q^*$  represents the standard deviation of meta-heuristic  $q$  solution,  $\alpha$  represents the confidence interval level, and  $\bar{n}$  represents total number of simulation.

## Results and discussion

The total value of the workforce return-on-investment for the six periods was about N591, 297.57, while the total workforce earned-value was about N849, 145,610.59 for the six periods. The average workforce reliability for the six periods was one. This implies that the workforce reliability for each period was the same (one). The value of the

**Table 3** Maintenance workforce information

Parameters	Full-time cleaning workers	Part-time cleaning workers	Full-time electrical workers	Full-time mechanical workers
Unit cost, $k = 1$ (( $\mathbb{N}$ ))	2760.59	2161.64	3161.30	3488.33
Unit cost, $k = 2$ (( $\mathbb{N}$ ))	2208.48	1729.31	2529.04	2790.67
Unit cost, $k = 3$ ( $\mathbb{N}$ ( $\mathbb{N}$ ))	1380.299479	1080.82	1580.65	1744.17
Earned value, (( $\mathbb{N}$ ))	2000	1500	2000	2000
Average workers, $k = 1$	7	4	10	10
Average workers, $k = 2$	7	4	10	10
Average workers, $k = 3$	7	4	10	10
Minimum value of workforce size for overhaul	6	2	8	8
Maximum value of workforce size for overhaul	8	6	12	12
Minimum value of workforce size for overtime	6	2	8	8
Maximum value of workforce size for overtime	8	6	12	12
Minimum value of workforce size for rework	6	2	8	8
Maximum value of workforce size for rework	8	6	12	12
Minimum value of service time for overhaul	368	368	184	368
Maximum value of service time for overhaul	1488	1488	744	1488
Minimum value of service time for overtime	0	0	0	0
Maximum value of service time for overtime	744	744	372	744
Minimum value of service time for rework	92	92	23	46
Maximum value of service time for rework	372	372	93	279
Minimum value of reliability for overhaul	0.7	0.7	0.7	0.7
Maximum value of reliability for overhaul	1	1	1	1
Minimum value of reliability for overtime	0.7	0.7	0.7	0.7
Maximum value of reliability time for overtime	1	1	1	1
Minimum value of reliability for rework	0.7	0.7	0.7	0.7
Maximum value of reliability for rework	1	1	1	1
Minimum worker availability for overhaul	0.742	0.742	0.742	0.742
Maximum worker availability for overhaul	1	1	1	1
Minimum workers availability for overtime	0.742	0.742	0.742	0.742
Maximum workers availability for overtime	1	1	1	1
Minimum worker available for rework maintenance	0.742	0.742	0.742	0.742
Maximum worker available for rework maintenance	1	1	1	1
Minimum worker performance for overhaul	0.8	0.8	0.8	0.8
Maximum worker performance for overhaul	1	1	1	1
Minimum workers performance for overtime	0.8	0.8	0.8	0.8
Maximum workers performance for overtime	1	1	1	1
Minimum worker performance rework maintenance	0.8	0.8	0.8	0.8
Maximum worker performance rework maintenance	1	1	1	1
Minimum quality of overhaul activities	0.6	0.6	0.6	0.6
Maximum quality of overhaul activities	1	1	1	1
Minimum quality of overtime activities	0.6	0.6	0.6	0.6
Maximum quality of overtime activities	1	1	1	1
Minimum quality of rework maintenance activities	0.6	0.6	0.6	0.6
Maximum quality of rework maintenance activities	1	1	1	1
Fatigue for overhaul (lower value)	4.08	4.08	4.08	8.16
Fatigue for overhaul (upper value)	8.16	8.16	8.16	16.32
Fatigue for overtime (lower value)	1.488	1.488	1.488	2.976

**Table 4** Meta-heuristics parametric settings

Parameters	DE	GA	PSO
Population size	50	50	50
Generations/iterations	200	200	200
Mutation rate	10–30%	10–30%	-
Crossover rate	10–45%	10–30%	-
C1	-	-	0.1–1
C2	-	-	0.1–1
Inertia weight range	-	-	0.10–0.50

maintenance workforce earned-value and return-on-workforce investment varies from one period to another (Fig. 4).

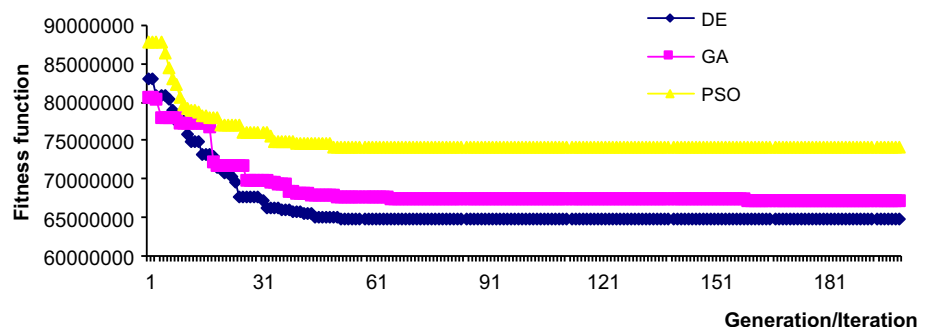
The model results showed that the total number of workers required for rework maintenance (176 workers) activities was less than those of overhaul (185 workers) and overtime maintenance (182 workers) activities. Based on the model results, the total number of full-time maintenance workers required for the different maintenance activities was more than those required for overtime and rework maintenance activities. The total number of casual cleaning maintenance workers required for overhaul and rework maintenance activities were the same (20 workers). This value was less by one maintenance worker when compared with the total number of maintenance workers (21 workers) required for overtime maintenance activities by the casual cleaning maintenance workers (Table 6).

The average size of the full-time cleaning maintenance workers for overhaul maintenance activity for the company was eight maintenance workers. The company required an average of seven full-time cleaning maintenance workers for

overtime and rework maintenance activities. The average number of casual maintenance workers required for overhaul, overtime and rework maintenance activities by the company were the same (four maintenance workers). The average full-time mechanical workers size for the various maintenance tasks were the same (ten maintenance workers). An average of ten full-time electrical maintenance workers was required for rework maintenance activity. The average number of full-time electrical maintenance workers required for overtime and overhaul maintenance tasks were the same (ten maintenance workers).

None of the periods had the same number of total maintenance workers for the various maintenance tasks (Fig. 5). The highest number of total maintenance workers for the different maintenance activities was in Period 5 (34 maintenance workers) during overhaul maintenance activities (Fig. 5). Rework maintenance activity required the lowest number of total maintenance worker (27 maintenance workers).

The model results showed that the total number of maintenance workers required to execute the different maintenance activities for the six periods was 543 maintenance workers (Table 6). Each of the periods required a minimum of workforce size of above 85 maintenance workers for the different maintenance activities (Fig. 5). Period 3 required the least number of workers, while Period 5 required the highest number of maintenance workers (96 maintenance workers) for the different maintenance activities (Fig. 5). Periods 4 and 6 required the same number of total maintenance workers for the different maintenance activities (90 maintenance workers).

**Fig. 3** Convergence curve for the model of the different meta-heuristics**Table 5** Statistical measures for the meta-heuristics

Measure	DE	GA	PSO
Best	64,728,629.26	67,313,354.30	74,155,387.49
Worst	83,055,286.59	80,673,775.09	87,702,199.56
Average	66,082,417.15	68,563,516.40	74,950,111.64
Solution range	65,803,640.34–66,700,651.34	68,326,154.06–69,043,322.01	74,781,639.50–75,373,625.53

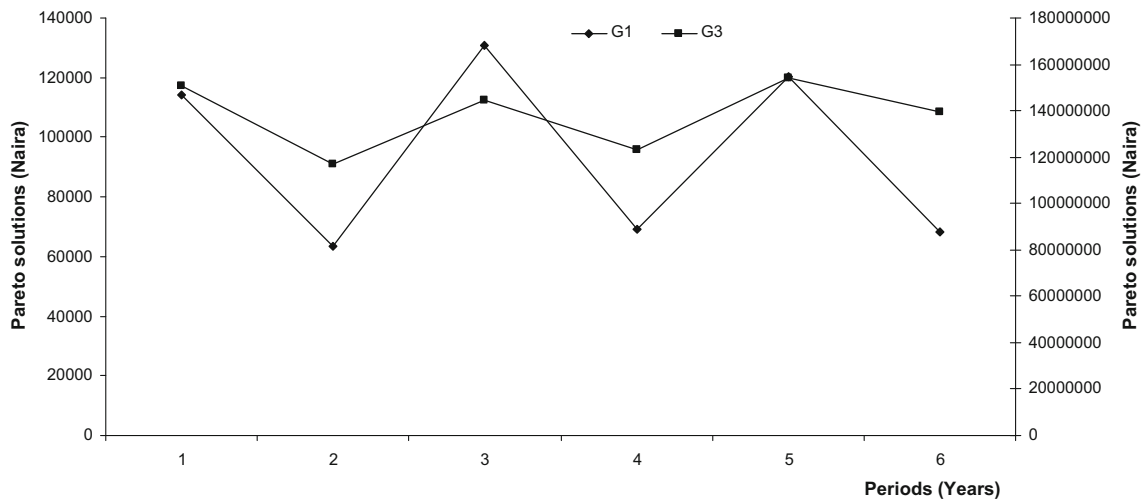


Fig. 4 Pareto solution for model objective functions for the different periods

Table 6 Maintenance workforce size distribution for the different periods

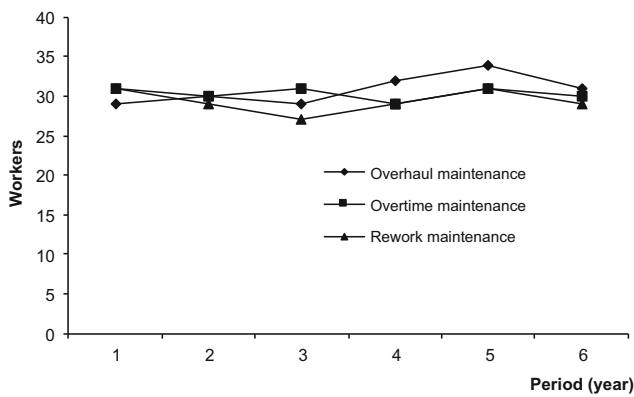
Parameters	Variables	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
Overhaul maintenance	$x_{111t}$	6	7	6	7	6	7
	$x_{121t}$	5	2	5	2	2	4
	$x_{211t}$	10	10	11	10	9	10
	$x_{221t}$	0	0	0	0	0	0
	$x_{311t}$	11	8	11	8	10	11
	$x_{321t}$	0	0	0	0	0	0
Overtime maintenance	$x_{112t}$	7	8	6	6	7	7
	$x_{122t}$	6	3	2	5	3	2
	$x_{212t}$	10	11	9	8	10	9
	$x_{222t}$	0	0	0	0	0	0
	$x_{312t}$	10	9	9	10	10	11
	$x_{322t}$	0	0	0	0	0	0
Rework maintenance	$x_{113t}$	8	7	7	6	7	8
	$x_{123t}$	5	5	2	5	3	3
	$x_{213t}$	11	9	9	11	11	9
	$x_{223t}$	0	0	0	0	0	0
	$x_{313t}$	9	9	12	10	11	11
	$x_{323t}$	0	0	0	0	0	0

During overhaul maintenance activities, the minimum amount of total maintenance workers required was 29 maintenance workers (Periods 1 and 3). The range of total number of maintenance workers required for overhaul maintenance activity was five maintenance workers. The amount of total number of maintenance workers required for overtime and rework maintenance activities in Periods 1 and 5 was 31 maintenance workers. Furthermore, Period 4 required the same number of total maintenance workers for overtime and rework maintenance activities (29 maintenance workers). The total number of maintenance workers required for overtime maintenance activity in Periods 1, 3 and 5 were the same (31 maintenance

workers). Similarly, Periods 2 and 6 required the same number of total maintenance workers for overtime maintenance activity (30 maintenance workers). The difference between the maximum (31 maintenance workers) and minimum (29 maintenance workers) number of total maintenance workers required for overtime maintenance activity was two workers (Fig. 5).

**Maintenance workloads**

The total amounts of overhaul maintenance workloads for the maintenance system increases from one period to another (Table 7). The values for total overtime and rework



**Fig. 5** Total number of maintenance workers for the different maintenance activities

maintenance workloads for the maintenance system did not follow a regular pattern. Apart from the full-time electrical maintenance workers, who did not have a workload of above 1000 h/period for any of the maintenance activities, the other worker categories had at least two periods that had workload of above 1000 h/period. The highest maintenance time for the full-time maintenance workers required for the different maintenance activities occurred during overtime maintenance activity (1738.4070 h). The full-time cleaning maintenance workers had the least maintenance time during overhaul maintenance activities when weighed against those of overtime and rework maintenance activities (Table 7).

The difference between the minimum and maximum amount of total workers’ maintenance time was about

45,952.94 h. For the six periods, the company required an average of 109,423.63 h as total workers’ overhaul maintenance time per period. The amount of average total workers’ maintenance time (106,363.83 h) required for overtime maintenance activities was about ten times the amount of average total workers’ maintenance time required for rework maintenance activity (19,681.96 h). The amount of total workers’ maintenance time for the six periods for the different maintenance activities was 1412,816.53 h. The period with the highest amounts of total workers’ maintenance time for the different maintenance activities was Period 1 (269,892.82 h). This was followed by Period 5 (254,910.91 h), while Period 3 had the lowest maintenance time for total workers’ maintenance time for the different maintenance activities (176,146.03 h).

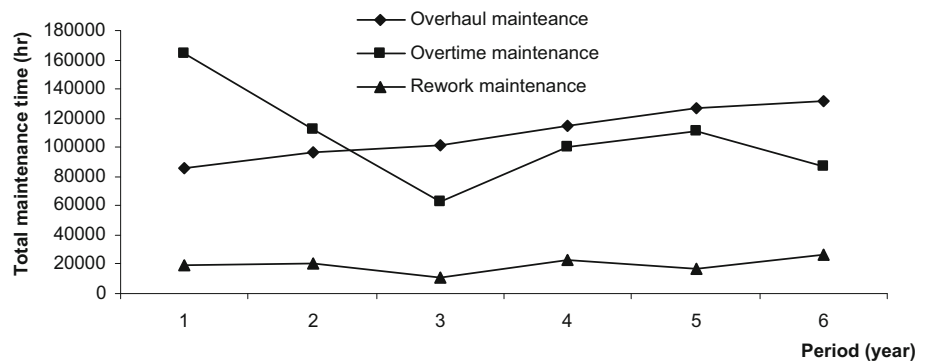
Apart from Periods 1 and 2, the amount of total workers’ maintenance time for overhaul maintenance activity was more than that of total workers’ maintenance time for overtime maintenance activity. The amounts of total workers’ maintenance time for Period 3 (101,905.72 h) was more than the sum of total workers’ maintenance time for overtime (63,100.49 h) and rework (11,139.82 h) maintenance activities with about 27,665.41 h (Fig. 6). The model results showed that the total workers’ maintenance time (114,204.74 h) of Period 4 for overhaul maintenance activities was less than the sum of total workers’ maintenance time for overtime (100,255.15 h) and rework (22,560.59 h) maintenance activities with about 8611.01 h (Table 7).

**Table 7** Maintenance workload (service time) distribution for the various periods

Parameters	Variables	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
Overhaul maintenance (h)	$w_{111t}$	463.5705	208.0196	1038.2831	806.4235	1045.9586	1509.1001
	$w_{121t}$	1159.3698	563.2209	766.9116	230.4122	924.5455	589.1797
	$w_{211t}$	413.1315	361.3545	506.5986	326.7713	230.9860	595.8457
	$w_{221t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$w_{311t}$	434.6115	1384.7603	525.4921	1484.2845	843.5887	689.6778
	$w_{321t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Overtime maintenance (h)	$w_{112t}$	1458.3135	584.0701	287.0270	477.5277	1738.4070
$w_{122t}$		1078.8200	1083.8812	585.9424	749.9360	567.1344	745.5036
$w_{212t}$		786.2420	132.5848	270.8702	280.2953	440.9824	594.2682
$w_{222t}$		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$w_{312t}$		956.0682	1272.4123	493.8677	1253.4518	200.4781	281.6272
$w_{322t}$		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rework maintenance (h)		$w_{113t}$	777.2224	459.1111	1000.0964	630.3484	424.6200
	$w_{123t}$	752.7356	250.5374	560.5938	61.4982	1135.9848	1184.6599
	$w_{213t}$	597.6906	608.0862	308.8623	261.1604	570.3416	400.9598
	$w_{223t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$w_{313t}$	504.2427	1182.1824	75.2994	1476.6878	437.9605	892.1212
	$w_{323t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000



**Fig. 6** Total maintenance time of the workers for the different maintenance activities



In Period 5, the sum of the total workers’ maintenance time for overtime (111,475.74 h) and rework maintenance (17,033.66 h) activities was more than that the total workers’ maintenance time for overhaul maintenance activity by 2107.88 h (Table 7). The difference between the total workers’ maintenance time for overhaul maintenance activities (131,593.48 h) and the sum of the total workers’ maintenance time for overtime (86,924.83 h) and rework (26,859.05 h) maintenance activities was about 13.53% (17,809.61 h).

**Maintenance workforce reliability**

During overhaul maintenance activity, the full-time cleaning maintenance workers had the highest maintenance workers’ reliability (Table 8). The period with the lowest maintenance workers’ reliability during overhaul maintenance activity was Period 3 (full-time electrical maintenance workers). However, none of the maintenance workers’ average reliability was less than 80% during overhaul maintenance activity (Fig. 7). The highest average maintenance workers’ reliability during overhaul maintenance activity occurred at Period 2 (0.9112), while Period 3 had the lowest average maintenance workers’ reliability (Table 8).

The full-time mechanical maintenance workers’ average reliability was the lowest when compared with those of other maintenance categories during overtime maintenance activity. A value of 0.8515 was obtained as the highest average maintenance workers’ reliability for a worker category (casual cleaning maintenance workers) during overtime maintenance activity (Fig. 7). During the six planning periods, the lowest maintenance workers’ reliability for overtime maintenance activities occurred at Period 4 (full-time cleaning maintenance workers). Period 5 had the highest maintenance workers’ reliability for overtime maintenance activities (Table 8). The average maintenance worker’s reliability for overtime maintenance activity was 83.13%.

The lowest maintenance workers’ reliability during rework maintenance activity occurred at Period 6 while Period 4 had the highest maintenance workers’ reliability during rework maintenance activity. A comparison of the values of the highest average maintenance workers’ reliability during overtime, overhaul and rework maintenance activity showed that Period 4 had the highest value during rework maintenance activity (Table 8). In terms of the average maintenance workers’ reliability for the different maintenance activity, the casual cleaning maintenance workers had the highest value, while the full-time electrical maintenance workers had the lowest value (Table 8).

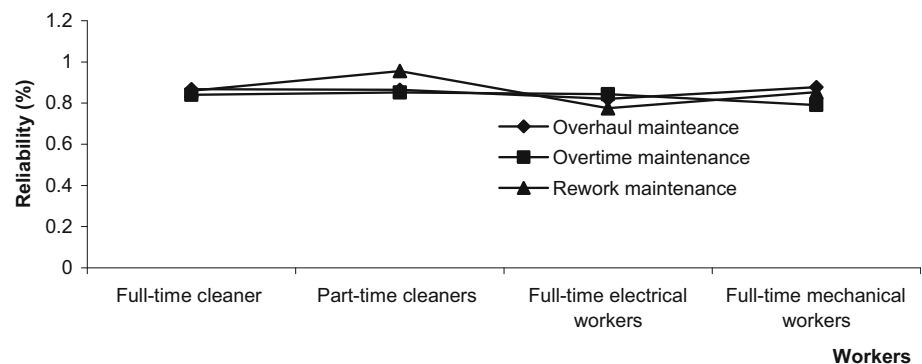
**Maintenance workforce availability**

During overhaul maintenance activity, the availability of the full-time and casual maintenance workers followed an alternating increasing and decreasing pattern from one period to another. The full-time electrical maintenance workers’ availability follows a steadily increasing pattern for the first four periods, after which a decline in their maintenance workers’ availability was observed during overhaul maintenance activity. The mechanical maintenance workers’ availability showed that it had an alternating increasing and decreasing patterns within the first three periods and then followed a steadily increasing pattern for the remaining periods (Table 9).

The maintenance workers’ availability results during overhaul maintenance activity showed that the casual cleaning maintenance workers had the highest number of time maintenance workers’ availability was more than 90% (five times). The full-time cleaning maintenance workers availability had only one period in which its maintenance workers’ availability was above 90%. The number of times in which the full-time electrical and mechanical maintenance workers’ availability was above 80% during overhaul maintenance activity was the same (two times). Equal number of maintenance workers’ availability that was less

**Table 8** Maintenance workforce reliability distribution for the different periods

Parameters	Variables	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
Overhaul maintenance	$R_{111t}$	0.9082	0.9044	0.8265	1.0107	0.7182	0.8393
	$R_{121t}$	0.7551	0.9568	0.7704	0.8113	0.8876	1.0021
	$R_{211t}$	0.8868	0.9077	0.7231	0.8050	0.9768	0.6193
	$R_{221t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$R_{311t}$	0.8242	0.8780	0.9320	0.8774	0.8188	0.9343
	$R_{321t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Overtime maintenance	$R_{112t}$	0.8850	0.7636	0.8659	0.5815	1.0310	0.9158
	$R_{122t}$	0.9763	0.8460	0.9215	0.8602	0.7433	0.7618
	$R_{212t}$	0.9920	0.8209	0.9516	0.9358	0.6728	0.6862
	$R_{222t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$R_{312t}$	0.7048	0.6960	0.7129	0.7756	0.8968	0.9531
	$R_{322t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rework maintenance	$R_{113t}$	0.8278	0.8249	0.8700	0.9286	0.8964	0.8099
	$R_{123t}$	0.9478	1.0689	0.9144	0.9340	0.9057	0.9640
	$R_{213t}$	0.7430	0.7171	0.9321	0.8511	0.6727	0.7355
	$R_{223t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$R_{313t}$	0.9595	0.7915	0.8153	0.9746	0.8082	0.7691
	$R_{323t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

**Fig. 7** Average reliability for the different maintenance workers

than 80% was obtained for the full-time cleaning and mechanical maintenance workers (two times). Furthermore, the casual cleaning and full-time electrical maintenance workers' availability that was less than 80% were the same (Table 9).

During overtime maintenance activity, only the full-time electrical maintenance workers did not have a period in which maintenance workers' availability was less than 80%. The full-time cleaning and mechanical maintenance workers as well as the casual cleaning maintenance workers had a period in which maintenance workers' availability was less than 80%. The full-time cleaning and electrical maintenance workers had equal number of maintenance workers' availability that was above 90% (two times) during overtime maintenance activity (Table 9).

The value of maintenance workers' availability that was above 90% during rework maintenance activities for the

different maintenance workers categories were the same. The number of times maintenance workers' availability values that was less and above than 80% for the full-time cleaning and electrical maintenance workers were the same. Furthermore, the casual and full-time mechanical maintenance workers had the same number of times in which maintenance workers' availability was less and above 80% (Table 9).

The model results for the maintenance workers' availability showed that for the different maintenance activities, the average maintenance workers' availability for all the worker classes was more than 80% (Fig. 8). None of the maintenance workers' availability of the different maintenance worker category during rework maintenance activity had a maintenance workers' availability value of above 90%. However, the casual cleaning maintenance workers had a value of maintenance workers' availability of above 90% during overhaul maintenance activity. Furthermore,



**Table 9** Maintenance workforce availability distribution for the various periods

Parameters	Variables	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
Overhaul maintenance	$a_{111t}$	0.7907	0.8871	0.8606	0.8911	0.7577	0.9578
	$a_{121t}$	0.9440	0.7979	0.9746	0.9122	0.9733	0.9298
	$a_{211t}$	0.7671	0.8690	0.9586	0.9887	0.9085	0.8455
	$a_{221t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$a_{311t}$	0.9084	0.9282	0.7735	0.7887	0.8273	0.8439
	$a_{321t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Overtime maintenance	$a_{112t}$	0.8158	0.9753	0.8849	0.9208	0.8145	0.7898
	$a_{122t}$	0.8032	0.8130	0.7755	0.8790	0.9512	0.8352
	$a_{212t}$	0.9518	0.8129	0.8695	0.8892	0.8715	0.9535
	$a_{222t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$a_{312t}$	0.9580	0.7944	0.8821	0.9676	0.8800	0.9396
	$a_{322t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rework maintenance	$a_{113t}$	0.9509	0.7844	0.8716	0.8245	0.8243	0.8322
	$a_{123t}$	0.8478	0.8777	0.8618	0.9858	0.7705	0.7498
	$a_{213t}$	0.9821	0.8911	0.7997	0.7691	0.8361	0.7474
	$a_{223t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$a_{313t}$	0.8497	0.7630	0.8764	0.8409	0.8499	0.9175
	$a_{323t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

the full-time mechanical workers’ availability during overtime maintenance activity was about 90% (Fig. 8). The expected average maintenance workers’ availability for a maintenance worker during overhaul (87.85%) and overtime (87.61%) maintenance activities were very close.

The full-time cleaning and mechanical maintenance workers’ availability for overtime maintenance activities was more than those of overhaul and rework maintenance activities. The casual cleaning and full-time electrical maintenance workers’ average maintenance workers’ availability for overhaul maintenance activity was more than those of overtime and rework maintenance activities (Fig. 8).

**Maintenance workforce efficiency**

During overhaul maintenance activity, it was only the casual maintenance workers that had a value of maintenance workers’ efficiency that was less than 80% (Period 2). The full-time electrical and mechanical maintenance workers had a period in which their maintenance workers’ efficiency was 100% (Table 10). The number of times in which the maintenance workers’ efficiency were more than 90% during overhaul maintenance activity for the full-time cleaning, electrical and mechanical maintenance workers were the same (four times). Apart from the full-time electrical maintenance workers, no other maintenance worker category had a value of maintenance workers’ efficiency that was up to 100% during overtime maintenance activity. The casual cleaning maintenance workers’ efficiencies during overtime maintenance activity were

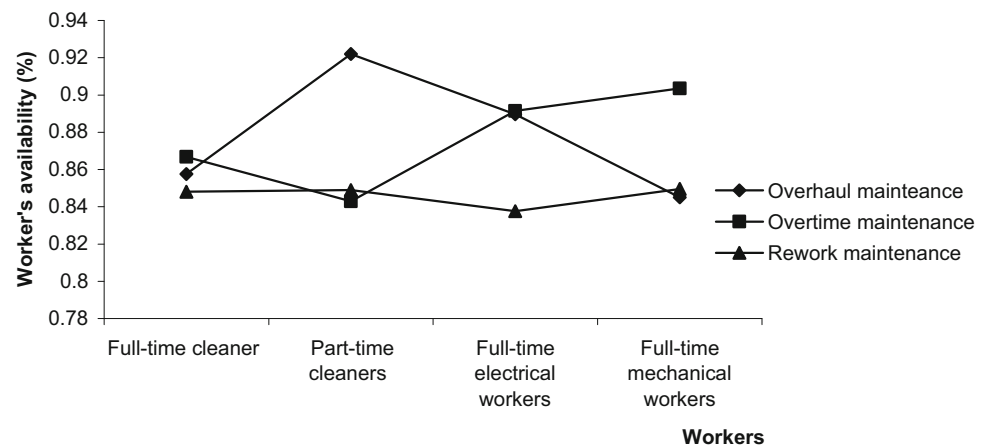
more than 80% for the different periods. The full-time cleaning maintenance workers’ efficiency had a value of about 83.33% that was above 80% for the different periods. The full-time mechanical maintenance workers had the highest number of times in which maintenance workers’ efficiency was above 90% (Table 10).

The results for rework maintenance workers’ efficiency showed that all the maintenance worker categories had a value of maintenance workers’ efficiency of 100% except the full-time cleaning maintenance workers. The number of times in which the full-time cleaning and electrical maintenance workers had a value that was above 70% (two times) and 80% (three times) was the same (Table 10). The full-time cleaning and mechanical maintenance workers had equal number of times in which the values of maintenance workers’ efficiency were less than 80%.

Furthermore, the casual cleaning and full-time electrical maintenance workers did not have a maintenance workers’ efficiency that was less than 80%. The casual cleaning and full-time mechanical maintenance workers had equal number of times in which the values of maintenance workers’ efficiency were more than 80% (three times) during rework maintenance activity.

The model results showed that the average maintenance workers’ efficiency for any of the periods for the different maintenance activities was above 80%. In Period 3, the highest value for average maintenance workers’ efficiency was obtained during rework maintenance activities. The lowest average maintenance workers’ occurred during overtime maintenance activities at Period 1 (Table 10). None of the maintenance worker category had an average

**Fig. 8** Average availability for the different maintenance workers



**Table 10** Maintenance workforce efficiency distribution for the various periods

Parameters	Variables	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
Overhaul maintenance	$p_{111t}$	0.9460	0.9601	0.8926	0.8866	0.9224	0.9222
	$p_{121t}$	0.9087	0.7846	0.9395	0.9013	0.9401	0.8139
	$p_{211t}$	0.8627	0.8610	0.8225	0.9366	0.8743	1.0076
	$p_{221t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$p_{311t}$	0.9782	0.9450	0.9571	0.8017	1.0009	0.9460
	$p_{321t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Overtime maintenance	$p_{112t}$	0.8717	0.8850	0.8152	0.8075	0.9670	0.8991
	$p_{122t}$	0.8535	0.8565	0.9047	0.9485	0.9254	0.8719
	$p_{212t}$	0.7905	1.0019	1.0145	0.9085	1.0076	0.9134
	$p_{222t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$p_{312t}$	0.8113	0.9035	0.9526	0.9658	0.9511	0.8749
	$p_{322t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rework maintenance	$p_{113t}$	0.9786	0.7960	0.8452	0.8521	0.9872	0.9109
	$p_{123t}$	0.9469	0.9009	1.0145	0.8552	0.8152	0.8737
	$p_{213t}$	0.9449	0.9348	1.0055	0.9372	0.8579	0.8428
	$p_{223t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$p_{313t}$	0.7416	0.8989	1.0146	0.8863	0.8821	0.9489
	$p_{323t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

maintenance workers' efficiency that were less than 85% for the different maintenance activities (Fig. 9). The highest average maintenance workers' efficiency among the different maintenance worker categories for the various maintenance activities was achieved by the full-time electrical maintenance (overtime maintenance activity). The full-time cleaning maintenance workers' had the lowest average maintenance workers' efficiency (overtime maintenance activity) when the different average maintenance workers' efficiencies were compared (Fig. 9).

### Quality of maintenance work done

The lowest quality of maintenance work done during overhaul maintenance activity was carried out by the full-

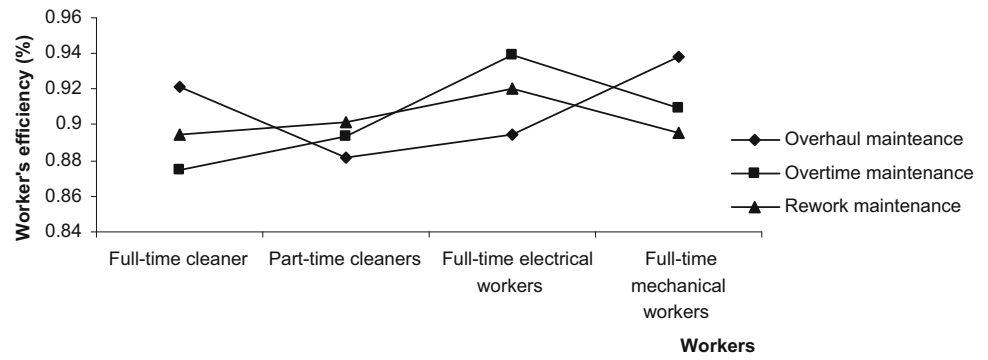
time cleaning maintenance workers (Period 5). However, they had the highest value of quality of maintenance work done during overtime maintenance activity. Furthermore, it was only the full-time cleaning maintenance worker category that had a value of above 85% for the quality of maintenance work done during rework maintenance activity (Table 11).

The casual cleaning maintenance workers were the only maintenance worker category which had three periods each for the different maintenance activities that were less than 70%. Furthermore, they had only one period (overhaul maintenance) in which the value of quality of maintenance work done was more than 90% (Period 1).

The full-time electrical maintenance workers were the only maintenance worker category which did not have a



**Fig. 9** Average efficiency for the different maintenance workers



value for the quality of maintenance work done that was less than 80% during overhaul maintenance activity. Also, they were the only maintenance worker category which had four consecutive periods in which the value for the quality of maintenance work done during overtime maintenance activity was more than 80%. Furthermore, they had a value for the quality of maintenance work done for four consecutive periods that was less than 80% during rework maintenance activity. The full-time mechanical maintenance workers were the only maintenance worker category which had at least a period in which the value of the quality of maintenance work done was more than 90%. The full-time mechanical maintenance workers had the highest value of quality of maintenance work done (Period 5) during overhaul maintenance activity (Table 11).

During overhaul maintenance activity, Period 1 had the highest workers' average quality of maintenance work

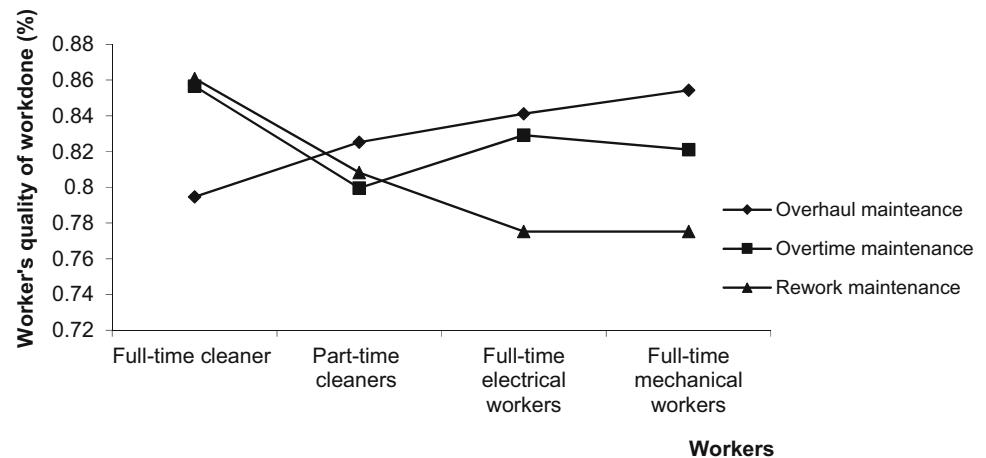
done for the maintenance workers, while Period 3 had the lowest value for the average quality of maintenance work done. The results for the average quality of maintenance work done by the maintenance workers during overtime maintenance activity showed that for the six periods, the value of the workers' average quality of maintenance work done was above 80%. The highest value for the workers' average quality of maintenance work done was recorded at Period 5, while Period 1 had the lowest value for the workers' average quality of maintenance work done during overtime maintenance activity (Table 11).

The value of the workers' average quality of maintenance work done during rework maintenance activities showed that it was only in four periods that a value of above 80% was recorded for the workers' average quality of maintenance work done (Periods 1, 2, 3 and 5). In Period 4, the lowest value for the maintenance workers' average quality of maintenance work done value was recorded

**Table 11** Quality of work done distribution for the different periods

Parameters	Variables	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
Overhaul maintenance	$q_{111t}$	0.8642	0.6689	0.8383	0.8277	0.6731	0.8955
	$q_{121t}$	0.9256	0.7969	0.8356	0.7333	0.8807	0.7797
	$q_{211t}$	0.8174	0.9361	0.8089	0.8482	0.8232	0.8131
	$q_{221t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$q_{311t}$	0.7957	0.8829	0.7963	0.9012	0.9365	0.8135
	$q_{321t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Overtime maintenance	$q_{112t}$	0.8331	0.8778	0.8623	0.9490	0.7989	0.8183
	$q_{122t}$	0.8448	0.7530	0.7424	0.8826	0.8065	0.7682
	$q_{212t}$	0.7468	0.8388	0.8408	0.8964	0.8598	0.7921
	$q_{222t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$q_{312t}$	0.8015	0.7762	0.7605	0.8619	0.9035	0.8235
	$q_{322t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Rework maintenance	$q_{113t}$	0.8667	0.8770	0.8684	0.8508	0.8757	0.8270
	$q_{123t}$	0.7794	0.8635	0.8220	0.7672	0.7547	0.8634
	$q_{213t}$	0.7640	0.8013	0.7746	0.7549	0.7991	0.7577
	$q_{223t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	$q_{313t}$	0.9413	0.9341	0.8926	0.7742	0.8713	0.6524
	$q_{323t}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

**Fig. 10** Average maintenance worker's quality of work done for the different maintenance activities



during rework maintenance activity when compared with other maintenance activities for the various periods. The value of the workers' average quality of maintenance work done during overtime maintenance activity was the highest among the various maintenance activities for the different periods (Table 11). The results for the average quality of work done by the different maintenance worker classes showed that they had values which were above 75% for the different maintenance activities (Fig. 10).

The full-time cleaning maintenance workers had the highest value for the average quality of maintenance work done (rework maintenance), while the full-time electrical maintenance workers had the lowest value of average maintenance work done (rework maintenance).

### Practical dimensions of the research and study implications for practice

This investigation offers significantly new and original knowledge in theory and practice of maintenance workforce optimisation. To this end, a number of implications of the research are discussed in this section. The current study, in an attempt to test the efficacy of the model developed, implemented a case study in the process industry and in particular, a brewery located in south-western Nigeria. This established the relevance of the model as well as the application steps for the FGP–DE-based optimisation framework presented in the current paper. It was affirmed that FGP–DE is employable for determining the optimal quantities in an efficient and cost saving manner since the variables are at their optimal thresholds. In practice, successful execution of such programmes as the FGP–DE framework implementation in the process industry requires the commitment of the maintenance manager as the anchor of the programme. However, from the scenario case study presented in this work, several important implications to maintenance managers emerge

clearly. Mainly, the results of this enquiry triggers noteworthy evidence, revealing that important and value-adding implementation of the FGP–DE framework is possible in the brewery industry. Nonetheless, the attainment of success in the programme implementation involves the totality of staff in the maintenance department, having a clear understanding that the implementation journey with success is not usually a straight-forward issue but a progressive in which steps are taken sequentially with care. The following should be noted:

- The FGP–DE framework implementation in the process industry is difficult, but could be systematically achieved.
- The analysis yielded an outcome which shows that the employment of return-on-investment concept in the FGP–DE framework was able to enhance the workforce performance. This innovative approach to human-side reliability evaluation and optimisation will impact on the management of the maintenance workforce. Since the work is computer-assisted, it showed how the FGP–DE approach may be harnessed to assist managers to proffer solutions to the continuous challenge being faced at work.
- Apart from the maintenance workforce reliability, which is a principal focus of the work, the analysis also revealed important measures of quality of maintenance work done, maintenance workforce efficiency, maintenance workforce availability and maintenance workloads. They are demonstrated to be of practical importance to the maintenance manager.
- The current paper reveals evidently that FGP–DE framework in the viewpoint of the Nigerian brewery industry, and that of process industries in developing countries in general, should be implemented in the circumstance of industrial environment. In addition, it aids scholarships, exposing increased insight of FGP–DE framework in the viewpoint of the developing nations, globally. In a nutshell, the current investigation



reveals outstanding implications from the perspective of theory and practice.

- A strong disposition in theory and practice relates to the fact that numerous situations of difficult control activities on the maintenance workforce are associated with the inability of the workers to appreciate maintenance as an income-earning function and not as bottomless-pit-of-expenses. Globally, this value-adding perception is expected to gradually erode the viewpoint of being in expenses all the time. As such, the maintenance workforce is linked to profit making. Following this background, the interacting complications of maintenance with return-on-profit as well as the optimisation variables of FGP-DE could be effectively understood by employing the optimisation approach of FGP-DE, which embeds a stochastic structure. This is a significant method to modelling maintenance workforce optimisation issues in a brewery plant, and by extension, the process plants in general.

Furthermore, this work is based on the strong belief that evolving largely efficient maintenance workforce schemes significantly enhance performance of work-systems. This may be achieved through modifications in current practice and models to involve the factor of return-on-investments, as reported in this work. Furthermore, some keys implications in the management and control of the maintenance arise as follows:

- It is acknowledged that managing the complex multi-factor maintenance system is difficult as inaccuracies in workforce determination, without considering all necessary variables will lead to sub-optimal results and wrong decisions. This step could jeopardise the progress of the manufacturing firm and poses a risk of survival for the company. This work therefore assists the maintenance manager on the correct selection of workforce progress; it helps in determining factors such as optimal return-on-workforce investment and the measure of the degree of maintenance goal attainment. Additionally, the work instils confidence in the maintenance manager to show colleagues, superiors and subordinates the nitty-gritty of the computations and the foreseen advantages of the method.
- A good implication of the results of this study is the need for amendment in the manner in which all future maintenance service team members should be trained, basically in the principle of return-on-workforce investment and goal-seeking behaviour in seeking maintenance targets.
- In this paper, a working interrelationship among maintenance managers (practitioner) and researchers in reliability engineering cybernetics as well as

behavioural scientists is created for the progress of the human reliability area.

## Conclusions

In this study, an enhanced multi-objective maintenance workforce optimisation model for maintenance workforce planning problem is presented. The presented model made use of an FGP-cum-DE approach. The FGP-cum-DE approach addresses the problem of incorporating decision-makers' opinions with respect to model objective function into an optimisation model. Based on a selected model from literature, the FGP-cum-DE approach generated satisfactory results for maintenance workforce reliability, efficiency, availability and quality of work done when tested with data from a brewery plant. This assertion was based on a comparative analysis of DE algorithm performance with those of GA and PSO algorithm. Furthermore, the FGP-cum-DE approach application can be easily be integrated into an existing optimisation model that is multi-objective. The method proposed in the current report probably will create an avenue for enhancing the decision-making capabilities of maintenance managers as information on the workforce planning is obtained in advance. So, the manager has a good control of budgetary plans and implementation. The built-up framework also provides a chance for maintenance managers to enhance their hiring and firing decision-making abilities, by hunting for candidates with the highest potentials of "return-on-investment". Employment of such candidates potentially puts the organisation at a technological advantage and a good chance to survive in these turbulent business times.

This study shows that the performance of DE algorithm in solving maintenance workforce optimisation is similar to those of GA and PSO algorithm. Although the current study considers an existing model, the FGP-cum-DE approach could be extended to other workforce models which were developed for manufacturing and service systems. The use of the FGP-cum-DE algorithm results in designing an expert system for maintenance workforce effectiveness or reliability could be considered as a further study. A limitation of the proposed FGP-cum-DE algorithm application is the use of range in selecting the DE algorithm parametric settings. More robust results await future analysts in further extending the foundation laid in this work according to the following issues, using the design of experiment as required. In addition, comparative analyses, which test the model using some new benchmark algorithms in the field of soft computing such as bat algorithm, bacterial foraging algorithm, colliding bodies



optimisation algorithm in solving the optimisation model would be more rewarding.

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## Appendix A

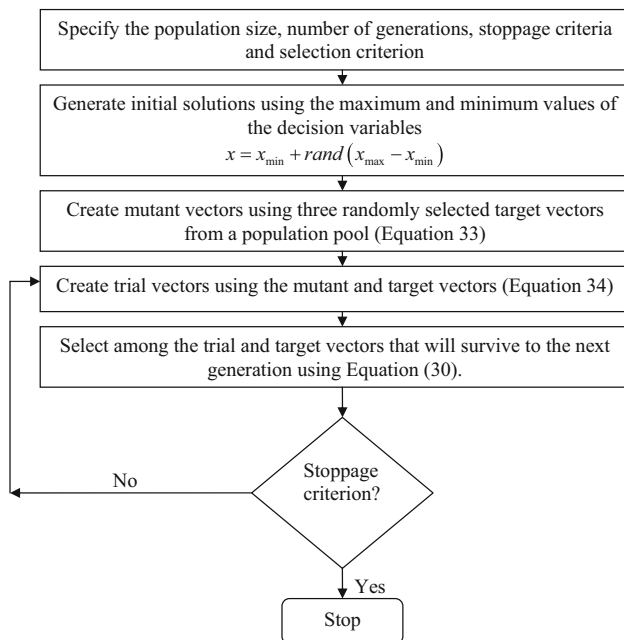
$x_{ijkt}$	Number of workers in maintenance section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$	$\hat{a}_k$	Minimum value of sectional workers' performance for maintenance activity $k$
$v_{ijkt}$	Earned-value expected of a worker in maintenance section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$	$\hat{b}_k$	Maximum value of sectional workers' performance for maintenance activity $k$
$w_{ijkt}$	Service time of a worker in maintenance section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$	$\tilde{a}_k$	Minimum value of quality of work done for maintenance activity $k$
$C_{ijkt}$	Unit cost of a worker in maintenance section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$	$\tilde{b}_k$	Maximum value of quality of work done for maintenance activity $k$
$RR_{ijkt}$	Reliability of a worker in maintenance section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$	$\bar{\alpha}_{kt}$	Confident level for workers availability of maintenance activity $k$ at period $t$
$x_{ijk,ave}$	Average number of workers expected in maintenance section $i$ belonging to worker category $j$ to be scheduled to carried out activity $k$ at period $t$	$\bar{\alpha}_{kt}$	Confident level for workers performance of maintenance activity $k$ at period $t$
$xx_{min,t}$	Minimum amount of maintenance workers required for overhaul, overtime and rework activities from section $i$ at period $t$	$\tilde{\alpha}_{kt}$	Confident level for quality of work done of maintenance activity $k$ at period $t$
$xx_{max,t}$	Maximum amount of maintenance workers required for overhaul, overtime and rework activities from section $i$ at period $t$	$f(\tilde{a})$	Probability density function for impact of training programme on rework maintenance time
$r_{kt}$	Expected workforce reliability for maintenance activity $k$ at period $t$	$f(\tilde{b})$	Probability density function for fatigue experienced during rework maintenance activities
$\lambda_{kt}$	Budgeted workforce cost for maintenance activity $k$ at period $t$	$f(\tilde{c})$	Probability density function for extra fatigue during rework maintenance activities
$\bar{\lambda}_t$	Total budgeted for rework, overhaul and overtime maintenance activities at period $t$	$W_{i4}^L$	Minimum amounts of rework workloads for maintenance workers in section $i$
$\mu_k'''$	Mean value for <i>WOE</i> expected for activity $k$	$W_{i4}^U$	Maximum amounts of rework workloads for maintenance workers in section $i$
$\sigma_k'''$	Standard deviation value for <i>WOE</i> expected for activity $k$	$\hat{a}_{ij41}$	Lower value of improvement in service time of a worker in section $i$ belonging to worker category $j$ that is required during rework maintenance activity
$\alpha_{kt}'''$	Confident level for <i>WOE</i> expected for activity $k$ at period $t$	$\hat{a}_{ij42}$	Upper value of improvement in service time of a worker in section $i$ belonging to worker category $j$ that is required during rework maintenance activity
$\hat{a}_k$	Minimum value of sectional maintenance workers' availability for maintenance activity $k$	$\hat{b}_{ij41}$	Lower value of fatigue experienced by a worker in section $i$ belonging to worker category $j$ that is required during rework maintenance activity
$\hat{b}_k$	Maximum value of sectional workers' availability for maintenance activity $k$	$\hat{b}_{ij42}$	Upper value of fatigue experienced by a worker in section $i$ belonging to worker category $j$ that is required during rework maintenance activity
		$\tilde{e}_{ij41}$	Lower value of experiential knowledge gained by a worker in section $i$ belonging to worker category $j$ that is required during rework maintenance activity
		$\tilde{e}_{ij42}$	Upper value of experiential knowledge gained by a worker in section $i$ belonging to worker category $j$ that is required during rework maintenance activity
		$f(\hat{a})$	Probability density function for impact of training programme on overtime maintenance time
		$f(\hat{b})$	Probability density function for fatigue experienced during overtime maintenance activities





$f(\hat{c})$	Probability density function for extra fatigue experienced during overtime maintenance activities	$\hat{a}_{ij22}$	Upper value of improvement in service time of a worker in maintenance section $i$ belonging to worker category $j$ that is required during overhaul activity
$W_{i3}^L$	Minimum amounts of overtime workloads for workers in maintenance section $i$	$\hat{b}_{ij21}$	Lower value of fatigue experienced by a worker in maintenance section $i$ belonging to worker category $j$ that is required during overhaul activity
$W_{i3}^U$	Maximum amounts of overtime workloads for workers in maintenance section $i$	$\hat{b}_{ij22}$	Upper value of fatigue experienced by a worker in maintenance section $i$ belonging to worker category $j$ that is required during overhaul activity
$\hat{a}_{ij31}$	Lower value of improvement in service time of a worker in maintenance section $i$ belonging to worker category $j$ that is required during overtime maintenance activity	$N$	Total number of worker category
$\hat{a}_{ij32}$	Upper value of improvement in service time of a worker in maintenance section $i$ belonging to worker category $j$ that is required during overtime maintenance activity	$M$	Total number of maintenance sections
$\hat{b}_{ij31}$	Lower value of fatigue experienced by a worker in section $i$ belonging to worker category $j$ that is required during overtime maintenance activity	$T$	Total number of planning periods
$\hat{b}_{ij32}$	Upper value of fatigue experienced by a maintenance worker in section $i$ belonging to maintenance worker category $j$ that is required during overtime activity	$K$	Total number of maintenance activities
$\hat{c}_{ij31}$	Lower value of extra fatigue experienced by a worker in maintenance section $i$ belonging to worker category $j$ that is required during overtime activity	$a_{ijkt}$	Actual number of days a technician in maintenance in section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$ is available in a maintenance system (days)
$\hat{c}_{ij32}$	Upper value of extra fatigue experienced by a worker in maintenance section $i$ belonging to worker category $j$ that is required during overtime activity	$\hat{a}_{ijkt}$	Planned number of days a technician maintenance in section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$ is available in a maintenance system (days)
$f(\hat{a})$	Probability density function for impact of training programme on overhaul maintenance time	$p_{ijkt}$	Actual performance of a technician in maintenance in section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$
$f(\hat{b})$	Probability density function for fatigue experienced during overhaul maintenance activities	$\hat{p}_{ijkt}$	Planned performance of a technician in maintenance in section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$
$W_{i2}^L$	Minimum amounts of overhaul workloads for workers in maintenance section $i$	$q_{ijkt}$	Actual quality of work done by a technician in maintenance in section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$ (kg)
$W_{i2}^U$	Maximum amounts of overhaul workloads for workers in maintenance section $i$	$\hat{q}_{ijkt}$	Planned quality of work done by a technician in maintenance in section $i$ belonging to worker category $j$ required for maintenance activity $k$ at period $t$ (kg)
$\hat{a}_{ij21}$	Lower value of improvement in service time of a worker in maintenance section $i$ belonging to worker category $j$ that is required during overhaul activity		

## Appendix B: DE algorithm flowchart



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